The Asymmetry in Responsible Investing Preferences

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ABSTRACT: We conduct an experiment designed to understand *how* social preferences affect investment decisions by observing subjects' stock allocations and probability assessments. Key to the design is that subjects' investment outcomes are treated by neutral, negative or positive payoff externalities on social causes. Our findings of asymmetric responses in probability perceptions and allocations suggest negative, but not positive, responsible investment (RI) externalities have significant effects. Thus, a taste for RI leads to significantly different investment choices, consistent with RI theory. Moreover, our results on probability perceptions and asymmetries between positive and negative treatments suggest important directions for accurately modeling RI tastes.

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Increasingly institutional investors are offering responsible investment (RI) products, which has attracted attention from regulators, practitioners, and academics. The growth of this approach, also termed environmental, social and governance (ESG) or sustainable and responsible investing (SRI), has been driven in large part by societal expectations arising from individuals' preferences. In particular, the products are a response to anticipated demand from millennials, who are expected to receive large transfers of wealth from baby boomers in coming years.[1] Yet questions arise as to why and how the social preferences of millennials and other investors affect their investment decisions. Two primary conceptual explanations exist for the incorporation of social preferences into investment decision-making. First, these preferences can affect investment decisions simply because they serve as a proxy for value-relevant information or risk. That is, social preferences conform to financial considerations because they enhance performance or reduce risk. Some supporting empirical evidence suggests that investors expect their social preferences to be aligned with higher returns or lower risks (e.g., Dimson, Karakas and Li, 2015, 2019; Hoepner, et al, 2018; Barber, Morse and Yasuda, 2020). Second, in an alternative, although not mutually exclusive, framework, social preferences affect investment decisions due to nonfinancial considerations – investors gain utility from aligning their investments with their social values; for example, by avoiding firms with unethical products or conduct. In fact, theoretical, empirical and experimental evidence suggests that nonfinancial considerations drive the linkage because some investors are willing to forgo returns in order to achieve their social preferences.[2] Moreover, many of these studies find that the heterogeneity across investors is an important aspect of the equilibrium in markets with responsible investors.

Although the evidence on financial and nonfinancial considerations helps us understand the motivations for RI better, we are still lacking an understanding of *how* these preferences enter into the investors' decision-making process. Consequently, in this paper we bring insights through an experimental setting in which we control for investors' information sets and test for the causal relationship between social preferences and investment decisions. In our experimental design, individual participants make investment decisions whose payoffs are linked to a set of societal challenges. Thus, their personal investment outcomes have

[1] See, for example, https://pewrsr.ch/2Op4i3b; https://go.ey.com/2XvjCiP; and https://bit.ly/2O1r5mS.
[2] See, for example, Heinkel, Kraus, and Zechner (2001), Reidl and Smeets (2017), Bonnefon, Landier, Sastry, and Thesmar (2019), Barber, Morse and Yasuda (2020), Bauer, Ruof, and Smeets (2020), Oehmke and Opp (2020), Pastor, Stambaugh, and Taylor (2020) and Pedersen, Fitzgibbons and Pomorski (2020).

externalities to nonprofits that focus on resolving the social challenges that they care about. Thus, if they wish, the participants can integrate their RI preferences with an investment objective of maximizing expected risk-adjusted returns. With this experimental setting, we unbundle the channels through which responsible investing is acting at the individual level. Specifically, we address the interrelated questions of whether responsible investing as an investment objective affects individuals' subjective likelihoods and beliefs about investing in a risky stock, whether it affects their risk attitudes, and ultimately whether it affects their investment strategies. Importantly, the setting allows us to control for beliefs – in our setting, across all treatments, the structure of payoffs from investment are identical.

Based on Kuhnen's (2015) experimental design, subjects receive an endowment to allocate between a risky stock and a risk-free investment (cash). The key element we introduce into this setting is a link between payoffs from the stock investment and payments made to causes. In particular, subjects select which nonprofit organizations they want linked to their investment returns. Depending on their personal priorities, they can choose among nonprofits that work on issues pertaining to animal welfare, environment, refugees, poverty, human trafficking and gender discrimination. Significantly, payments to the causes do not come out of subjects' payoffs or endowments but are furnished by the experimenters. Thus, "neoclassical" investors – those who care only about their own payoffs – would be insensitive to the link with a social cause.

The design incorporates three treatments based on the sign of the linkage between subjects' payoffs from the stock and payments to the causes. In the Neutral treatment, the two are unrelated (there are no payments to causes). In the Positive treatment, each dollar earned from the stock is matched by a contribution toward the cause. Thus, the more the subject earns from the stock, the more the nonprofit receives. In the Negative treatment, for each dollar earned from the stock, one dollar less is contributed to the cause. That is, the more the subject earns from the stock, the smaller the contribution to the nonprofit. In the Positive and Negative treatments, a subject may weigh how an allocation to the risky asset will impact both personal gain and the nonprofit goals with which they are most aligned.

The experiment has key design elements that allow us to draw causal inferences. First, the payouts to the nonprofits are paid by the experimenters, not the subjects. Thus, we abstract from the idea that stocks aligned with one's social preferences can provide higher returns (for example, due to avoidance of risk; e.g., Hoepner, et al, 2019) or lower returns (for example, due to a constrained investment opportunity set; e.g., Fabozzi, Ma and Oliphant, 2008). Consequently, the experiment provides us with a clear null hypothesis – allocations and beliefs should be similar across the different treatments.

Furthermore, we also investigate whether information about the stock's RI linkage impacts subjects' beliefs about the probability distributions of return. Following the design in Kuhnen (2015), the stock is known to be either one that pays high returns with high probability or one that pays high returns with low probability. Subjects are able to learn about a stock's true payoff distribution by observing its payoff over a sequence of rounds. In particular, given the information available at each round there exists an objective payoff distribution that is unrelated to the stock's RI linkage and that can be deduced by applying Bayes' Law. Before making each allocation decision, subjects are asked to report their beliefs about the probability that the stock they are facing is the high-paying one. Probability estimates that fall within a certain range from the true (i.e., objective) probabilities add to subjects' end-of-experiment payment. Kuhnen (2015) demonstrates that the deviation of elicited beliefs from the objective distribution can depend on whether payoffs are in a loss or gain domain. Our design incorporates and allows inferences regarding a similar link with RI information.

The two main outputs from the experiment are the individuals' choices on allocations to the stock and their stated beliefs regarding the stock payoffs. Our experiment documents a strong RI impact on both outputs. We find a significant effect from individuals avoiding negative RI externalities, relative to the baseline provided by the Neutral treatment, and this influence is both statistically and economically important. That is, we find a pronounced impact on the individual's asset allocation choice given the negative RI externality. In stark contrast, we find little internalization of positive RI externalities, providing us with asymmetric outcomes.

These findings are consistent with both academic research and practice. For example, our asymmetric results on preferences over negative versus positive externalities are consistent with Krueger's (2015) findings that market reactions to negative ESG information about firms are greater in absolute magnitude than market reactions to positive ESG news. The results also conform to what we observe in practice in the RI market where the avoidance of negative externalities is clearly seen in the predominance of negative screening in RI products. Indeed, the roots of responsible investment derive from negatively screening investments in order to avoid certain products or corporate behaviors that are viewed as harmful.[3] Although much of RI has evolved to include positive tilting toward companies that have better environmental, social and governance practices, negative screening still exists as many investors do not want to be complicit by holding stocks that have harmful products or objectionable corporate behavior. Examples of such decisions include no coal products (or even fossil fuels in general), no palm oil (because of destruction of forests), no tobacco, no alcohol, no companies that have human rights abuses or that violate labor rights. For example, the Norwegian sovereign wealth fund (the Government Pension Fund Global) invests sustainably but also excludes companies that they believe do not meet their ethical norms.[4]

Negative screening is also a predominant strategy in the United States as detailed in surveys conducted by the PRI and the US SIF.[5] For example, of the 86 U.S. investment managers who reported their screening technologies to the PRI, 91% use some type of negative screening strategy. In fact, 33% use only negative screening while 58% use negative screening combined with some form of positive screening.[6] Similarly, a recent US SIF survey finds that 66% of the managers use negative screening in their investment decisions (US SIF, 2018).

We also find significant heterogeneity across our subjects in their choices, both in terms of the magnitude of sensitivities to the RI information, and some investors also being sensitive to the positive RI externalities. This heterogeneity is consistent with theoretical literature on the equilibrium effects of responsible investing (Heinkel, Kraus, and Zechner, 2001; Pastor, Stambaugh and Taylor, 2020; Pedersen, Fitzgibbons and Pomorski, 2020) as well as with the empirical and experimental literature (e.g., Bauer, Rouf and Smeets, 2019; Bonnefon et al., 2019; and Brodback, Guenster and Mezger, 2019).

Beyond the results on changes in asset allocation caused by the negative externalities, our experiment reveals a surprising outcome in terms of the effects of RI preferences on investors' subjective beliefs. We find that RI information has some impact on the subjects' beliefs

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[3] See Renneboog, ter Horst and Zhang (2008b) for a description of the early responsible investors such as the Quakers during the 1800s who did not want gains derived from weapons or slavery.
[4] https://www.nbim.no/en/the-fund/responsible-investment/
[5] The PRI is an organization originally founded by the United Nations to support responsible investing. Similarly, the US SIF: The Forum for Sustainable and Responsible Investment seeks to advance sustainable, responsible and impact investing across all asset classes.
[6] We acknowledge the source of these data is the PRI and refers to the year 2018. The PRI has not reviewed the methodology, the data use or the conclusions in this paper that have been based on the PRI's data. We thank the PRI for providing us with these data.

regarding the probability distribution of the risky asset. Here too, the effect is driven by negative RI information.

These results, particularly the results regarding the effects of negative RI information on investors' asset allocations and beliefs, have implications for financial markets. As the percentage of RI investors grows in the economy, asset pricing will be affected by their allocation choices as has been shown both theoretically and empirically. For example, Heinkel, Kraus and Zechner (2001) provide theoretical evidence that if the percentage of green investors in the economy is large enough, asset prices would be affected because of the non-green stocks that they shun. Luo and Balvers (2017) also show how shunning of sin stocks would have the effect of driving these stocks' prices high, which has empirical support in Hong and Kacperczyk (2009). Similarly, Fama and French (2007) provide a simple theoretical framework to demonstrate that investor tastes, such as tastes for responsible investing, can distort pricing in asset markets. They show that these distortions in prices could be large under certain circumstances: when investors with particular tastes represent a substantial fraction of invested wealth; when the investors have such tastes for a wide range of assets; when investors' positions vary quite a bit from the market portfolio; and when the returns on the investors' underweighted assets are not highly correlated with the returns on their over-weighted assets. In other words, it is plausible to expect an impact on asset prices when responsible investors represent a substantial percentage of investors in the market.

Importantly, our study points to another potential channel impacting asset markets by RI investors. If the ability of individuals to infer the likelihood of outcomes is impacted by their RI preferences, asset prices would be affected beyond what is suggested in earlier theoretical work that focuses only on the impact of tastes on allocations. Here too, if a sufficiently large proportion of RI investors in the economy is sensitive to RI, beyond the asset allocation distortions, distortions could arise from the effective presence of "pessimistic" investors (see, for example, Scheinkman and Xiong, 2003).

Our study is related to earlier work in responsible investing on returns, flows and investor motivations. The question of whether responsible investing generates outperformance or underperformance has long been a heavily debated question, particularly with regard to causality. Theoretical arguments suggest that companies which exhibit more social responsibility should outperform.[7] This has often been tested using Sustainable and Responsible Investment (SRI) funds or the performance of firms judged to have high Corporate Social Responsibility (CSR) attributes. These studies have used short-term market reactions, valuation levels and long-run stock returns, but have come to disparate conclusions as to the value of such investment strategies.[8] In a meta-analysis of over 2,000 published empirical academic studies (in fields such as management science, finance, and economics), Friede, Busch and Bassen (2015) report that for those studies that examine return performance of firms, about 57% document a significantly positive relationship with CSR strategies and only 5.8% a significantly negative relationship, with the rest being either neutral or mixed in their results. In contrast, in studies that employ portfolios (such as SRI mutual funds or indices), the authors find that 15.5% document a significantly positive relationship with SRI strategies, while the majority of the studies find either no significant difference in returns or mixed results. Our work contributes by showing a strong link between investors' tastes (rather than outcomes) and their allocations, and that this link is somewhat asymmetric in being more strongly driven by negative RI association. This is consistent with the stronger evidence of sin stock outperformance (e.g., Hong and Kacperczyk, 2009), as compared to the mixed evidence found for strategies favoring SRI funds and CSR firms. Thus, our findings provide a way to interpret the array of evidence documented in a large and growing literature and point a way towards developing new theories.

Substantial work has examined the effects of RI concerns on mutual fund flows. For example, studies have generally found that responsible investing matters for fund flows as the flows into SRI/ESG funds tend to be stickier and have less performance sensitivity.[9] Our work contributes by showing experimentally how investor attitudes toward RI information affect allocations, holding constant the return distribution. This has a natural analogy in the mutual fund context in terms of fund flows. Further, our results showing the asymmetry in how individuals treat

[7] See, for example, Benabou and Tirole (2010); Baron (2007, 2008); and Albuquerque, Koskinen, and Zhang (2018).

[8] From some of the earliest research (e.g., Hamilton, Jo and Statman, 1993, which found no significant difference in the returns on SRI funds), studies have varied in their conclusions as to whether CSR/SRI/ESG attributes adds to corporate value and the risk premiums that can arise. See, for example, Edmans (2011); Humphrey, Lee and Shen (2012); Lins, Servaes and Tamayo (2017); Bolton and Kacperczyk (2019) among many others.

[9] See for example, Bollen (2007), Benson and Humphrey (2008), Renneboog, ter Horst and Zhang (2008a), Bialkowski and Starks (2018), and Hartzmark and Sussman (2019).

“negative” versus “positive” RI externalities are consistent with studies that find fund flows and stock market reactions are more strongly affected by negative RI events.[10]

Three recent studies, all of which are based on Dutch investors, examine investors’ choices of responsible investing strategies. Reidl and Smeets (2017) conclude that intrinsic social preferences and social signaling are the primary motivations and that while financial motivations enter into the decision-making, they play a relatively minor role. Brodback, Guenster and Mezger (2019) find a positive link between altruistic values and the relative importance of social responsibility to investors. They also find that the link strengthened under certain conditions: when individuals believe their investments can make a social or environmental impact or when they feel moral obligations regarding their investments. In contrast, the authors also find a link with egoism in that more egoistic investors avoid responsible investing. Lastly, Bauer, Rouf and Smeets (2019) conduct a field experiment in which Dutch pension participants are allowed to vote on whether the pension system will follow 3 or 4 of the sustainable development goals. They conclude that the choice of 66% of the participants to follow more of the goals, i.e., engage in more responsible investing activities, is based on nonfinancial rather than financial considerations. Whereas these papers seek to answer the question of *why* investors select into being RI investors, our work shows *how* the RI information is incorporated into investors’ decisions.

In a closely related contemporaneous study, Bonnefon et al. (2019) examine the private valuation assigned by MTurk subjects to direct giving to (or taking from) charities. They find that this private valuation is roughly linear in the small stakes considered. Moreover, private valuations do not significantly depend on whether or not a subject is pivotal to the giving (i.e., whether the amount the charity receives depends on actions taken by the subject). Our design is fundamentally different in that it incorporates and examines dimensions of quantity, uncertainty, and learning linked to the RI decision. On the other hand, we do not test for a difference between pivotal and non-pivotal treatments. Whereas both we and Bonnefon et al. (2019) find strong evidence that tastes matter in evaluating RI, they appear to find no evidence for the strong asymmetric results discovered in our setting.[11]

[10] See, for example, Bialkowski and Starks 2018; Hartzmark and Sussman 2019; Krueger 2015.

[11] The significantly smaller stakes employed in Bonnefon et al. (2019) for both subjects and charities might serve to mask a difference between the pivotal and non-pivotal treatments, or an asymmetry between the impact of negative versus positive charity payoffs.

Finally, we point out that a vast literature exists on "other-regarding behavior", mostly focused on strategic choice problems.[12] Although gain-loss asymmetry, introduced in Kahneman and Tversky (1979), is one of the most influential and persistent stylized facts in human decision making, the evidence we find for its social preference manifestation appears to be new.

I. Experimental Design

A. Description of experiment

Participants were told that they would be taking part in an experiment in decision-making, and their job would be to choose how to allocate an investment of 100 experimental currency units (ECU - equivalent to $10) between a risky stock and cash over six rounds. The stock could be one of two types, either a high payoff stock that would double with a probability of 2/3 and halve with a probability of 1/3 or a low payoff stock that would double with a probability of 1/3 and halve with a probability of 2/3. The participants were also informed that a computer would randomly choose one of these stocks, with equal probability, and the stock type would remain fixed for six rounds. Although the payoff would be disclosed, the stock type would not be disclosed. In each round, participants were told that they would be asked to estimate the probability that the stock is the high payoff type.

Participants were told that their payment at the end of the experiment would be randomly chosen from one of the rounds of the experiment. The payment would comprise a $7 participation fee, plus the total stock and cash payoff from the selected round, plus $1 if the stock-type probability estimate made by the participant was within 5% of the true probability.[13]

Before the round started, participants were asked to estimate the probability that they were facing the high payoff stock. The correct answer here is 50% as the computer would randomly choose the stock type with a 50% probability. Participants were asked to allocate 100 ECU between the stock and cash. A snapshot of the initial round allocation screen is displayed in panel A of Appendix 1.

[12] See Cooper and Kagel (2016) for a review.

[13] Subjects were told that, given the stock's track record, there is an objectively true probability that the stock is the high payoff type.

They were then told in that round whether the stock doubled or halved, and the total winnings from the round was displayed. Having observed whether the stock doubled or halved in the first round, participants were asked to again estimate the probability that the stock was high payoff and allocate 100 ECU between the stock and cash. This process was repeated for six rounds. In each round, participants were shown their probability estimate, their stock allocation, the stock outcome (whether it doubled or halved) and their winnings from the round. Panel B of Appendix 1 shows a snapshot of the outcome page after three rounds.

To encourage attentiveness, the experiment included prompts asking participants if they were sure of their decisions whenever they appeared to violate a monotonicity condition (under the assumption that they were not intentionally randomizing). For example, a prompt appeared if the stock outcome was "halved" and the participant *increased* either the estimated probability of, or the allocation to, the stock.

The experiment began with a six-round practice block to familiarize participants with the process. This practice block was then followed by what we henceforth designate the Neutral block, comprising two trials of six rounds, identical in construction to the practice round. At the beginning of each trial, the computer randomly chose whether the stock was high or low payoff, and participants then make a series of six allocation decisions and probability estimates. This Neutral block serves as our baseline against which to compare the remaining results in which we include participants' social preferences.

Once the participants completed the Neutral block, social preferences were elicited by asking participants to rank six social issues in order of importance to them. The six issues were: animal welfare, environment, refugees, poverty, human trafficking and gender discrimination. Participants were then taken to a screen where two non-profit organizations working in the area of their top ranked social issue were described and were asked to choose one of the non-profit organizations. This process was repeated for the second-ranked social issue. A snapshot of the social issues decision screens is in panel C of Appendix 1.

Participants were then told that their trading profits would be linked to payoffs to the chosen non-profit organizations. In the Positive blocks, an amount of money equal to the stock payoff *would be donated* to the chosen non-profit. In the Negative blocks, an amount of money equal to the stock payoff *would be deducted* from the chosen non-profit's donation account. It is important to note, as emphasized to the participants, that the amounts donated to (or deducted from) their chosen non-profit would not be affecting their own gains during the experiment. Each treated block consisted of two trials of six rounds. For each trial, the non-profit remained fixed, but the computer again randomly chose whether the subject faced the high or low payoff stock. Panels D and E of Appendix 1 show the instructions for the Positive and Negative blocks, respectively.

The experimental choice remained the same as in the Neutral block, in other words, participants faced six rounds in which they had to allocate 100 ECU between the stock investment and cash, and then estimate the probability of the stock being the high payoff stock. The only difference in these blocks is that stock payoffs now determine whether the non-profit received (lost) money in the Positive (Negative) blocks. Participant payments would be treated the same as in the Neutral block. Panels D and E of Appendix 1 display a snapshot of the outcome page after three rounds for the Positive and Negative block, respectively.

Although the Neutral block always came between the practice trial and the elicitation of social preferences, we randomized whether participants first faced the Positive block or the Negative block. We also randomized whether the first or second ranked social issue's non-profit was assigned to the Positive or Negative block. Within each block, the randomly selected non-profit remained fixed.

B. Description of subjects

We recruited 160 participants from the University of Texas at Austin (62 identified as male, 97 as female). The age of the participants ranged from 18 to 34 with a median of 20. Since we are particularly interested in the potential effects of millennials on asset markets, this age group is almost ideal. During our study period millennials ranged in age from 23 to their mid-30s. Most participants were students at the school, with 50 enrolled in business-related degrees, 39 in natural sciences, 19 in medicine, 16 in engineering, 10 in social sciences, and the remainder in arts/humanities, law, nursing, mathematics and communication.

II. Empirical Results

A. Overview

The two dependent variables that we analyze are the participants' probability estimates of the stock being of the high payoff type and their allocations (in ECU) to the stock investment. To analyze the treatment effect on each of these dependent variables we first compare their average levels across the three treatments (Negative, Neutral, and Positive), treating each subject-treatment as a single observation. This, of course, is the most conservative use of data as it ignores variation among the 12 observations within a subject-treatment.

In Table 1 we report the average level of the participants' estimates of the probability that the stock is the high payoff type. As the table shows, in Panel A, the RI conditions only have marginal effects on the participants' probability estimates as they are similar across the treatments at 46.7%, 49.0%, and 48.6% for the Negative, Neutral, and Positive treatments, respectively. We also report *t*-tests for the differences in probability estimates across the treatment cells and find that only the difference between the Negative and the Neutral conditions is significant at the 10% level (Panel B). There appears to be no significant difference between the Positive and the Neutral treatments.

In contrast, Panel C shows that differences across RI conditions are much more pronounced in the allocations to the risky stock: on average, subjects allocated 28.1, 36.7, and 39.0 (all out of 100 ECU) in the Negative, Neutral, and Positive conditions. That is, the average allocation to the stock is 23% lower in the Negative condition, relative to the Neutral one, but it is only 6% higher in the Positive condition, with the former difference being statistically significant at the 1% level and the latter only at the 10% level (Panel D).

Although the allocations are affected by subjective probabilities, the summary statistics provide evidence that RI considerations are affecting allocation to the stock above and beyond what can be easily explained by shifts in beliefs alone.

Table 1
Probability Estimates and Stock Investment Allocations

This table reports the means, standard deviations, and ranges of the participants' probability estimates that they were facing a high payoff stock and their choices regarding the stock investment allocations in each of the conditions, as well as tests for whether the estimates and allocations are different across conditions. "=Netural" and "=Positive" denote matched sample *t*-tests comparing with the Neutral and Positive treatments, respectively. p-values are reported for these tests.

Panel A: 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 B: p-values from matched sample *t*-tests on probability estimates

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

Panel C: 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 D: p-values from matched sample *t*-tests on stock allocation

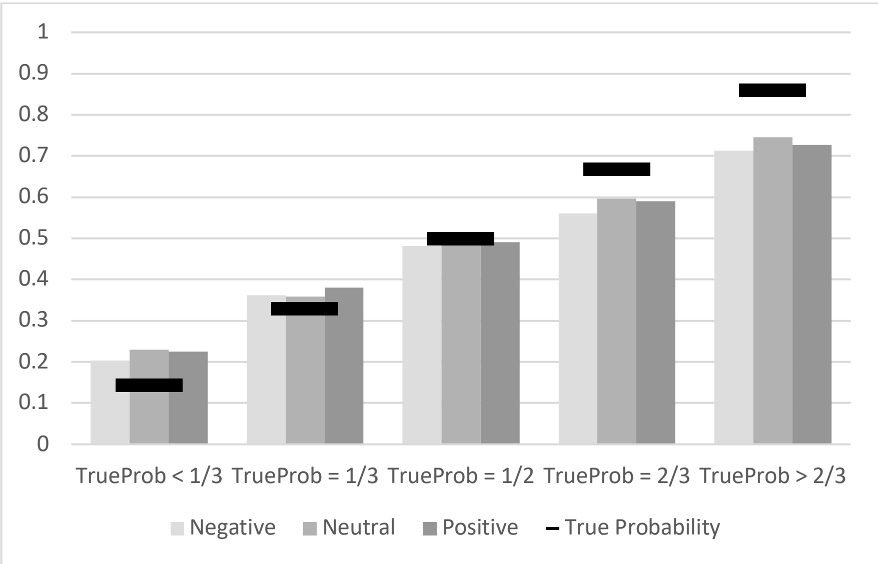
	Negative=Neutral	Negative =Positive	Positive = Neutral
Probability	0.0%	0.0%	7.1%

To help disentangle the effects, we first more closely examine the effects of RI on probability estimates and follow with a detailed analysis of the allocation decision. Before applying a more structured approach to the data, it is important to acknowledge that we assume weakly rational behavior on the part of the participants. By that, we refer to the existence, for each subject, of a (weakly) increasing function mapping objective to subjective probabilities, and they are assumed to have a (weakly) increasing function mapping their subjective probabilities with risky stock allocations. Of the 160 subjects, 25 were dropped since they violated one or both of these assumptions in the *Neutral* condition. We proceed by analyzing the data from the remaining 135 subjects.[14]

B. Probability Estimates

To examine the mapping of objective probabilities of the stock's type to subjective ones, we bucket observations based on objective probabilities, which by the nature of the experiment are clustered around discrete masses – below 1/3, exactly 1/3, exactly 1/2, exactly 2/3, and above 2/3.[15] The results are depicted in Figure 1, which clearly demonstrates patterns in the data.

Figure 1
Objective and subjective probabilities
This figure maps objective probabilities of the stock's type to subjective probabilities.



First, consistent with a large prior literature (e.g., Tversky and Kahneman, 1992, Abdellaoui, et. al., 2011, and Kuhnen, 2015), we find that subjective probabilities are "shrunk" toward the unconditional prior of 1/2. That is, when objective probabilities are less (more) than 1/2, subjective probabilities are too high (low). Second, we find that subjective probabilities in the *Negative* condition tend to be lower than the probabilities in the *Positive* condition. This difference is around 0.2 percentage points for both high and low objective probabilities.

[14] Note that this condition is based on the data collected only in the *Neutral* condition only and thus this filter is unlikely to bias our analysis.

[15] There are objective point masses at 1/3, 1/2, and 2/3, depending on whether the number of halving minus doubling outcomes in the history of draws is, respectively, 1, 0, or -1. The remaining possible objective probability assessments are either below 1/3 or above 2/3.

One formulation that captures how objective and subjective probabilities differ comes from Cumulative Prospect Theory. In particular, Prelec (1998) suggests the following two-parameter probability weighting function:

$$Subjective\ Prob = \exp\left(-\delta * (-\log(True\ Prob))^{\gamma}\right). \qquad (1)$$

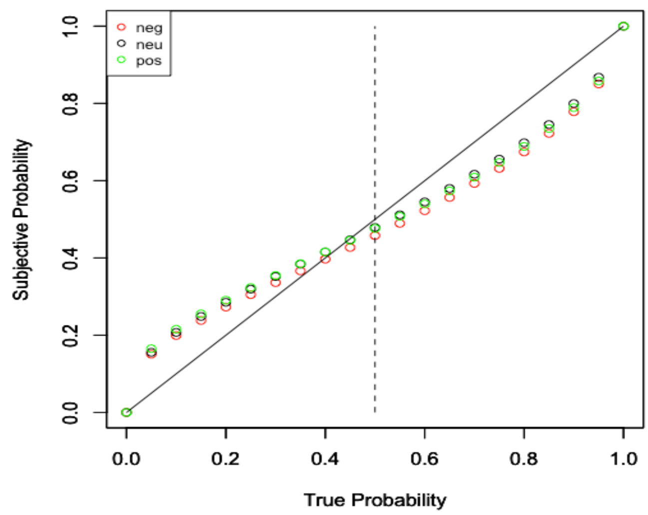
Over the range of observations, we can roughly think of δ as a level parameter, shifting subjective probabilities up or down relative to objective probabilities, and γ as a curvature parameter. We take this formulation to our data by fitting it with treatment dummies. That is, we allow both δ and γ to vary with the treatment.

With the baseline being the Negative treatment, we report in Figure 2 that the level of shift away from objective probabilities is statistically significant for both the Neutral and Positive treatments (D1 and D2 are statistically different from zero).

Figure 2
Cumulative Probability Function

This figure shows the maximum-likelihood estimation of equation (1) along with a plot that depicts the estimated parameters. Standard errors are in parentheses.

Variable	Estimate
D0	0.974
	(0.012)
G0	0.604
	(0.0167)
D1	-0.0484
	(0.0164)
D2	-0.0462
	(0.0164)
G1	0.0019
	(0.0236)
G2	0.0287
	(0.024)



It is easy to observe the treatment effect in the plot – the points associated with the Negative treatment lie below the ones associated with the Neutral/Positive treatments. The magnitude of these differences is similar suggesting no treatment effect when comparing the Neutral and

Positive treatments to each other. We also find no treatment effect for the curvature of the function (G1 and G2 are not statistically different from zero).

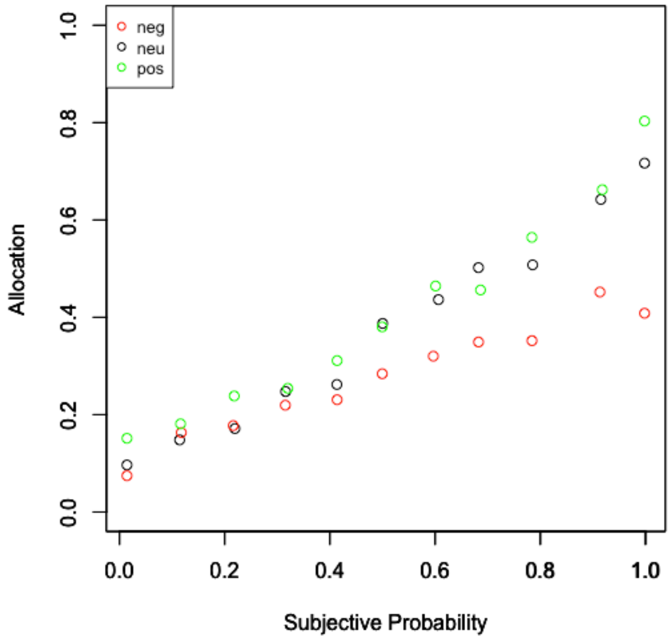
In Figure 2 we also plot subjective probabilities as a function of objective probabilities, for each of the treatments, based on the estimation procedure above. We can that subjective probabilities in the Positive and Neutral treatments are very close together, while these of the Negative treatment are consistently below, across the entire range of objective probabilities. The shift down, in the Negative treatment, appears to be similar across the range, consistent with the treatment effect on curvature being insignificant.

C. Allocations

Given that subjective probabilities are lower across the board in the Negative treatment relative to the Neutral/Positive ones, one may expect allocations that are uniformly smaller in the Negative treatment. To control for the impact on probability assessment and examine the treatment effects on allocation separately from their effects on probability estimates, we bucket allocation observations based on subjects' *reported* probabilities as illustrated in Figure 3.

Figure 3
Treatment Effects on Allocations

This figure shows the treatment effects on allocation (y-axis) against subjective probability estimates (x-axis). We group observations based on the subjects' reported rather than objective probabilities to control for allocation differences that may arise from different assessment of probabilities.



A number of suggestive patterns emerge from the plot. First, allocations under the Negative treatment are lower across almost the entire range of subjective probabilities compared with the Neutral or Positive treatments. Second, the effect does not appear to be uniform – instead, the difference between the allocations in the Negative treatment and the other treatments appears to increase as subjective probabilities increase. Finally, there appears to be little treatment effect on allocations when comparing the Positive condition to the Neutral one.

To test for these patterns more formally, we conduct several regressions. First, we regress allocations on treatment dummies corresponding to the subjective probability buckets. Second, we regress the allocations on treatment dummies as well as on treatment dummies interreacted with reported probabilities. All regressions include subject fixed effects. We first include all observations and then segment observations based on the range of reported probabilities.

Table 2 confirms some of the visual patterns observed in the mean allocations of Table 1: allocations in the Negative treatment are, on average 9.6 ECUs lower than in the Neutral treatment. The increase in allocation observed in the Positive treatment is 1.6 (=11.2-9.6) ECUs higher than in the Neutral treatment, and the difference is significant at the 5% level. Next, we observe that the Negative treatment effects on allocations increase as reported probabilities increase, rising from 5.1 ECUs in the low range to 8.2 ECUs in the middle range, and then to 11.7 ECUs in the high range. The Positive treatment effect is consistently larger than that of the Neutral treatment, but only significantly different for low probabilities (the difference is insignificant in the middle range and marginally significant in the high range).

When we further interact reported probabilities with treatment effects, controlling for subject fixed effects, we find similar patterns. Overall, there does not appear to be a constant treatment effect (the un-interacted treatment dummies). Instead, the treatment effects impact the slope of the mapping between probabilities and allocations. We find that the response of allocations to probabilities is much lower in the Negative treatment relative to the Neutral one: 0.381 vs. 0.589; a similar difference is observed for the Positive treatment.

Table 2
Stock allocations and probabilities

The table reports regressions of allocations to the stock on reported probabilities ("prob"), dummies for the Neutral treatment (factor(Block)Neutral) and the Positive treatment (factor(Block)Positive), and interactions between reported probabilities and the treatment dummies. Note that the Negative treatment is the baseline. Standard errors are in parentheses. All regressions include subject fixed effects.

	Dependent variable				
	ECU				
	(1)	(2)	(3)	(4)	(5)
	All	Prob<1/3	1/3<=Prob<=2/3	Prob>2/3	All
Prob					0.381***
					(0.023)
Factor(Block)Neutral	0.096***	0.051***	0.082***	0.117***	-0.012
	(0.008)	(0.018)	(0.008)	(0.023)	(0.017)
Factor(Block)Positive	0.112***	0.110***	0.093***	0.156***	0.018
	(0.008)	(0.018)	(0.008)	(0.022)	(0.017)
Prob:factor(Block)Neutral					0.208***
					(0.032)
Prob:factor(Block)Positive					0.182***
					(0.033)
Observations	4,500	815	2,918	767	4,500
R2	0.369	0.551	0.488	0.603	0.527
Adjusted R2	0.351	0.472	0.465	0.527	0.513
Residual Std. Error	0.219 (df = 4373)	0.175 (df = 692)	0.181 (df = 2791)	0.212 (df = 643)	0.189 (df = 4370)
					Note: *p<0.1; **p<0.05; ***p<0.01

D. Heterogeneity of Treatment Effects

The results so far focus on the average treatment effect across subjects. However, individuals may exhibit substantial heterogeneity, which may affect both the interpretation and the robustness of the results. A number of papers show that the fraction of agents that incorporate social preferences when making investment decisions is a critical determinant of equilibrium outcomes (e.g., Heinkel, Kraus, and Zechner, 2001; Pastor, Stambaugh, and Taylor, 2020).

The primary focus of this subsection is to study the degree of heterogeneity of the social preferences we observe. Put differently, do subjects exhibit heterogeneous treatment effects? Is the average treatment effect coming from a few subjects with very strong preferences combined with many other subjects with very weak social preferences?

To answer the question, we employ a framework that allows us to capture subject and treatment-level variations while accounting for the fact that subjects randomly face higher/lower probability draws in some treatments than others, and that errors may be heteroskedastic across treatments. We do that by estimating a treatment-subject random effects model that makes efficient use of our data. In a naïve approach we would regress allocations on estimated probabilities for each subject and treatment, but there exist two primary issues with that approach. First, such a specification ignores the fact that allocations are bounded and thus would result in predictions that go outside of these bounds. A simple utility model implies that the optimal allocation resembles a sigmoid function of the probability rather than a linear one. Second, a subject-by-subject regression analysis lacks power because we have only twelve decisions for each subject per treatment.

To address the first issue, we assume that the allocation ("ECU") can be approximated by a sigmoid function of the outcome probability. In other words, holding the treatment constant we assume that the following transformation of the allocation is a linear function of the probability:

$$ECU^T = -\ln\left(\frac{100}{ECU} - 1\right).$$

In our analysis, we Winsorize allocations at 1 and 99 because ECU^T is ill-defined at allocations of 0 or 100. To test the robustness of this choice, we changed the bounds of the Winsorization procedure to 5 and 95 and the results are virtually unchanged.

To address the issue of statistical power, we adopt a random effect framework that we estimate at the treatment level. That is, we allow each subject to have a different average level of investment (intercept) and a different allocation sensitivity to probabilities (slope) in each of the treatments. However, given that these effects are assumed to be drawn from a distribution whose mean and standard deviation we estimate, we end up estimating 12 parameters (= 3 (treatments) x 2 (moments) x 2 (intercept and slope)) instead of 960 (= 160 (subjects) x 3 (treatments) x 2 (intercept and slope)). That is, we estimate:

$$ECU_{i,n}^{T} = a_i + b_i Prob_{i,n} + e_{i,n}.$$

Where i denotes the subject ID, n is the round number, and *Prob* is the probability reported by the subject. We estimate this model three times, once for each treatment.

Before analyzing the distribution of treatment effects, we examine the estimation results reported in Table 3, which correspond to each of the treatments: the fixed (or average) effects, and the random effects (the covariance matrix for slope and intercept). Table 3 also reports the residual variance. First, consistent with prior results, we observe that in the Negative treatment, relative to the Neutral one, both the baseline allocation and the sensitivity to probabilities are lower. Thus, allocations are unambiguously lower in the Negative treatment relative to the Neutral treatment. The picture is not as clear when comparing the Positive treatment to the Neutral treatment, since the baseline allocation is higher but the sensitivity is lower. Second, the table shows that the slope dispersion estimate is larger in the Negative and Positive treatments, compared with the Neutral treatment. This result also strongly points to heterogeneous responses to the treatments across subjects. Third, we observe different levels of residual variation across the treatments.

The results in Table 3 document a strong and negative within-subject covariance between baseline allocation and sensitivity to probability. Because an increase in both measures is associated with higher allocations, this hinders further interpretation about behavior across treatments. To overcome this, we use the model estimates of each subject's intercept and slope parameters to calculate that subject's *expected allocations* in the treatment. We do this using the theoretical distribution of stock probabilities in the six rounds.[16]

[16] For example, a 50% probability that the stock is high is expected to be observed in 0.29 of the rounds: it is sure to be observed in all first rounds, in half of the of the third rounds, and in a quarter of the fifth rounds (and in none of the second, fourth, and sixth rounds), thus adding up we get 1/6+1/6*1/2+1/6*1/4 = 0.29.

Table 3
Random effects regression of transformed allocation on reported probabilities

The table reports random-effect regressions of transformed allocations on reported probabilities, ("Prob"), estimated separately for each of the treatments. Standard errors are in parentheses.

	(1)	(2)	(3)
Variables	Neutral	Positive	Negative
Prob	4.176***	3.994***	3.396***
	(0.295)	(0.337)	(0.362)
Constant	-2.757***	-2.511***	-2.984***
	(0.181)	(0.213)	(0.179)
var(Prob)	8.003	11.092	13.061
	(1.471)	(1.999)	(2.158)
var(_cons)	3.611	5.384	3.12
	(0.581)	(0.815)	(0.568)
cov(Prob,_cons)	-3.834	-6.172	-4.328
	(0.831)	(1.17)	(0.968)
var(Residual)	1.686	1.503	1.769
	(0.059)	(0.053)	(0.062)
Observations	1,920	1,920	1,920
Number of groups	160	160	160

Note: $*p<0.1$; $**p<0.05$; $***p<0.01$

Table 4 reports the average of this estimated expected allocation across all subjects in each of the treatments. Consistent with the results discussed before, we find that expected allocations are much lower in the Negative treatment (0.29) relative to the Neutral treatment (0.38). The allocation in the Positive treatment (0.41) is higher than in the Neutral one but the treatment effect is much smaller than we observe in the Negative treatment. To perform statistical tests for these differences, we apply a matched sample *t*-test, with p-values reported in Panel B of the table. We observe a statistically significant effect across all treatment cells at the 5% level. The effect that we observe in the Negative treatment is not just statistically but also economically very significant: going from an expected allocation in the Neutral treatment of 0.38 to 0.29 in the Negative treatment is almost a 25% reduction.

Table 4
Average allocation in each treatment

The table reports the expected average allocation in each of the treatments (see Table 3 for details); the bottom panel tests the null that allocations are the same across treatments using the expected allocation, per subject, as the unit of analysis.

Panel A: expected average allocations

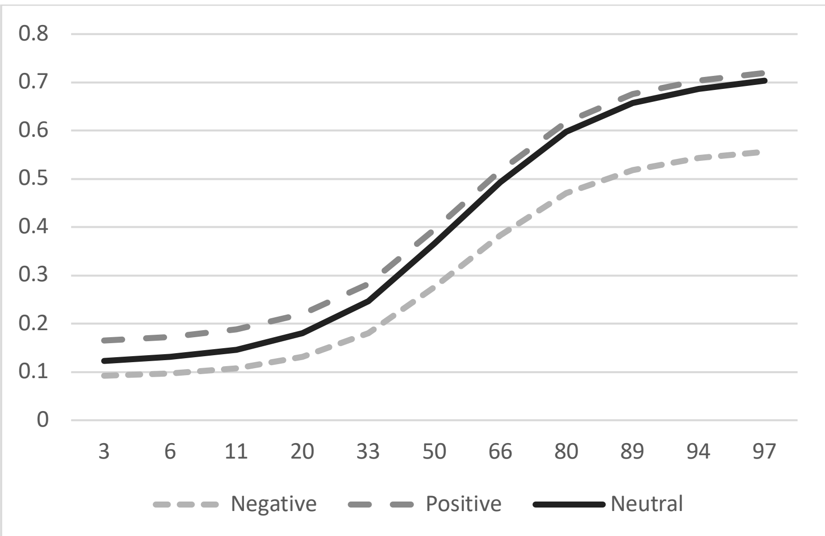
Variable	Obs	Mean	Std. Dev.	Min	Max
Exp_Neg_All	160	0.290	0.187	0.012	0.927
Exp_Neu_All	160	0.379	0.199	0.030	0.980
Exp_Pos_All	160	0.409	0.209	0.046	0.984

Panel B: p-values from matched sample *t*-tests

	Negative=Neutral	Negative =Positive	Positive = Neutral
Probability	0.0%	0.0%	2.0%

Another striking result comes out of plotting the expected allocations for each treatment across the spectrum of probabilities. Figure 4 shows that the estimated expected allocations are uniformly higher in the Positive treatment, and substantially lower in the Negative treatment, relative to the Neutral one. In addition, it appears that the Positive treatment effect is most pronounced when probabilities are low, compared to when probabilities are high, while the opposite is true for the Negative treatment effect.

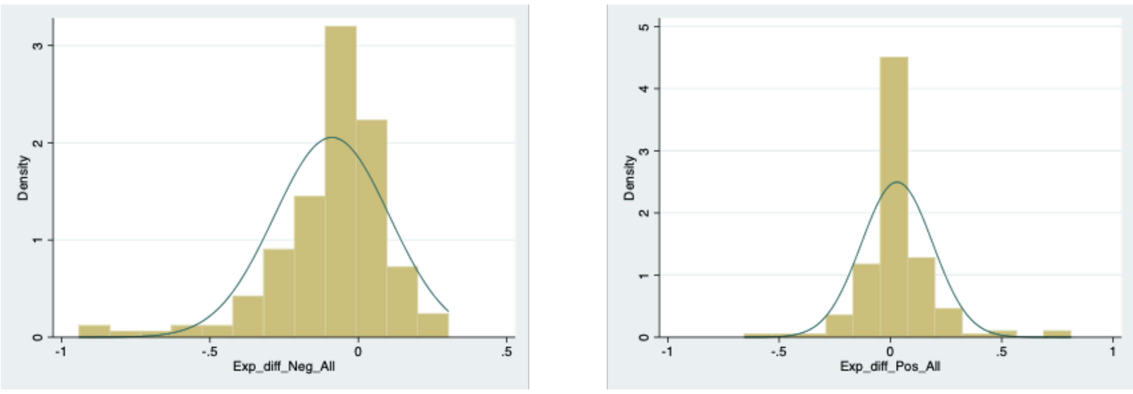
Figure 4
Expected Allocations Across Treatments



To study 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 allows us to compute one relative treatment effect number per subject. We plot the distribution of these relative treatment effects in Figure 5. Under the null that differences in behavior across treatments are noise, the distribution of relative treatment effects should be symmetric about zero. This is roughly true in the case of the Positive treatment but varies from that in the Negative treatment. In the latter case, the probability of observing 109 subjects out of 160 having lower allocation in the Negative treatment by chance is less than 0.01%. Thus, the treatment effect is not just strong in aggregate but also pervasive across subjects.

Figure 5
Distribution of allocations

The figure reports the distribution of allocation treatment effects, relative to the *Neutral* treatment, (see Table 3 for details).



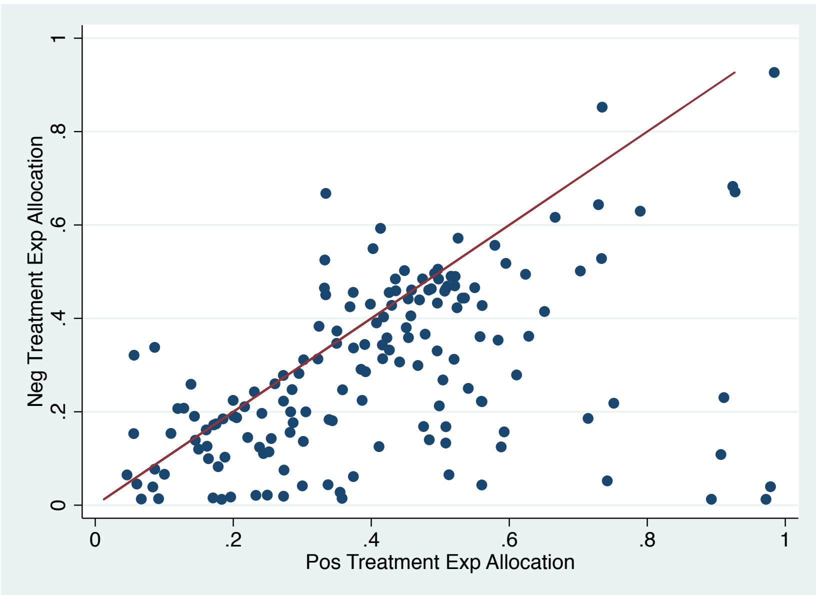
To further quantify the impact of treatment across subjects, we estimate from the model that over 20% of subjects reduce their allocation by more than 20% in the Negative treatment relative to the Neutral one. Interestingly, Bauer et al. (2019) find that a very similar fraction of individuals exhibits social preferences in their investment when they survey Dutch pension plan participants.

By comparison, the Positive treatment effect is present but much less pronounced. As Figure 5 suggests, the Positive treatment effect distribution is both much narrower, compared with the Negative treatment effect, and closer to zero. Overall, we find that 58% of subjects allocate more in the Positive treatment relative to the Neutral one.

Further insight into the difference in behavior across subjects can be obtained by plotting the expected allocation in the Negative treatment against the Positive treatment, by subject, against the 45-degree line (see Figure 6). 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, except for subjects that were estimated to allocate close to zero in the Positive treatment.

Figure 6
Expected allocations in positive and negative treatments

The figure reports the expected allocations in the Positive and Negative treatments (see Table 3 for details). Each dot corresponds to a subject.



E. Subject Demographics and Treatment Effects

At the end of each session, subjects were asked to provide anonymous demographic data. Given the differences in preferences for RI that have been reported in the media (which we discuss in the introduction), we are particularly interested in examining variations in the results according to these demographics. For example, the majority of subjects provided their gender, age, university major, and education level. We proceeded to regress the estimated subject-level treatment effects derived in the previous section against these characteristics. The main question to be answered by this analysis is whether demographic characteristics are associated with the degree to which the Negative and Positive treatments affect allocations.The results are reported in Table 5.

As the table shows, gender appears to play an important role in the difference in allocation across treatments. Of all subjects, 78 were women and 46 were men (1 subject preferred not to reply). We find that men allocate more in the Negative treatment than do women – i.e., are less affected by the Negative treatment than women. The effect is rather large, economically: male subjects allocate 4% less in the Negative treatment compared with the Neutral treatment, while female subjects allocate 12% less. Put differently, female subjects are three times more sensitive to the Negative treatment effect than male subjects.

Next we examine the potential influence of participants' ages, which ranged from 17 to 34 with a median of 20. This distribution is consistent with subjects being recruited at a university and results in a somewhat limited cross-section. Nonetheless, we find that older subjects are more likely to increase their allocation in the Positive treatment, relative to the Neutral treatment, compared with younger subjects.

Subjects reported a wide array of majors. Given prior literature suggesting that business students tend to exhibit differences in other-regarding behavior (see Baran, Sapienza, and Zingales, 2010), we codify majors into business (49 subjects), natural sciences (57 subjects), and other majors (44 subjects). In all, we find no difference in allocation between business and non-business majors.

Finally, we classify subjects into a group with a bachelor's degree (or higher) and into a group that includes those participants still in college or that had only lower level education. The results suggest that subjects who have a degree are more responsive to the *Positive* treatment than subjects that have lower levels of education.

Table 5
Demographics and treatment effects

This table reports regressions of expected allocation treatment (Negative/Positive) effects on the subjects' demographic characteristics: gender, age, major (business, natural sciences, and other), and education (bachelor's degree or higher and other). Standard errors are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	Negative	Negative	Negative	Negative	Positive	Positive	Positive	Positive
Gender	0.077**				0.015			
	(0.03)				(0.03)			
Age		0.010				0.015***		
		(0.01)				(0.01)		
Major(bus)			-0.026				0.014	
			(0.04)				(0.03)	
Major(sci)			-0.032				0.008	
			(0.04)				(0.03)	
Education				0.035				0.061**
				(0. 04)				(0.03)
Constant	-0.118***	-0.290**	-0.070**	-0.097***	0.024	-0.200***	0.020	0.016
	(0.02	(0.13)	(0.03)	(0.02)	(0.02)	(0.10)	(0.02)	(0.01)
Observations	159	160	150	160	159	160	150	160
R^2	0.038	0.015	0.005	0.005	0.002	0.053	0.002	0.025

Note: *p<0.1; **p<0.05; ***p<0.01

III. Conclusions

In this paper we employ an experimental setting in order to examine how social preferences influence individuals' investment decisions. We find that these preferences regarding responsible investing affect individuals' choices on allocations between a risky asset and cash as well as their subjective investment beliefs. Adapting the Kuhnen (2015) experimental design to focus on the effects of social preferences, our study participants confront a question of allocating funds between investments in a risky stock investment and a risk-free investment (cash) when their investment choices affect payments made to a nonprofit they select. Through their selection of a nonprofit, the individual participants are investing to support a chosen social issue which, depending on the treatment, serves to either align or drive a wedge between their social preferences and personal investment returns.

Our experimental results, which are designed to allow for differential choices regarding negative and positive RI externalities while keeping the strength of the externalities constant, demonstrate strong differential impacts on investor risk attitudes. Their asset allocation decisions indicate that investors are much more inclined to avoid the negative externalities of their investments than they are to embrace the positive externalities. Another novel experimental finding is that social preferences affect investors' subjective probabilities about their investments. Although the effect is modest, it reflects the importance that social preferences can have on how investors process information (e.g., update their beliefs). Our results that responsible investing preferences are driven by aversion to negative externalities rather than affinity for positive externalities are consistent with the prevalence of negative screening – an important component of the majority of responsible investing strategies.

Responsible investing has become an increasingly more important aspect of individuals' investment opportunity sets. Theory and empirical evidence demonstrated that growing tastes for responsible investing can impact asset pricing. Our findings help refine existing facts and insights by pointing to novel drivers of responsible investment.

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Appendix: Experiment Snapshots

Panel A: Initial round allocation screen

First Block, Trial One

You are about to begin a new trial consisting of six investing rounds.

The **computer will now randomly select the type of** stock you will be facing during this trial.
There is a **50% chance that the computer will select a high payoff stock** and a 50% that it will select a low payoff stock.

A **high payoff doubles with probability 2/3** and halves with probability 1/3.
A **low payoff stock doubles with probability 1/3** and halves with probability 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 B: 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 C: 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 D: 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 E: 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: