Pre-Analysis Plan:
How does choice affect learning?

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1 Introduction

1.1 Motivation

People often receive information about products after their choice, which in turn affects future buying/selling decisions (e.g. financial assets, switching markets). This project studies how choice itself – beyond the effect of ownership – changes how people use information to update their beliefs about products.

In the lab, using a between-subject design, participants learn about the fundamental quality of financial investments by observing price changes. We examine how they update beliefs after positive (e.g. price increase) and negative (i.e. price decrease) signals. The goal is to compare people who choose the investments themselves to people who receive the same investments exogenously. This comparison allows us to isolate the effect of choice from the effect of ownership.

1.2 Research questions

- **Primary research question:**
  - Beyond the effect of ownership, how does choosing a product affect learning about owned and not owned products?
- **Secondary research questions (payoff consequences and mechanism):**

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- Does choosing a product, as opposed to simply receiving it, makes learning closer to or further away from Bayesian updating?
- Can the effect of choice on learning be explained with differences in attention?

1.3 Hypotheses

1.3.1 Effect of choice on beliefs

Hypothesis 1. *(Motivated learning) Choice, compared to assignment, makes participants update more optimistically for own investments and more pessimistically for not own investments. That is, they respond more to good news and less to bad news for own investments while they respond less to good news and more to bad news for not own investments.*

Hypothesis 2. *(Stronger reaction) Choice, compared to assignment, makes participants respond more to both good news and bad news for both own and not own investments.*

Hypothesis 3. *(Weaker reaction) Choice, compared to assignment, makes participants respond less to both good news and bad news for both own and not own investments.*

1.3.2 Effect of choice on attention

Hypothesis 4. *(Attention on signals) Choice, compared to assignment, increases the accuracy of recalling earlier signals, especially, when the previous signal matches the current signal.*

Hypothesis 5. *(Attention on previous beliefs) Choice, compared to assignment, increases the accuracy of recalling earlier predictions.*

2 Experimental design and procedure

2.1 Design

Participants face 6 investment opportunities in the experiment. Each investment has the same initial price (100) and a fixed but unknown quality s_i. In each round, each investment price either increases – with probability s_i –, or decreases – with probability $1 - s_i$. There are 20 rounds. In each round, participants observe the sequence of all previous prices and they have to predict each investment's probability of a price increase. Participants receive a £1 bonus if a randomly selected prediction is within 10 percentage points of the true probability of a price increase. Predictions are reported by sliders and we also record the order in which participants move the sliders.

Participants are randomly assigned to one of two treatment conditions after round 4. In the *Choice* condition, participants have to choose 3 investments. In the *Allocation* condition, participants are assigned the 3 investments with the highest current prices. In both conditions, ownership means that the participant's final payoff depends on the final price of the own investments (converted at the rate of 400 points = £1). Importantly, choosing or receiving investments will come as a surprise, thus we expect that beliefs will not differ across treatment conditions up to round 4.

Our main goal is to compare predictions about chosen, not chosen, received and not received investments. This design allows us to study the causal effect of choice on beliefs because the investment choice is non-trivial but predictable. Participants should choose investments with higher s_i as these investments are expected to yield higher payoff. As a price increase is a positive signal and a price decrease is a negative signal about s_i, participants should choose investments with the highest actual price. Therefore, if an investment's price after round 4 is among the three highest, then the participant should choose the investment. We call these 3 investments *High*, and the other 3 investments *Low*.

To learn about the mechanism, we add two unexpected recall questions. First, we ask participants about price changes of a randomly selected *High* and *Low* investment in the previous round. They receive this question in a randomly selected round between round 14 and 16. Second, we ask participants about their predictions of a randomly selected *High* and *Low* investment in the previous round. They receive this question 3 rounds after the price recall task. For each recall task, participants receive a £0.50 bonus if they answer both questions correctly.

Finally, participants are asked in a survey about personal characteristics and way of thinking.

Besides the treatment assignment, we randomize the order of investments on the screen and the round in which participants receive the recall tasks.

2.2 Data collection

The experiment is run using the experimental software oTree (Chen et al., 2016). We recruit participants through Prolific, a crowd sourcing platform designed specifically for academic studies. We estimate the completion time to be 30 minutes and offer a £2.5 show-up fee. Participants may earn bonus payments on top of this as described in the previous section. We require participants to have US nationality, to be located in the US and to speak English as a first language in order to minimize language barriers. We drop observations from participants who don't finish the entire experiment.

3 Empirical strategy

3.1 Sample restriction

We restrict the sample to participants who give reasonable predictions in order to reduce noise. We require that participants change their predictions in the direction of price changes for at least half of the cases between round 2 and 4. We chose these rounds because they precede treatment assignment. As a robustness test, we will repeat the analysis using the entire sample.

3.2 Reaction to news

We compare how participants respond to recent price changes by treatment and investment category. As described above, we categorize investments based on round 4 prices to be *High* and *Low*. In the *Allocation* treatment, participants receive the *High* investments and do not receive the *Low* investments. In the *Choice* treatment, participants should choose the *High* investments and should not choose the *Low* investments.

We estimate the following regression:

$$\begin{aligned}\Delta y_{ijt} = {}& \beta_1 Inc_{jt} + \beta_2 Inc_{jt} \times High_j + \beta_3 Inc_{jt} \times Low_j \times Choice_i + \beta_4 Inc_{jt} \times High_j \times Choice_i + \\ & + \beta_5 Dec_{jt} + \beta_6 Dec_{jt} \times High_j + \beta_7 Dec_{jt} \times Low_j \times Choice_i + \beta_8 Dec_{jt} \times High_j \times Choice_i + \varepsilon_{ijt},\end{aligned} \tag{1}$$

where Δy_{ijt} is the belief change for participant i and investment j in round t. Inc_{jt} and Dec_{jt} are dummy variables for recent price increases and decreases, respectively. $High_j$ and Low_j are dummy variables for investment categories and $Choice_i$ is a dummy variable for being assigned to the $Choice$ condition. We cluster the standard errors at the participant level.

We can distinguish between the hypotheses on beliefs in the following way:

1. *Motivated learning*: participants in the *Choice* treatment are more optimistic about own investments ($\beta_4 > 0$ and $\beta_8 > 0$), while they are more pessimistic about not own investments ($\beta_3 < 0$ and $\beta_7 < 0$).

2. *Stronger reaction*: participants in the *Choice* treatment change their beliefs by more in the direction of the price change for all investments ($\beta_3 > 0$ and $\beta_4 > 0$, $\beta_7 < 0$ and $\beta_8 < 0$)

3. *Weaker reaction*: participants in the *Choice* treatment change their beliefs by less in the direction of the price change for all investments ($\beta_3 < 0$ and $\beta_4 < 0$, $\beta_7 > 0$ and $\beta_8 > 0$)

Since belief changes could depend on previous beliefs, we will estimate the same regression including fixed effects for lag belief intervals (0-9, 10-19, ..., 91-99).

In Equation (1) we compare beliefs between *High* and *Low* investments because these variables are exogenous and expected to be highly correlated with own and not own investments. In addition, we will report results using similar specification and dummies for own and not own investments instead of *High* and *Low*.

3.3 Direction and magnitude

We are interested in where does the difference in average belief changes come from. First, participants in the *Choice* treatment may change their beliefs consistently with price changes more or less often. Second, participants in the *Choice* treatment may change their beliefs by more or less controlling for the direction of the belief change.

We use an Oaxaca-decomposition to assess the importance of these factors. Let Δy^1 and Δy^0 denote average belief changes for consistent and inconsistent belief changes, respectively. Furthermore, let ω denote the share of consistent belief changes. Then we can decompose the difference between treatments in the following way:

$$\Delta y_C - \Delta y_A = \underbrace{\omega_C(\Delta y_C^1 - \Delta y_A^1) + (1-\omega_C)(\Delta y_C^0 - \Delta y_A^0)}_{Magnitude} + \tag{2}$$

$$+ \underbrace{(\omega_C - \omega_A)(\Delta y_A^1) + ((1-\omega_C) - (1-\omega_A))\Delta y_A^0)}_{Direction} \tag{3}$$

We will calculate this decomposition separately for four cases (*High* vs *Low* investments, price increases vs decreases).

3.4 Structural analysis

Besides studying how beliefs respond to news, we want to compare beliefs to a rational benchmark. Thus, we build a structural model to construct such a benchmark.

We assume that participants have a $Beta(\alpha_t, \beta_t)$ distribution over the probability of a price increase in each round t[a]. We specify the law of motion for α and β as

$$\alpha_t = \alpha_{t-1} + x_t \hat{s}_t \tag{4}$$
$$\beta_t = \beta_{t-1} + x_t(1 - \hat{s}_t), \tag{5}$$

where $\hat{s}_t$ is the perceived signal and x_t is the weight on the perceived signal. Note that this model embeds rational Bayesian beliefs by setting $\hat{s}_t$ to be a dummy variable for a recent price increase and $x_t = 1$.

We start by assuming that participants have a uniform prior before they see any price change ($\alpha_0 = \beta_0 = 1$). We infer perceived price changes from observed belief changes:

$$\hat{s}_t = \begin{cases} 1 \text{ if } y_t \geq y_{t-1} \\ 0 \text{ if } y_t < y_{t-1} \end{cases} \tag{6}$$

Then we can find x_t consistent with reported beliefs in a recursive way:

$$y_t = \frac{\alpha_t}{\alpha_t + \beta_t} = \frac{\alpha_{t-1} + x_t \hat{s}_t}{\alpha_{t-1} + \beta_{t-1} + x_t} \tag{7}$$

This procedure results in a sequence of α_t and β_t that fully characterizes participants' belief distribution. Thus, we can compute how beliefs at any given round should be updated according to Bayes rule. Note that we get Bayesian updating by setting $\hat{s}_t = s_t$ and $x = 1$.

$$\Delta \hat{y}_t = \frac{\alpha_{t-1} + s_t}{\alpha_{t-1} + \beta_{t-1} + 1} - \frac{\alpha_{t-1}}{\alpha_{t-1} + \beta_{t-1}} \tag{8}$$

We treat $\Delta \hat{y}_t$ as the benchmark belief change and will estimate (1) with $\Delta y_t - \Delta \hat{y}_t$ as the dependent variable.

We implement robustness checks by assuming different initial beliefs. First, we use the estimates $\alpha_0 = \beta_0 = 2.62$ from Hartzmark et al. (2019). Second, we estimate the mean prior beliefs (y_0) by taking the average of first round average beliefs after a price increase and first round average beliefs after a price decrease. Then we calibrate the prior distribution by

$$\frac{\alpha_0}{\alpha_0 + \beta_0} = y_0 \tag{9}$$
$$\alpha_0 + \beta_0 = 2 \tag{10}$$

[a] To simplify notation, we drop the i (participant) and j (investment) subscripts.

3.5 Heterogeneity analysis

We conduct the analysis separately for females and males to study if there is any gender difference in the effect of choice on learning.

3.6 Attention

To learn about the mechanism, we study how participants pay attention to different investments.

First, we assume that if participants pay more attention to an investment then they can recall the associated previous signals more accurately. Hence, we compare recall accuracy – measured by fraction of accurate recalls – between the *Choice* and *Allocation* treatments. Furthermore, we estimate recall accuracy separately for observations where the current signal matches the previous signal and for observations where the current signal is different from the previous signal.

Second, we assume that if participants pay more attention to an investment then they can recall their associated previous predictions. Hence, we compare recall accuracy – measured by squared error – between the *Choice* and *Allocation* treatments.

4 Power Calculation

We conducted power calculations using data from a pilot session. We plan to run the study with 750 participants. The simulations suggest that the minimum detectable effect for each coefficient of interest in Equation (1) is 1.0 percentage point (80% power, $\alpha = 5\%$).

References

Chen, D. L., Schonger, M., and Wickens, C. (2016). otree—an open-source platform for laboratory, online, and field experiments. *Journal of Behavioral and Experimental Finance*, 9:88 – 97.

Hartzmark, S. M., Hirshman, S., and Imas, A. (2019). Ownership, learning, and beliefs. *Available at SSRN 3465246*.