How selective access to financial information affects how investors learn

Author: **Josep Gisbert** (IE)

Discussant: **Jesus Villota** (CEMFI)

32nd Finance Forum. Session 10: News and Investor Learning

Pamplona, 03/07/2025

Outline

Paper Overview

- The paper investigates how selective access to financial information affects the way investors learn and form beliefs.

- It compares two environments:
  - **Selective feedback**: Investors only observe the outcome of an investment (the stock) if they choose it.
  - **Full feedback**: Investors observe the outcome of the stock regardless of their choice.

- The study is motivated by real-world settings where information is sometimes only available through active participation (e.g., entrepreneurship, hiring, investment projects).

Experimental Design

1. Adult participants (via MTurk) repeatedly chose between a bond and a stock.
2. Random assignment to either selective or full feedback conditions.
3. After each choice, participants estimated the probability that the stock was "good" (i.e., paid from a favorable distribution).
4. The experiment measured both belief formation and choice behavior, as well as risk preferences and financial literacy.

The study aims to disentangle the effects of information acquisition (how much and what kind of data is gathered) and information processing (how well that data is used) on investor learning.

Main Findings

- Selective feedback leads investors to process information more accurately: their beliefs are, on average, 5% closer to the Bayesian benchmark than those in the full feedback condition.
- However, selective feedback also results in smaller, less representative samples of information, introducing a sampling error of similar magnitude.
- The two effects—better processing but more sampling error—**offset each other**, so overall learning outcomes are similar across environments.
- The study reveals a dynamic process: selective feedback triggers more adaptive learning, especially after negative outcomes, and helps explain why previous literature found mixed results.

Outline

- The papers is already quite polished
- The experiment design is clear and well-executed
- My comments will be related to avenues for extension

How would results compare to... LLMs?

Key Insight

LLMs are shown to **inherit human biases** from training on human data!

Advantages:

- Cost-effective scaling
- Consistent participation
- Reproducible results
- Large sample sizes

e.g.: [Bowen et al., 2024]

- **Setup:** Ask LLMs to propose an interest rate for loan applicants
- **Result:** Show that LLM presents the same biases as humans, giving better rates to white males while penalizing females, Latinos, and Blacks

Proposed Implementation

Run your experimental design across multiple LLM models and average results to obtain **model-averaged bias estimates** that mirror human behavior.

How would results compare to... rational, utility-maximizing agents?

Reinforcement Learning (RL) provides a benchmark for comparing human biases with rational decision-making.

Explanation: They are agents with a utility function, that, given a observed state at each point in time, take an action within an action space

Benefits:

- Controlled environment
- Purely rational decision-making
- No behavioral biases
- Utility maximization focus

Natural Parallel: Same type of "conflict" applies to RL agents, who need to balance exploration and exploitation effectively

ϵ-Greedy Strategy

Control exploration through randomized actions

$$\text{Action} = \begin{cases} \text{Random} & \text{w.p. } \epsilon \\ \text{Greedy} & \text{w.p. } 1-\epsilon \end{cases}$$

Expected Outcome: Clean baseline showing optimal learning without human biases

Can awareness of biases improve human decision-making?

Bias-Aware Experimental Design

Before the experiment, explicitly explain:

- The specific behavioral biases that affect belief formation
- How these biases deviate from Bayesian updating
- The importance of rational information processing

Expected Results:

- Closer to Bayesian benchmark
- Reduced behavioral biases
- Improved learning outcomes

Precedent:

- [Bowen et al., 2024]: Instructing LLMs to avoid biases **works**
- Similar principle applies in humans

Summary of Extensions

These extensions would provide a comprehensive view of learning across the **rationality spectrum**, from purely rational (RL) to naturally biased (humans/LLMs) to bias-aware (humans/LLMs).

Approach	Bias Level	$ Cost	Sample Size
Human	Human	High	Limited
LLM	Human-inherited	Low-Medium	Large
Bias-Aware Human	Reduced	High	Limited
Bias-Aware LLM	Reduced	Low-Medium	Large
RL	None	None-Low	Large

References I

Bowen, D. E., Stein, L. C., Price, S. M., and Yang, K. (2024).
Measuring and mitigating racial disparities in large language model mortgage underwriting.