How Does Choice Affect Beliefs?*

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Abstract

We investigate how *choosing* one of two products influences beliefs about their quality. In a laboratory experiment, we deal with the endogeneity in choices by carefully constructing information that we provide to participants. This information is both sufficiently clear to allow us to predict choices and sufficiently unclear to leave room for participants to distort their beliefs about product qualities. Simultaneously, we vary the choice set and whether participants — after viewing both products — can choose a product or simply have one of the two products assigned to them. We find that choosing to own a product — rather than passively owning it — increases the perceived quality gap between owned and non-owned products (i.e., the *choice effect*). This *choice effect* is driven by non-chosen products. In particular, rejecting a product causes it to be perceived as worse than if that same product was simply not assigned to be owned. We show that having participants focus on product qualities before making their choice eliminates the *choice effect*, suggesting that attention is an important driver. The *choice effect* explains several empirical observations and provides support for active choice policies over opt-out defaults.

KEYWORDS: biased beliefs, ownership, behavioral economics, choice effect

JEL Classifications: D9, C91, G4

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1 Introduction

People tend to be optimistic about future events that make them better off. Entrepreneurs think their business is far more likely to succeed than a typical similar business (Cooper et al., 1988) and many CEOs hold optimistic beliefs about the future performance of their company (Otto, 2014). In line with these observations, previous research has documented that owning a product leads to more optimistic beliefs about its value. For example, investors overestimate their portfolio returns compared to both realized values and market performance (Merkle, 2017). In many important economic contexts, people choose the products for themselves (e.g., they *choose* which fund to invest in). We investigate whether an informed, active choice of one of two products changes beliefs about their quality. Using a lab experiment, we isolate the effect of *choice* from passive ownership and find that choice increases the belief difference between owned and not owned products (i.e., *choice effect*).

In addition to establishing causality between important primitives of economic analysis (i.e., choice and beliefs), we argue that the *choice effect* could also be empirically relevant in all markets where consumers make repeated purchase decisions (e.g., service providers, insurance companies, branded products, credit cards etc.). Since choice increases the belief difference between owned and not owned products, the *choice effect* makes consumers more reluctant to switch between product alternatives in any later decisions.

The findings also inform economic theory. Since choice itself does not convey any instrumental information, a change in beliefs about product qualities means that, at the minimum, one of the beliefs (i.e., beliefs before or after the choice) and corresponding valuations of the products are mistaken. This is not the case if choice was to only affect preferences.[1] Lastly, the *choice effect* has interesting policy implications. Recent research documents that default policies are significantly less effective in the long run than in the short run. For example, Beshears et al. (2018) study the effect of automatic enrollment on retirement savings over an eight-year horizon. They find that withdrawals and borrowing against savings offset approximately 40% of the positive effect of

[1] If choice only affects valuations via changing preferences, then choice itself doesn't affect whether the valuations are correct. In our experiment we shut down the role of preferences by design, hence, can analyze whether choice affects beliefs.

automatic enrollment. Our results suggest that active choice policies may be more effective policy tools than opt-out defaults.[2]

In the experiment, we construct 12 products that we refer to as portfolios. In each of four consecutive rounds, participants observe a set of two portfolios. Each portfolio pays off at the end of the experiment with a fixed but unknown probability. The participants' main task is to estimate these payoff probabilities. We use a between-subjects design where participants – for all four rounds – either receive one of the portfolios (*Allocation* condition) or choose one of the portfolios (*Choice* condition). Participants know they will get a reward if the portfolio they own – chosen or received – pays off. The key challenge is that we cannot directly impose a choice on participants. Instead, we aim for participants to make a non-trivial choice that we are still able to predict. Our solution is to provide a strong signal about the *relative ranking* of the portfolios to participants in both conditions. In addition, we vary the choice set, such that the same portfolio is sometimes paired with a worse alternative and sometimes paired with a better alternative. Thus, the variation in the choice set introduces exogenous variation in whether the same portfolio is chosen or not. Therefore, we can use the objective ranking of the portfolios to predict choice with high accuracy. Indeed, 90% of our participants managed to choose the better portfolio. At the same time the *absolute level* of payoff probabilities remains sufficiently uncertain, so there is room for belief distortion.

The main concern with simply comparing beliefs about chosen and not-chosen portfolios is reverse causality: participants choose a product because they think it is the better one. Hence, it is expected to bias the estimate of the effect of choice on beliefs upwards. By providing information that allows participants to learn which of the two portfolio is the better one and varying the choice set we introduce exogenous variation in choice. Of course, beliefs about a portfolio quality might be higher when it is compared to a worse as opposed to a better alternative (i.e., *contrast effect*).[3] We can account for this effect using the *Allocation* condition that allows us to control for ownership,

[2] Rather than setting an option as a default, policymakers could try to make people choose that option instead. Of course, the benefit of using an active choice policy — as opposed to a default — depends on whether policymakers can set up the decision environment such that people choose the default option by themselves.

[3] The contrast effect is a cognitive bias that enhances the difference between things when we make a comparison between them. For example, the same color is perceived to be lighter when it is surrounded by a darker background. In the economic domain, Hartzmark and Shue (2018) find a contrast effect in the perception of earnings news for investors who receive these news sequentially.

while having an exogenous variation in the consideration set. After accounting for the contrast effect, being the better portfolio in the *Choice* condition serves as an instrument for choice. Therefore, we can measure the effect of owning a portfolio through choice. *Ownership effect* itself predicts that participants are more optimistic about owned portfolios even when ownership is not determined by the participants' own choice. We can measure this effect as well, as the *Allocation* condition allows us to control for the consideration set, while having an exogenous variation in ownership. Finally, the *Allocation* condition and *Choice* condition comparison allows us to measure the *choice effect* (i.e., the increase in belief difference between owned and not owned portfolios as a result of choice). This effect can be broken down into two parts: the effect on beliefs about chosen versus received portfolios and the effect on beliefs about non-chosen versus non-received portfolios.

We find that the total *choice effect* is 5.1 percentage point and it is almost fully explained by non-chosen portfolios. In particular, rejecting a portfolio causes it to be perceived as worse than if that same portfolio was simply not assigned to be owned. There is a sizable *contrast effect*: beliefs are 5 percentage point higher when the portfolio is compared to a worse as opposed to a better alternative, controlling for ownership. Interestingly, our data does not feature the *ownership effect*, we do not find statistically significant difference between beliefs about received and non-received portfolios.

To learn about the mechanism, we add two treatment conditions: *Delayed Choice* and *Ego Choice*. In the *Delayed Choice* condition participants choose a portfolio but we shift their attention from choosing to estimating the payoff probabilities. In particular, the choice buttons only appear on the screen after participants recorded their estimates. Importantly, participants know ahead of time that they have to choose, hence, the intervention only affects the order of reporting beliefs and choice. In the *Ego Choice* condition, participants — before making a choice — read an excerpt about the relationship between a high IQ and better asset choice. The rationale behind this manipulation is to increase the perceived ego-relevance of choice.[4]

We find that the *choice effect* disappears when the participants record their estimates first and indicate their choice in the subsequent screen (i.e., *Delayed Choice* condition). When an excerpt

[4] A similar manipulation was used by Drobner and Goerg (2024) to study how perceived ego-relevance of a task matters for belief updating about relative performance.

about the relationship between a high IQ and asset choice is provided (i.e., *Ego Choice* condition), the *choice effect* is slightly larger (5.7 pp). It comes — almost equally — from *pessimism* about non-chosen and *optimism* about chosen portfolios. The total *choice effect*, however, is not significantly different from the *choice effect* in the baseline *Choice* condition.

This paper builds on recent research that explores different drivers of belief distortions (Mayraz, 2013; Coutts, 2019).[5] We contribute to this research in two ways: First, we find that after controlling for ownership, making a choice leads to additional belief distortions. Second, we show evidence that choice can affect beliefs about a portfolio which is not even in one's possession. Namely, there is *pessimism* about non-chosen portfolios compared to having the same portfolios not received.

The mechanism we identify helps explain empirical observations in a number of domains. First, recent work in behavioral finance has shown that investors are more likely to hold on to their losing assets if they chose the assets themselves. Evidence comes both from observational data (Chang et al., 2016; Calvet et al., 2009; Ivković and Weisbenner, 2009; Jin and Scherbina, 2010) and experiments (Lehenkari, 2012; Summers and Duxbury, 2012). While this pattern is robustly documented, the mechanism behind it is not yet well understood. Our contribution is to provide clean evidence on a belief-based mechanism that can explain this observation. Our results suggest that investors who made the choice themselves become more pessimistic about the fundamentals of other assets and, given these beliefs, they will be less willing to switch. On the other hand, our results do not explain a related finding, that investors sell winning assets too early.

Second, consumers often fail to switch to better offers even in markets where products are similar. Examples include credit cards (Ausubel, 1991; Stango, 2000), mutual funds (Hortaçsu and Syverson, 2004) or social security insurance (Hastings et al., 2017). Our results suggest the novel explanation that consumers stick to their chosen products because they became more pessimistic about the non-chosen alternatives. We expect this effect to be especially prevalent in markets in which the choice set contains a few items that do not change over time. Moreover, even if there

[5] People have also been found to be overoptimistic in ego-related settings. For example, they tend to overestimate their performance in IQ tests (Eil and Rao, 2011; Mobius et al., 2014; Exley and Kessler, 2018; Zimmermann, 2020), or underestimate how selfish their behavior is (Di Tella et al., 2015; Exley, 2016; Exley and Kessler, 2018; Dezső and Loewenstein, 2019). Others, however, focusing on the effect of ownership, find no significant asymmetry in belief updating in the financial domain (Barron, 2021; Hartzmark et al., 2021). The psychology literature investigates the effect of choice on how preferences are constructed after the choice (Simon et al., 2004).

are many options, consumers may start by choosing between groups of products. For example, when purchasing a new smartphone, consumers may first decide which producer to buy from before selecting a specific product.

The paper proceeds as follows. First, we describe the experimental design in Section 2. Then, we discuss the empirical strategy in Section 3 and present the results in Section 4. Finally, we conclude in Section 5.

2 Experimental design

2.1 Setup

First, we describe how we constructed the financial products. There is an imaginary economy, populated by firms. Each firm makes either a profit or a loss. Firms are divided into two industries, which we denote here for simplicity as A and B. Each industry contains the same number of firms but they differ in the share of profitable firms. In the experiment these shares are set to $p_A = 0.5$ and $p_B = 0.3$. While participants do not observe the shares, they can learn that $p_A > p_B$.

A financial product in this economy is a portfolio that contains shares of N firms. Let N_A and N_B denote the number of firms from industry A and B, respectively. Each firm is randomly selected from its industry. A portfolio pays a fixed amount if the number of profitable firms is at least K and pays nothing otherwise.

In the experiment, participants complete four rounds. In each round, they observe a pair of portfolios with the same N and K but different N_A. The key feature is that the payoff probability is increasing in N_A if $p_A > p_B$ (holding N and K constant). Participants only need to understand this relationship to figure out the *relative ranking* of the portfolios and to make a good choice. However, there remains significant uncertainty about the *absolute level* of the payoff probabilities.[6]

[6] This setup reflects the complexity of real-life ambiguous situations, allowing participants to form subjective beliefs that are meaningful, rather than approaching it as a straightforward calculation exercise. The payoff probability of a portfolio is given by the following formula:

$$P(\lambda \geq K) = \sum_{k=K}^{N} \sum_{i=0}^{k} \binom{N_A}{k-i} \binom{N_B}{i} {p_A}^{k-i} (1-p_A)^{N_A-(k-i)} {p_B}^{i} (1-p_B)^{N_B-i}, \tag{1}$$

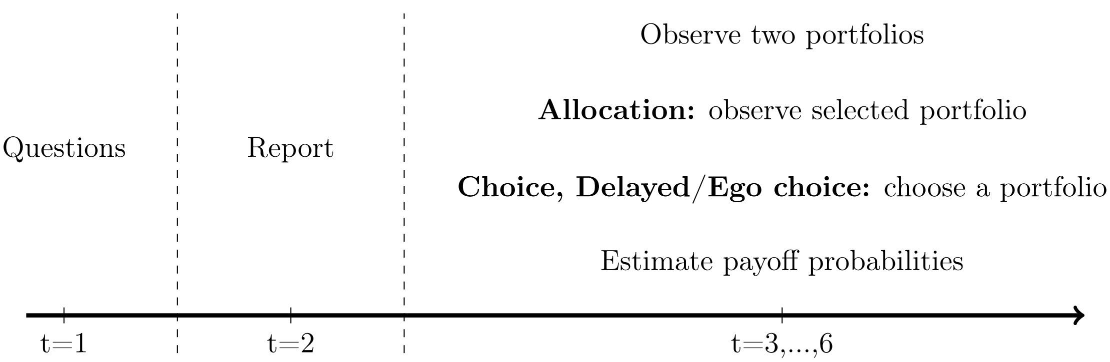
where λ denotes the number of profitable firms. Participants do not have all the necessary information as they do not observe p_A and p_B.

We vary N and K across rounds and construct three portfolios by varying N_A within rounds.[7] We label the resulting portfolios as Low, Medium, and High in increasing order of N_A. In each round, participants observe either a {Low, Medium} or a {Medium, High} pair. As a result, participants should choose the Medium portfolio in some cases (when it is compared to the Low portfolio), while they should not choose it in other cases (when compared to the High portfolio).

2.2 Timeline

We use a between-subjects design where we randomly assign participants into the *Allocation*, *Choice*, *Delayed Choice* or *Ego Choice* conditions. The experiment has three stages. Figure 1 shows the timeline.

Figure 1: Timeline



After participants are familiarized with the instructions through examples and control questions,[8] in the *Questions* stage, they have to answer three economics-related questions. They are told that they will see a report containing the name of one of the two industries, however, the informativeness of this report depends on their performance in the following way: if they give at least two correct answers, then they will receive a perfectly informative report. That is, the report will contain the name of the industry that has the higher share of profitable firms.[9] If they fail to give at least two correct answers, then they might receive a less informative report. Specifically, participants are told the report does not necessarily select the industry with the higher share of

[7] Table A4 in the Appendix provides a detailed description of the portfolios.

[8] They have to answer all control questions correctly to proceed in the experiment. If they give an incorrect answer, they have to try again. See Appendix E for the actual instructions participants received.

[9] We label industries with the openly made-up names of Eclipse and Rosepaw. We randomize these labels.

profitable firms. The reason for including the *Questions* stage is to strengthen the link between knowledge and the ability to make a good choice. As a result, participants do not make a blind or absolutely trivial choice: they know which portfolio to choose because they were smart enough to give correct answers. We believe that an important distinction between real choice and blind choice is the *reason* why one can be proud of having made the right choice: luck or knowledge. On the one hand, if a blind choice turns out to be a good choice (a randomly picked product has a high quality) then one can be proud of being lucky. On the other hand, if a real choice turns out to be a good choice (an intentionally selected product has a high quality) then one can be proud of being smart.[10]

In the *Report* stage, participants observe the content of the report. Importantly, they do not know whether they will receive the fully informative or the potentially less informative report. Hence, the portfolio with more of the industries mentioned in the report is weakly more likely to be the better one. As a result, participants can easily infer the *relative ranking* of the portfolios in the choice set. While figuring out the *relative ranking* is an easy task, it is not possible to determine the true payoff probabilities from the information provided. That is, there is room for belief formation. We elicit the beliefs of participants about the likelihood that the report correctly identifies the industry that has the higher share of profitable firms. We emphasize that the experiment is identical across conditions until the end of the *Report* stage. It ensures that participants in the *Choice* condition do not put more effort into answering the three economics-related questions to increase the chance of receiving the informative report.

The *Portfolio evaluation* stage consists of four rounds. In each round, participants observe two portfolios with different industry compositions (N and K are the same within rounds). We also give them information about the magnitude of the payoff probabilities: the payoff probability of a benchmark portfolio where each firm is randomly selected regardless of its industry. In the *Allocation* condition, participants randomly receive one of the two portfolios. In the *Choice* condition, participants have to choose between one of the two portfolios. To learn about the mechanism of

[10]In a recent paper, Hartzmark et al. (2021) study the effect of ownership on learning. They report no difference between exogenous product allocation and blind choice (when participants make a choice from a set of identical products). Besides focusing on instantaneous beliefs instead of learning, our design is different in that participants make an informed choice.

belief distortion due to choice, there are two additional treatment conditions. The third treatment condition, called the *Delayed Choice* condition, serves the purpose of diverting participants' attention from the act of choosing to estimating the payoff probabilities. Participants know ahead of time that they have to choose a portfolio, the only difference compared to the *Choice* condition is that participants can indicate their choice only after they have estimated the payoff probabilities. The fourth, and last treatment condition is the *Ego choice* condition. It differs from the *Choice* condition only in that it provides subjects with the information that people with higher IQs tend to choose assets that are more likely to provide high payoffs. Additionally, participants are asked to keep information in mind until the end of the experiment. The rationale behind this treatment condition is to potentially increase participants' perception of the ego relevance of their choice. Hence, it allows us to test whether ego relevance contributes to the size of the *choice effect*.

Importantly, participants are informed that they will earn a £3 bonus[11] at the end of the experiment if their own portfolio pays off in a randomly selected round. For all participants, we elicit incentivized beliefs about the payoff probabilities for both portfolios.[12] Figures 2 and 3 show the portfolio evaluation screen in the *Allocation* and *Choice* conditions, respectively.

[11] It is equivalent to $4.25.

[12] We use the Becker-DeGroot-Marschak method adapted to elicit probabilities (Grether, 1981; Karni, 2009), and set the reward to £0.5. Participants are told that we are incentivizing them to tell the truth. They can also click on a link that explains the procedure in detail.

Figure 2: Portfolio evaluation screen in the *Allocation* condition

Information

- Each portfolio **contains 6 firms** and **pays off if at least 3 firms make a profit.**
- Recall, the report says that **the Eclipse industry has better outlook.**
- The computer **randomly selected Portfolio 1** for you. Remember, you can earn **£3.00** if this portfolio pays off.

Questions

For each portfolio, estimate the chance that it pays off.

- Hint: A hypothetical portfolio, where each firm is **randomly selected regardless of its industry**, would pay off with **46%** chance.

	Firm 1	Firm 2	Firm 3	Firm 4	Firm 5	Firm 6	Chance of paying off (%)
Portfolio 1	Eclipse	Eclipse	Rosepaw	Rosepaw	Rosepaw	Rosepaw	
Portfolio 2	Eclipse	Rosepaw	Rosepaw	Rosepaw	Rosepaw	Rosepaw	

Figure 3: Portfolio evaluation screen in the *Choice* condition

Information

- Each portfolio **contains 5 firms** and **pays off if at least 2 firms make a profit.**
- Recall, the report says that **the Eclipse industry has better outlook.**

Questions

1. **Indicate which portfolio you would like to choose** by using the buttons in the table. Remember, you can earn **£3.00** if the portfolio you choose pays off.
2. For each portfolio, estimate the chance that it pays off.
   - Hint: A hypothetical portfolio, where each firm is **randomly selected regardless of its industry**, would pay off with **66%** chance.

	Firm 1	Firm 2	Firm 3	Firm 4	Firm 5	Chance of paying off (%)
Portfolio 1	Eclipse	Eclipse	Eclipse	Rosepaw	Rosepaw	
Portfolio 2	Eclipse	Eclipse	Eclipse	Eclipse	Rosepaw	

2.3 Implementation

2.3.1 Data collection

We pre-registered the experimental design, the hypotheses, and the empirical strategy in the American Economic Association's Randomized Control Trials Registry (ID: AEARCTR-0005974). The experiment was run using the experimental software oTree (Chen et al., 2016). We recruited participants through Prolific, a crowdsourcing platform designed specifically for academic studies. A very useful feature of Prolific is that it allows the researcher to pre-screen participants on various dimensions. We made two sets of restrictions. First, participants needed to be located in the US and to speak English as a first language in order to minimize language barriers. Second, we only considered participants who had answered basic demographic questions when they registered on Prolific. As we had access to these answers we did not have to include them in the experiment.

We posted the study on July 9, 2020. The participation fee was set to £2. On average, participants completed the experiment in 16 minutes and earned £4 (including bonuses). The relevant number of participants who completed the experiment is 993.

2.3.2 Treatment assignment

We assigned the treatment status in two steps. First, each participant was assigned to one of the four conditions. Table 1 shows that 362 participants ended up in the *Allocation* condition and 340 participants in the *Choice* condition. The *Delayed Choice* condition had 143 participants while the *Ego Choice* condition had 148.

Second, in each of the four rounds in the *Allocation* condition one of the two portfolios was selected for each participant. In order to increase statistical power by making the *Allocation* condition similar to the other conditions, we set the probability of receiving the better portfolio to 80%.[13] It was important to randomize whether Portfolio 1 or Portfolio 2 was the better one. Participants were only informed that they could have received Portfolio 1 or Portfolio 2 with equal chances. Therefore, observing the received portfolio did not contain information about its likelihood of paying off.

[13] Of course, the exact fraction does not affect the empirical strategy. However, for reasons of statistical power, we wanted to get close to the fraction in the *Choice* condition, so we therefore based this number on our pilot.

Table 1 shows that participants in the *Allocation* condition received the better portfolio in 79% of cases.

Table 1: Treatment assignment

	Allocation	**Choice**	**Delayed Choice**	**Ego Choice**
Number of participants	362	340	143	148
With better portfolio	79%	90%	92%	94%
Choice is consistent with beliefs		95%	98%	96%

In Table 1 we also report statistics on the choices. Participants in the *Choice* condition chose the better portfolio in 90% of cases and slightly even more frequently in the *Delayed Choice* and *Ego Choice* conditions. The participants' choices were mostly consistent with their stated beliefs. In the *Choice* condition, participants chose the portfolio that they estimated as having a (weakly) higher payoff probability in 95% of cases and slightly more often in the other two treatment conditions involving a choice.[14]

2.3.3 Balance tests

During the instructions, participants had to answer 10 control questions in total. They could proceed to the next screen only if the answer was correct. While participants could complete the control questions by random guessing, we observe very few incorrect submissions (less than one, on average). This indicates that those who completed the experiment understood the setup well and quickly. In the *Report* stage, 93% of the participants managed to answer at least two of the three questions correctly. On average, they estimated that the reported industry is the good industry with 79% probability. As both the *Questions* stage and the *Report* stage preceded the treatment assignment, we expect no difference across treatment conditions neither between these variables nor in personal characteristics and this is indeed the case.[15]

[14] Similar to the comparison between the *Allocation* and *Choice* conditions, the exact fraction of correct choices does not affect the empirical strategy.

[15] The only significant difference is that participants in the *Ego Choice* condition report slightly lower income than participants in the *Allocation* condition. See Table B1 in the Appendix.

3 Empirical strategy and hypotheses

We think about the timing of forming/altering beliefs and choice as the following. Participants form beliefs about the two portfolios in the choice set and choose one of the two portfolios. As a result of this choice, participants potentially inflate their beliefs about the chosen and deflate their beliefs about the non-chosen portfolio. It's important that even prior to choice, the same portfolio may seem more likely to pay off if it is compared to a worse as opposed to a better portfolio (i.e., *contrast effect*). This contrast effect is identified from the *Allocation* condition that varies whether the medium portfolio is paired with a better or a worse alternative.

When participants decide which portfolio to choose, they may self-select into owning a portfolio based on their beliefs, even if it is not objectively superior. To address this selection bias, we use whether the portfolio is objectively the better quality in the choice set as an instrument for ownership, assuming that this quality influences beliefs only through the participant's choice, while controlling for portfolio-specific characteristics and contrast effects (Assumption 1).[16] By varying the choice set in the *Choice* condition, we introduce exogenous variation in which portfolio is objectively better, thus affecting the likelihood of selection. Therefore, the choice effect is identified from the between choice set variation.[17]

Assumption 1. *For the same pair of portfolios the contrast effect is the same regardless of whether participants have a choice or not. That is, on top of the contrast effect, being the better portfolio affects beliefs only through affecting choice.*

Importantly, the unit of observation for this empirical strategy is a portfolio-participant pair (i.e., a participant and a portfolio out of the two portfolios she sees). The effect of ownership through allocation on beliefs (i.e., *ownership effect*) is identified from the *Allocation* condition, that varies whether the same portfolio is assigned or not assigned.

[16] In the experiment, participants face identical portfolio pairs, ensuring consistent comparisons.
[17] See the analytical discussion in the Appendix.

To understand the empirical strategy better, consider first the following difference-in-differences regression:

$$Belief_{ij} = \beta_0 + \beta_1 Own_{ij} + \beta_2 Own_{ij} \times Choice_i + \beta_3 Choice_i + \beta_4 Better_{j,-j} + \alpha_j + \varepsilon_{ij}, \quad (2)$$

where $Belief_{ij}$ is participant i's belief about portfolio j, Own_{ij} is a dummy for owning the portfolio (either via assignment or via choice), $Choice_i$ is a dummy for being in the *Choice* condition, $Better_{j,-j}$ is a dummy for portfolio j being the better portfolio in the portfolio pair participant i sees, and α_j is a portfolio fixed effect.

Then, *Ownership effect* is measured by β_1. β_2 measures the difference between the effect of ownership with choice and allocation (*choice effect*). We can decompose the total effect into *pessimism* about non-chosen portfolios compared to non-received portfolios (β_3) and *optimism* about chosen portfolios compared to received portfolios ($\beta_2 + \beta_3$). Finally, β_4 measures the *contrast effect*.

However, Own_{ij} is endogenous in Equation 2. Recall that ownership is determined randomly in the *Allocation* condition, therefore endogeneity comes entirely from the *Choice* condition. We can instrument ownership with being the assigned portfolio in the *Allocation* condition and being the optimal choice in the *Choice* condition. It is random which portfolio is assigned in the *Allocation* condition and whether a portfolio is the better one in the *Choice* condition. Since participants indeed choose the better portfolio in most cases, we know that it allows us a strong first stage. Combining these considerations, we use the following instrument for Own_{ij}:

$$Own^*_{ij} = Own_{ij} \times (1 - Choice_i) + Better_{j,-j} \times Choice_i \quad (3)$$

Similarly, Own^*_{ij} with the $Choice_i$ directly gives us the instrument for $Own_{ij} \times Choice_i$:

$$Own^*_{ij} \times Choice_i = Better_{j,-j} \times Choice_i \quad (4)$$

We estimate Equation 2 by using instruments (3) and (4) for Own_{ij} and $Own_{ij} \times Choice_i$, respectively. The exclusion restriction is described in Assumption 1.

Medium portfolios are the better ones around 50% of the time and the worse ones around 50% of the time making a restricted sample to Medium portfolios balanced with respect to the — now exogenous — probability, $\widehat{Own}_{ij} \times Choice_i$, of owning the portfolio in the *Choice* condition. In addition, Low and High portfolios do not have a within portfolio variation in $\widehat{Own}_{ij} \times Choice_i$ in the Choice condition. For these reasons, our preferred specification is the IV regression on the restricted sample, that includes beliefs about only the Medium portfolios.[18]

We predicted the following hypotheses:

Hypothesis 1. *(Choice effect) Compared to assignment, choice increases the difference in beliefs about payoff probabilities between owned and not-owned portfolios* ($\beta_2 > 0$).

Hypothesis 2. *(Optimism) Choice increases beliefs about payoff probabilities of chosen portfolios compared to received portfolios* ($\beta_2 + \beta_3 > 0$).

Hypothesis 3. *(Pessimism) Choice decreases beliefs about payoff probabilities of not-chosen portfolios compared to not-received portfolios* ($\beta_3 < 0$).

While it is not the focus of this paper, our framework allows us to test auxiliary hypotheses on the effect of ownership without choice and on the *contrast effect*.

Hypothesis 4. *(Ownership effect) Beliefs about received portfolios are greater on average than beliefs about non-received portfolios (*$\beta_1 > 0$*).*

Hypothesis 5. *(Contrast effect) Controlling for ownership, beliefs are greater on average if the portfolio is compared to a worse alternative than if it is compared to a better one (*$\beta_4 > 0$*).*

[18] In addition, the Medium portfolios, with the objective probabilities being in the middle range, offer more scope to distort beliefs. While we think that the restricted sample provides a cleaner test for our hypotheses, we would like to be transparent that the restriction was not part of the registered pre-analysis plan.

4 Results

We estimate Equation 2 by OLS and IV and report the results in Table 2. The standard errors are clustered at the individual level. We use the IV strategy with the sample restricted to Medium portfolios (Column 3) as the baseline specification.[19]

Table 2: Main results

	(1)	(2)	(3)
Dependent variable: Belief	OLS	OLS	IV
Better	3.804***	4.511***	5.104***
	(0.897)	(1.088)	(1.246)
Own	2.037**	0.974	0.630
	(0.736)	(1.218)	(1.263)
Own × Choice	5.935***	5.991***	5.065**
	(1.105)	(1.614)	(1.879)
Choice	-4.450***	-4.543***	-4.079**
	(1.021)	(1.329)	(1.397)
Observations	5616	2808	2808
R^2	0.377	0.218	0.217
Portfolio FE	Yes	Yes	Yes
Sample		Medium	Medium

Notes: This table reports the coefficient estimates for Equation 2. The unit of observation is a participant × portfolio. The baseline is non-received portfolios, hence, the coefficients are percentage point differences showing the estimates of contrast effect, ownership effect, choice effect and pessimism, respectively. Column 1 uses the full sample while Column 2 and Column 3 restrict the sample to only Medium portfolios for which participants had more space to distort beliefs. Column 3 presents the IV estimates. Standard errors are in parentheses and clustered at the individual level.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

We find a large and significant *contrast effect* showing that participants' beliefs about a portfolio are 5.1 pp higher when the portfolio is paired with a worse as opposed to a better alternative. This makes up for the total belief difference between received and non-received portfolios resulting in

[19] While we believe that the restriction is methodologically justified and necessary, we would like to note that it was not part of the pre-analysis plan. Nonetheless, we added the regression results to the appendix (Table C3).

a small and non-significant *ownership effect*. There is a *choice effect*, that is, choosing a portfolio increases the difference between beliefs about the same portfolio by 5.1 pp when the portfolio is owned compared to when it is not. The *choice effect* comes almost entirely from *pessimism* about non-chosen portfolios compared to having the same portfolio not received. Namely, beliefs are 4.1 pp lower when the portfolio is not chosen than having the same portfolio not received.

As a next step, we estimate the effect for both delaying the choice and making the choice more ego relevant by including observations from all treatment conditions. In the extended specification, we have separate dummy variables for the *Choice*, *Delayed Choice*, and *Ego Choice* conditions and we construct the instruments analogously to Equation 3 and Equation 4. As a result, the identification assumptions are also similar: we assume that the *contrast effect* is the same across all treatment conditions.

We report the estimates in Table 3. Observe that the previous estimates are robust to including observations from the *Delayed Choice* and *Ego Choice* conditions. The coefficient on Own $\times$ Delayed Choice shows the *choice effect* separately for the *Delayed Choice* condition. It is small and not significant in most specifications, indicating that delaying the choice counteracts the baseline *choice effect*. We included a manipulation check question at the end of the experiment to assess the results from the *Delayed Choice* condition. Specifically, we asked participants how much they had focused on comparing the portfolios rather than estimating the payoff probabilities separately. Table C2 reports the results. Participants in the *Choice* condition concentrated more on comparing the portfolios than participants in the *Allocation* condition. Participants in the *Delayed Choice* condition are in between these two groups, but the difference from the *Choice* condition is not statistically significant (p-value = 0.16).

Table 3: *Choice effect* with all four treatment conditions

Dependent variable: Belief	(1) OLS	(2) OLS	(3) IV
Better	3.261***	5.060***	5.136***
	(0.820)	(0.978)	(1.248)
Own	2.551***	0.644	0.600
	(0.741)	(1.189)	(1.265)
Own × Choice	6.173***	5.903***	5.061***
	(1.092)	(1.606)	(1.879)
Choice	-4.573***	-4.499***	-4.077***
	(1.017)	(1.326)	(1.397)
Own × Delayed Choice	3.944***	1.470	1.801
	(1.244)	(1.850)	(2.224)
Delayed Choice	-1.835	-0.668	-0.830
	(1.380)	(1.550)	(1.640)
Own × Ego Choice	4.803***	4.597**	5.717**
	(1.486)	(2.108)	(2.448)
Ego Choice	-1.873	-2.071	-2.625
	(1.222)	(1.599)	(1.711)
Observations	7944	3972	3972
R^2	0.377	0.215	0.215
Portfolio FE	Yes	Yes	Yes
Sample		Medium	Medium

Notes: This table reports the coefficient estimates for a regression analogous to Equation 2, but this time including the observations from the *Delayed Choice* and *Ego Choice* conditions as well. The unit of observation is a participant × portfolio. The baseline is non-received portfolios, hence, the coefficients are percentage point differences showing the estimates of contrast effect, ownership effect, choice effect and pessimism, respectively. The estimates of the interactions of *Own* and the different choice dummies show the choice effect separately in the three choice conditions. Column 1 uses the full sample while Column 2 and Column 3 restrict the sample to only Medium portfolios for which participants had more space to distort beliefs. Column 3 presents the IV estimates. Standard errors are in parentheses and clustered at the individual level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

The coefficient on Own $\times$ Ego Choice shows the *choice effect* for the *Ego Choice* condition. As expected, it is slightly larger (5.7 pp) than in the baseline *Choice* condition and comes — almost equally — from *pessimism* about non-chosen and *optimism* about chosen products. The total *choice effect*, however, is not significantly different from the *choice effect* in the baseline *Choice* condition. We included a manipulation check for the *Ego Choice* treatment as well. We asked participants how proud they were of themselves for having chosen portfolios that were more likely to pay off. For this question, we find no statistically significant difference between the *Choice* and *Ego* choice conditions (Table C2).

We also look at whether making a choice leads to more accurate beliefs. It is possible that having to make a choice increases the stakes, hence inducing higher cognitive effort. This, in turn, might lead to more accurate beliefs. We define several variables to measure accuracy.

- *Squared error* is the negative of the squared difference between the reported belief and the true payoff probability.
- *Seconds eval* measures the time in seconds spent on the portfolio evaluation screen.
- *Set ranking* measures whether participants get the ranking between the portfolios right. That is, whether the reported belief is higher for the portfolio that contains more good industry firms.
- *Relative to benchmark* measures whether participants get the ranking between the portfolio and the random benchmark right. That is, whether the reported belief is higher than the benchmark probability if and only if the portfolio contains more good industry firms than bad industry firms.
- *Rank correlation* is the Spearman's rank correlation coefficient for the reported beliefs and the true payoff probabilities.

Table 4: Accuracy of beliefs across conditions

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	Squared error	Seconds eval	Set ranking	Rel. to benchmark	Rank correlation
Choice Baseline	-23.92	3.140	0.0369*	-0.0256*	0.00449
	(36.93)	(2.784)	(0.0210)	(0.0133)	(0.0276)
Delayed Choice	-6.424	5.961	0.0274	-0.0218	0.0115
	(48.04)	(4.663)	(0.0288)	(0.0176)	(0.0367)
Ego Choice	18.58	7.251**	0.0797***	-0.0169	0.0379
	(46.19)	(3.395)	(0.0234)	(0.0167)	(0.0369)
Constant					0.435***
					(0.0199)
Observations	7944	3972	3972	7944	980
R^2	0.132	0.149	0.014	0.187	0.001
Control variables:					
Set FE	No	Yes	Yes	No	No
Portfolio FE	Yes	No	No	Yes	No
Better portfolio	Yes	No	No	Yes	No
Round FE	No	Yes	No	No	No

Notes: The table compares different belief accuracy measures across the three treatment conditions. The baseline group is the *Allocation* condition, hence, the estimates of the different choice dummy variables show the differences from the *Allocation* condition. In Column 1 and Column 4 the unit of observation is participant $\times$ portfolio and we include portfolio fixed effects and the Better dummy as controls. In Column 2 and Column 3 the unit of observation is participant $\times$ portfolio pair and we control for portfolio pair fixed effects. In Column 2 we also include round fixed effects, because time spent on the portfolio evaluation screens decreases substantially over time as participants are becoming more familiar with the task. In Column 5 the unit of observation is a participant. Standard errors are in parentheses and clustered at the individual level.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

We regress each accuracy variable on the treatment assignment and a set of control variables depending on the unit of observation. Table 4 reports the estimates. The dependent variable measures how well participants did, therefore higher accuracy is indicated by a positive coefficient. Participants in the *Choice* condition rank the portfolios correctly a few more times, however, they are less correct in ranking the portfolio relative to the benchmark than participants in the *Allocation* condition. Interestingly, participants in the *Ego Choice* condition spent slightly more time on the task and had more accurate beliefs. [20] Considering the baseline *Choice* and *Allocation* comparison, if anything, participants in the *Choice* condition reported slightly less accurate beliefs.

5 Discussion and conclusion

5.1 Evidence of Choice-induced Preference Change in Psychology

While we study the effect of choice on beliefs, in psychology, there is a history of studying choice-induced preference change. A major change in the designs used was brought by Chen and Risen (2010) who showed that the free choice paradigm, that had been used since Brehm (1956) to test for choice-induced preference change, suffers from a major methodological flaw. By ignoring that choice — even when inconsistent with reported preferences — is informative about underlying preferences, a statistical bias can result in apparent preference change. Therefore, one might document positive spreading after choice, even when participants have stable preferences. Alós-Ferrer and Shi (2015) adds by showing that reasonable models of human behavior need not predict consistent positive spreading and previous results are still informative. As a result of the criticism, some researchers started to use blind choices (e.g., Sharot et al. (2010)), where the options are ex-ante identical, while others (e.g., Voigt et al. (2017, 2019)) adopted the methodology recommended by Chen and Risen (2010) and found choice-induced preference change. In an economic context, using lotteries, where one option clearly first-order stochastically-dominates the other option, Alós-Ferrer and Granic (2023) finds no mere-choice effect on preferences.[21] In the current study, by varying the choice set and whether the same portfolio is the better one or the worse one, we can use an instrumental variable approach. Since the likelihood of choosing a portfolio is exogenous, and it is an attribute of the portfolio itself, it is not informative about the participants' underlying preferences nor beliefs. That is, our design is not susceptible to the criticism raised by Chen and Risen (2010).

[20] Together with the slight increase in the *choice effect* and *optimism* compared to the baseline *Choice* condition, this is consistent with the findings of Hartzmark et al. (2021).

[21] For a more extensive review of the literature on choice-induced preference change see Alós-Ferrer and Granic (2023).

5.2 Choice and the endowment effect

It has been documented that people attach additional value to things they own simply as a result of ownership (i.e., endowment effect).[22] Our finding of the *choice effect* implies that ownership — when it happens through choice — changes beliefs not only about products that are owned but also about products that are not owned. Additionally, our results on the *contrast effect* show that having alternative options can in itself increase the wedge between the beliefs about the two observed options. Specifically, facing a consideration set is always an inherent part of choice. Hence, *contrast effect* plays a role in all active choices. However, in the absence of an active choice (e.g., default or random assignment), people might pay less attention to alternative options, making the *contrast effect* less prevalent.

5.3 Difficulty of making a choice

In our setup, participants had to exert cognitive effort to be able to interpret the options in the consideration set, prior to the act of choice. We chose this strategy to make the choice ego relevant but keep the exerted cognitive effort comparable across conditions. This, however, leaves the decision of which option to choose easy. In psychology, the free choice paradigm usually gives a choice to participants between items they ranked close to each other (e.g., rank 7 and 9). The emerging dissonance, as a result of choice, might be higher for alternatives that look similar. Consequently, a choice between such alternatives might require a stronger dissonance reduction. In addition, the ego relevance of making a good choice might be more salient if it requires a higher cognitive effort. For our setup, this could mean that when choices look similar, and making a good choice requires cognitive effort, belief distortion is potentially larger. Changing the choice environment this way, however, comes with additional methodological challenges, as it makes the choice less predictable and the *Choice* condition different — in terms of exerted cognitive effort — to the *Allocation* condition.

[22] See Marzilli Ericson and Fuster (2014) for an overview of the literature.

5.4 Summary and future research

In this paper we design an experiment to study the effect of choice on beliefs. We show that making a choice considerably increases the difference between beliefs about owned and non-owned products. This effect comes mostly from participants forming pessimistic beliefs about products that are not chosen compared to beliefs about products that are not received. The effect of pessimism disappears when participant attention is diverted from choice to having accurate beliefs. This suggests that pessimism is mostly driven by attention. While facing a choice situation may induce higher cognitive effort, participants who make a choice do not form more accurate beliefs. As choices are often made under uncertainty, the mechanism we identify may play a role in a potentially wide range of settings.

While our findings focus on beliefs at the time of making a choice, it's important to consider that in many situations, people receive information after they have made their decision. In a follow-up study, we investigate the effect of choice on learning in a similar environment where optimal choice is a cognitively challenging task (Hajdu and Krusper, 2023).

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Appendix A Analytical discussion of the IV

There are $i = 1, .., 2N$ agents who choose between options A and B. Options contain a fixed payoff F and a lottery with expected payoff V. Agents observe F perfectly but they only get a signal $\hat{V} = V + \varepsilon$ where $\varepsilon \sim N(0, 1/\sqrt{2})$.

Agents choose the option with higher expected payoff and then distort their belief about the chosen lottery:

$$\tilde{V}_j = \begin{cases} \hat{V}_j + d & \text{if } \hat{V}_j > \hat{V}_{-j} \\ \hat{V}_j & \text{if } \hat{V}_j < \hat{V}_{-j} \end{cases}, \quad j = A, B \tag{5}$$

Consider the following payoffs where the lotteries are the same, while the difference between the fixed payoffs are 1 for half of the agents and -1 for the other half.

i	F_A	F_B	V_A	V_B
1,..,N	3	2	5	5
N+1,...,2N	2	3	5	5

Table A1: Payoffs

Suppose we observe the choice ($D_A = 1$ if option A was chosen and $D_A = 0$ otherwise) and the difference in the beliefs about lotteries ($\Delta\tilde{V}$). We want to estimate the effect of choice on belief distortion.

It is useful to derive how agents choose and the belief differences (note that $\Delta\varepsilon \sim N(0, 1)$).

	$\Delta F = F_A - F_B$	
D_A	1	-1
1	$\Delta\varepsilon > -1$	$\Delta\varepsilon > 1$
0	$\Delta\varepsilon < -1$	$\Delta\varepsilon < 1$

Table A2: Choice

	ΔF	
D$_A$	1	-1
1	$\Delta\varepsilon + d$	$\Delta\varepsilon + d$
0	$\Delta\varepsilon - d$	$\Delta\varepsilon - d$

Table A3: Belief difference ($\Delta\tilde{V}$)

A.1 IV reduced form

We can use ΔF to instrument for D_A. Consider first the reduced form regression.

$$\Delta\tilde{V}_i = \alpha_0 + \alpha_1 \Delta F_i + v_i \tag{6}$$

As ΔF is either -1 or 1, the constant gives the unconditional mean of the LHS variable:

$$\alpha_0 = E[\Delta\tilde{V}] = \frac{E[\Delta\tilde{V}|\Delta F = 1] + E[\Delta\tilde{V}|\Delta F = -1]}{2} \tag{7}$$

We can compute each term:

$$\begin{aligned}
E[\Delta\tilde{V}|\Delta F = 1] &= \frac{P(\Delta F = 1, \Delta\varepsilon < -1)E[\Delta\tilde{V}|\Delta F = 1, \Delta\varepsilon < -1] + P(\Delta F = 1, \Delta\varepsilon > -1)E[\Delta\tilde{V}|\Delta F = 1, \Delta\varepsilon > -1]}{P(\Delta F = 1)} \\
&= P(\Delta\varepsilon < -1)(E[\Delta\varepsilon|\Delta\varepsilon < -1] - d) + P(\Delta\varepsilon > -1)(E[\Delta\varepsilon|\Delta\varepsilon > -1] + d) \\
&= E[\Delta\varepsilon] + d(P(\Delta\varepsilon > -1) - P(\Delta\varepsilon < -1)) \\
&= d(1 - 2\Phi(-1)) \\
E[\Delta\tilde{V}|\Delta F = -1] &= \frac{P(\Delta F = 1, \Delta\varepsilon < 1)E[\Delta\tilde{V}|\Delta F = 1, \Delta\varepsilon < 1] + P(\Delta F = 1, \Delta\varepsilon > 1)E[\Delta\tilde{V}|\Delta F = 1, \Delta\varepsilon > 1]}{P(\Delta F = -1)} \\
&= P(\Delta\varepsilon < 1)(E[\Delta\varepsilon|\Delta\varepsilon < 1] - d) + P(\Delta\varepsilon > 1)(E[\Delta\varepsilon|\Delta\varepsilon > 1] + d) \\
&= E[\Delta\varepsilon] + d(P(\Delta\varepsilon > 1) - P(\Delta\varepsilon < 1)) \\
&= d(1 - 2\Phi(1))
\end{aligned}$$

Collecting the terms yields:

$$\alpha_0 = \frac{d(1 - 2\Phi(-1)) + d(1 - 2\Phi(1))}{2} = d - d\Phi(-1) - d\Phi(1) = d(1 - \Phi(-1)) - d\Phi(1) = 0 \tag{8}$$

Similarly, α_1 gives the half of the conditional means:

$$\alpha_1 = \frac{E[\Delta\tilde{V}|\Delta F = 1] - E[\Delta\tilde{V}|\Delta F = -1]}{2} = \frac{d(1-2\Phi(-1)) - d(1-2\Phi(1))}{2} = d(\Phi(1) - \Phi(-1)) \tag{9}$$

A.2 IV (2sls)

Finally, consider the 2SLS estimation. The first stage:

$$D_{A,i} = \gamma_0 + \gamma_1 \Delta_{Fi} + w_i \tag{10}$$

Using that this is a univariate regression:

$$\gamma_1 = \frac{cov(D_A, \Delta F)}{var(\Delta F)} = cov(D_A, \Delta F) = E[I(\Delta F + \Delta\varepsilon > 0)\Delta F] = \frac{E[I(1+\Delta\varepsilon > 0)\cdot 1] + E[I(-1+\Delta\varepsilon > 0)\cdot(-1)]}{2} =$$

$$= \frac{1 - \Phi(-1) - (1 - \Phi(1))}{2} = \Phi(1) - \frac{1}{2} \tag{11}$$

$$\gamma_0 = \overline{D_A} - \gamma_1 \overline{\Delta F} = \overline{D_A} = \frac{1}{2} \tag{12}$$

Thus the predicted value of D_A:

$$\hat{D_A} = \frac{1}{2} + \left(\Phi(1) - \frac{1}{2}\right)\Delta F \tag{13}$$

Then the second stage becomes:

$$\Delta\tilde{V}_i = \delta_0 + \delta_1 \hat{D}_{Ai} + \eta_i = \delta_0 + \delta_1\left(\frac{1}{2} + \left(\Phi(1) - \frac{1}{2}\right)\Delta F\right) + \eta_i = \delta_0 + \frac{\delta_1}{2} + \delta_1\left(\Phi(1) - \frac{1}{2}\right)\Delta F \tag{14}$$

We know the estimated coefficients from the reduced form regression:

$$\delta_1\left(\Phi(1) - \frac{1}{2}\right) = d(\Phi(1) - \Phi(-1))$$

$$\delta_1\left(\Phi(1) - \frac{1}{2}\right) = d(2\Phi(1) - 1)$$

$$\delta_1 = 2d \tag{15}$$

$$\delta_0 + \frac{\delta_1}{2} = 0$$

$$\delta_0 + d = 0$$

$$\delta_0 = -d \tag{16}$$

Appendix B Portfolio characteristics

Table A4: Portfolios

N	K	Type	N_A	Payoff probability
6	3	Benchmark		0.456
		Low	1	0.317
		Medium	2	0.385
		High	4	0.526
5	3	Benchmark		0.317
		Low	2	0.279
		Medium	3	0.350
		High	4	0.425
4	2	Benchmark		0.525
		Low	1	0.437
		Medium	3	0.613
		High	4	0.688
3	1	Benchmark		0.784
		Low	0	0.657
		Medium	1	0.755
		High	2	0.825

Notes: In the Benchmark portfolios firms are randomly selected regardless of their industry.

Appendix C Balance table

Table B1: Balance table

	(1)		(2)		(3)		(4)		T-test					
	Allocation		Choice		Relative choice		Ego choice		Difference					
Variable	N	Mean/SE	N	Mean/SE	N	Mean/SE	N	Mean/SE	(1)-(2)	(1)-(3)	(1)-(4)	(2)-(3)	(2)-(4)	(3)-(4)
Age	361	32.626	340	31.929	143	33.147	148	32.446	0.697	-0.521	0.180	-1.217	-0.517	0.701
		(0.621)		(0.658)		(0.982)		(0.994)						
Female	361	0.496	339	0.510	143	0.441	148	0.534	-0.014	0.055	-0.038	0.070	-0.023	-0.093
		(0.026)		(0.027)		(0.042)		(0.041)						
Any degree	362	0.588	340	0.526	143	0.545	148	0.574	0.062*	0.043	0.014	-0.019	-0.048	-0.029
		(0.026)		(0.027)		(0.042)		(0.041)						
High income	339	0.448	313	0.396	133	0.383	138	0.341	0.052	0.065	0.108**	0.013	0.056	0.043
		(0.027)		(0.028)		(0.042)		(0.040)						
Mistakes	362	0.448	340	0.391	143	0.378	148	0.331	0.056	0.070	0.116	0.014	0.060	0.047
		(0.072)		(0.065)		(0.083)		(0.069)						
Puzzle correct	362	2.630	340	2.638	143	2.650	148	2.669	-0.008	-0.021	-0.039	-0.012	-0.031	-0.019
		(0.034)		(0.034)		(0.054)		(0.051)						
Puzzle confidence	362	79.166	340	78.550	143	79.056	148	82.115	0.616	0.110	-2.949	-0.506	-3.565	-3.059
		(1.323)		(1.382)		(2.103)		(1.872)						

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

Appendix D Additional results

Table C1: Number of correct answers out of the 3 economics-related questions.

Correct solutions	No.	Col %	Cum %
0	10	1.0	1.0
1	55	5.5	6.5
2	216	21.8	28.3
3	712	71.7	100.0
Total	993	100.0	

Table C2: Manipulation check questions

	(1)	(2)
	Focusing on comparison	Proud of making good choice
Allocation	-0.646***	
	(0.118)	
Delayed Choice	-0.217	0.159
	(0.155)	(0.134)
Ego Choice	0.147	-0.140
	(0.153)	(0.133)
Constant	4.853***	4.715***
	(0.0845)	(0.0732)
Observations	993	631
R^2	0.041	0.006
Choice vs Delayed Choice p-value	0.16	0.24
Choice vs Ego Choice p-value	0.34	0.29

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C3: Pooled IV estimates

	(1)	(2)
Dependent variable: Belief	IV	IV
Better	6.359***	6.785***
	(0.986)	(0.958)
Own	0.556	0.510
	(0.717)	(0.718)
Own × Choice	1.951	1.944
	(1.394)	(1.395)
Choice	-2.458**	-2.459**
	(1.095)	(1.095)
Own × Delayed Choice		-1.285
		(1.681)
Delayed Choice		0.780
		(1.392)
Own × Ego Choice		2.960*
		(1.751)
Ego Choice		-0.952
		(1.329)
Observations	5616	7944
R^2	0.373	0.372
Portfolio FE	Yes	Yes
Sample		

Notes: This table reports the coefficient estimates for Equation 2. The unit of observation is a participant × portfolio pair. The baseline is non-received portfolios, hence, the coefficients are percentage point differences showing the estimates of *contrast effect*, *ownership effect*, *choice effect* and *pessimism* respectively. Column 1 and Column 2 use the full sample and present the IV estimates. Standard errors are in parenthesis and clustered at the individual level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Appendix E Instructions - For Online Publication

General overview

This study includes problem-solving and a post-completion questionnaire. After completing the study, you will earn a completion payment plus you may earn some bonus payment. The bonus scheme is designed in a way that you always benefit from telling the truth. For each question, we will explain clearly how you can earn bonus payments.

We will ask you to evaluate various financial investments. The following screens will explain the task and walk you through a few examples. The role of these examples is to make sure you understand the financial investments and how your payoff will depend on them. You have to answer all example questions correctly to continue to the main part. (There is no restriction on how many times you can try.)

Click on the Next button to get started!

Next

Example 1/7

Firms
Imagine that there are a lot of firms in the economy. Some firms make a profit while other firms make a loss. In the table below, represent firms that make a profit and represent firms that make a loss.

Portfolio
Consider a portfolio that contains 5 randomly selected firms. By clicking on the "Show" buttons you can see which firms are selected into the portfolio.

The return of the portfolio depends on the number of firms that turns out to make a profit:

- **If at least 3 firms make a profit then the portfolio pays off.**
- Otherwise, the portfolio is unsuccessful and it pays nothing.

Task
We ask you to do two things:

1. For each firm, reveal whether it makes a profit by clicking on the Show buttons.
2. Indicate whether the portfolio pays off.

Firms

Firm 1	Firm 2	Firm 3	Firm 4	Firm 5	Does the portfolio pay off?
Show	Show	Show	Show	Show	---------

Example 2/7

Portfolio
Similarly to the previous example, this portfolio contains 5 randomly selected firms and **it pays off if at least 3 firms make a profit.**

Task
We ask you to do two things:

1. Reveal the firms.
2. Indicate whether the portfolio pays off.

Firms

Firm 1	**Firm 2**	**Firm 3**	**Firm 4**	**Firm 5**	**Does the portfolio pay off?**
Show	Show	Show	Show	Show	---------

Example 3/7

Portfolio
In this example, the portfolio contains 3 randomly selected firms and **it pays off if at least 2 firms make a profit.**

Task
We ask you to do two things:

1. Reveal the firms.
2. Indicate whether the portfolio pays off.

Firms

Firm 1	**Firm 2**	**Firm 3**	**Does the portfolio pay off?**
Show	Show	Show	---------

Example 4/7

Portfolios
In this example, the portfolio contains 6 randomly selected firms and **it pays off if at least 4 firms make a profit.**

Task
We ask you to do two things:

1. Reveal the firms.
2. Indicate whether the portfolio pays off.

Firms

Firm 1	Firm 2	Firm 3	Firm 4	Firm 5	Firm 6	Does the portfolio pay off?
Show	Show	Show	Show	Show	Show	---------

Example 5/7

Industries

Now imagine that firms belong to one of two industries. As you can see in the table below, the industries have the same number of firms. In addition to that, **the share of firms that make a profit is also identical.**

Portfolio

For each firm in the portfolio, you can see the industry it belongs to. While previously firms were randomly selected from the entire economy, now **they are randomly selected from the given industries.**

In this example, the portfolio contains 4 randomly selected firms and **it pays off if at least 3 firms make a profit.**

Task

We ask you to do three things:

1. Indicate the number of Industry A firms in the portfolio.
2. Reveal the firms.
3. Indicate whether the portfolio pays off.

Industry A	Industry B
	

	Firm 1	Firm 2	Firm 3	Firm 4	Number of Industry A firms	Does the portfolio pay off?
Industry	A	A	A	B		---------
Profit	Show	Show	Show	Show		

Example 6/7

Industries

This example is similar to the previous one. However, note that **Industry A has a higher share of firms that make a profit** than Industry B.

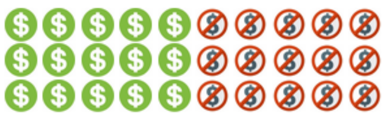
Portfolio

The portfolio contains 5 randomly selected firms and **it pays off if at least 2 firms make a profit.**

Task

We ask you to do three things:

1. Indicate the number of Industry A firms in the portfolio.
2. Reveal the firms.
3. Indicate whether the portfolio pays off.

Industry A	**Industry B**
	

	Firm 1	**Firm 2**	**Firm 3**	**Firm 4**	**Firm 5**	**Number of Industry A firms**	**Does the portfolio pay off?**
Industry	A	A	B	B	B		---------
Profit	Show	Show	Show	Show	Show		

Example 7/7

Industries

In this example, **Industry A has a lower share of firms that make a profit** than Industry B.

Portfolio

The portfolio contains 6 randomly selected firms and **it pays off if at least 3 firms make a profit.**

Task

We ask you to do three things:

1. Indicate the number of Industry A firms in the portfolio.
2. Reveal the firms.
3. Indicate whether the portfolio pays off.

Industry A	Industry B
	

	Firm 1	Firm 2	Firm 3	Firm 4	Firm 5	Firm 6	Number of Industry A firms	Does the portfolio pay off?
Industry	A	B	B	B	B	B		---------
Profit	Show	Show	Show	Show	Show	Show		

Examples finished

You answered all example questions correctly. Now you can continue with the main part of the study.

Please pay attention to all questions. At the end of the study, one question will be randomly selected and you may earn an additional bonus of £0.50 depending on your answer to that question.

Keep in mind that the bonus scheme is always designed in a way that you benefit from telling the truth. For each question, we will explain the exact method that we use to calculate your bonus.

Click on the Next button to get started!

Next

Industries

Eclipse and **Rosepaw** are fictional industries for the purpose of this task. First, we ask you to identify which one has a better outlook.

On the next screen, you will receive a report about which industry has a better outlook. **The report may or may not be correct.** Importantly, it depends on you what kind of report you get: we ask you to solve 3 exercises below.

- **If you solve at least 2 exercises correctly, you will see a report that reveals correctly which industry has a better outlook.**
- **Otherwise, the report will not necessarily pick the industry with a better outlook.**

---

1. A gardener charges a $60 call-out fee and then $30 for each hour he spends on the job. How long did he work on the job if the total bill is $180?

- ◯ 3 hours
- ◯ 4 hours
- ◯ 4.5 hours
- ◯ 6 hours

---

2. Suppose you had $100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow?

- ◯ More than $102
- ◯ Exactly $102
- ◯ Less than $102

---

3. Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, how much would you be able to buy with the money in this account?

- ◯ More than today
- ◯ Exactly the same
- ◯ Less than today

Next

Report

The report says that the **Rosepaw** industry has a better outlook.

We would like to know how confident you are about the industry outlooks. Remember, there are two cases:

- If you solved at least 2 exercises correctly on the previous screen, the report reveals correctly which industry has a better outlook.
- Otherwise, the report does not necessarily show the industry with a better outlook.

Question
Please report the chance in percentages that the Rosepaw industry has a better outlook.

Recall, it pays to honestly report your estimates. In case you are interested in the details, click here.

Next

Portfolio evaluation

Now, we will ask you to evaluate pairs of portfolios in 4 rounds. The setup will be the same as in the examples in the beginning.

Industries

- There are two industries: Eclipse and Rosepaw.
- Industries contain the same number of firms.
- **The industry with better outlook has a higher share of firms that make a profit.**

Portfolios

- Portfolios contain firms that are randomly selected from the given industries.
- In each round, portfolios differ only in the number of Eclipse firms and Rosepaw firms.

Task

- Estimate each portfolio's chance of paying off.
- Choose one of the portfolios.

Bonus payments

- The computer will randomly select one of the rounds at the end of the study. **If the portfolio you chose in that round pays off, you will earn an additional £3.00.**
- One of the questions for the entire study will also be randomly selected. **You may earn an additional bonus of £0.50 depending on your answer to that question.** Keep in mind that you always benefit from telling the truth.

Next

Only in the *Ego Choice* condition:

Read the summary of a scientific article published in the *Journal of Financial Economics*. Later you will need to remember its conclusion.

The researchers analyzed how people make investment decisions. This is what they observed:

- People with higher IQ invested in stocks that turned out to provide higher returns.
- People with lower IQ invested in stocks that turned out to provide lower returns.

To conclude, the research provides evidence that **people with higher IQ tend to choose assets that are more likely to provide high payoff.**

Next

PortEval (1/4)

Information

- Each portfolio **contains 3 firms** and **pays off if at least 2 firms make a profit.**
- Recall, the report says that **the Eclipse industry has better outlook.**

Questions

1. **Indicate which portfolio you would like to choose** by using the buttons in the table. Remember, you can earn **£3.00** if the portfolio you choose pays off.
2. For each portfolio, estimate the chance that it pays off.
   - Hint: A hypothetical portfolio, where each firm is **randomly selected regardless of its industry**, would pay off with **35%** chance.

	Firm 1	**Firm 2**	**Firm 3**	**Chance of paying off (%)**
Portfolio 1	Rosepaw	Rosepaw	Rosepaw	
Portfolio 2	Eclipse	Rosepaw	Rosepaw	

Recall, it pays to honestly report your estimates. In case you are interested in the details, click here.

Next

PortEval (2/4)

Information

- Each portfolio **contains 6 firms** and **pays off if at least 3 firms make a profit.**
- Recall, the report says that **the Eclipse industry has better outlook.**

Questions

1. **Indicate which portfolio you would like to choose** by using the buttons in the table. Remember, you can earn **£3.00** if the portfolio you choose pays off.
2. For each portfolio, estimate the chance that it pays off.
   - Hint: A hypothetical portfolio, where each firm is **randomly selected regardless of its industry**, would pay off with **46%** chance.

	Firm 1	Firm 2	Firm 3	Firm 4	Firm 5	Firm 6	Chance of paying off (%)
Portfolio 1	Eclipse	Eclipse	Rosepaw	Rosepaw	Rosepaw	Rosepaw	80
Portfolio 2	Eclipse	Eclipse	Eclipse	Eclipse	Rosepaw	Rosepaw	68

Recall, it pays to honestly report your estimates. In case you are interested in the details, click here.

Next

PortEval (3/4)

Information

- Each portfolio **contains 4 firms** and **pays off if at least 2 firms make a profit.**
- Recall, the report says that **the Eclipse industry has better outlook.**

Questions

1. **Indicate which portfolio you would like to choose** by using the buttons in the table. Remember, you can earn **£3.00** if the portfolio you choose pays off.
2. For each portfolio, estimate the chance that it pays off.
   - Hint: A hypothetical portfolio, where each firm is **randomly selected regardless of its industry**, would pay off with **52%** chance.

	Firm 1	Firm 2	Firm 3	Firm 4	Chance of paying off (%)
Portfolio 1	Eclipse	Rosepaw	Rosepaw	Rosepaw	
Portfolio 2	Eclipse	Eclipse	Eclipse	Rosepaw	

Recall, it pays to honestly report your estimates. In case you are interested in the details, click here.

Next

PortEval (4/4)

Information

- Each portfolio **contains 5 firms** and **pays off if at least 2 firms make a profit.**
- Recall, the report says that **the Eclipse industry has better outlook.**

Questions

1. **Indicate which portfolio you would like to choose** by using the buttons in the table. Remember, you can earn **£3.00** if the portfolio you choose pays off.
2. For each portfolio, estimate the chance that it pays off.
   - Hint: A hypothetical portfolio, where each firm is **randomly selected regardless of its industry**, would pay off with **66%** chance.

	Firm 1	Firm 2	Firm 3	Firm 4	Firm 5	Chance of paying off (%)
Portfolio 1	Eclipse	Eclipse	Eclipse	Eclipse	Rosepaw	
Portfolio 2	Eclipse	Eclipse	Eclipse	Eclipse	Eclipse	

Recall, it pays to honestly report your estimates. In case you are interested in the details, click here.

Next

Only in the *Ego Choice* condition:

What was the conclusion of the article about IQ and investment decisions?

People with higher IQ tend to make:

- ○ better investment decisions.
- ○ worse investment decisions.

Next

Read the statements below and indicate how much you agree with them.

	Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree or Disagree	Somewhat Agree	Agree	Strongly Agree
I focused more on comparing the portfolios rather than estimating the payoff probabilities separately.	○	○	○	○	○	○	○
I was proud of myself because I was able to choose portfolios that were more likely to pay off.	○	○	○	○	○	○	○
I am a person willing to take risks.	○	○	○	○	○	○	○
I am an optimistic person.	○	○	○	○	○	○	○

Next

With the following questions, we would like to understand better how you were thinking about the portfolios.

1. How difficult was to estimate the portfolios' chances of paying off? (1: Easy, 7: Difficult)

4

2. Do you think that you should have been able to calculate the answer exactly from the given information?

----

3. How much did you think about the industry outlooks when you were estimating the portfolios' chances of paying off? (1: Not at all, 7: A lot)

4

4. Did you think that chances are likely to be low because the experimenter wanted to minimize payoffs?

----

5. How difficult was to decide which portfolio to choose? (1: Easy, 7: Difficult)

4

6. Did you think that there must be some trick, so you should choose the portfolio that looks worse?

----

7. Walk us through your thought process: How did you estimate the portfolios' chances of paying off?

Next

Finally, please tell us about your experience with this study.

1. How clear were the instructions of the study? (1: Confusing, 7: Clear)

4

2. Which part of the study, if any, was confusing/difficult to understand? Explain why.

3. Have you participated in similar experiments before?

----

4. Here you can share any feedback or comments you might have on this study.

Next

Payoffs

Thanks for participating in the study! Below you can see how your bonus payment is determined.

Bonus payment

The computer selected round 2. It turns out that your portfolio in that round does not pay off.

Based on your answer to a randomly selected question, you did not earn additional bonus.

Thus, your total bonus payment is £0.00

Finish

Please click on the Next button to receive the link to submit the study.

Next