Trading gamification and investor behavior

Philipp Chapkovski, Mariana Khapko, and Marius Zoican*

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Abstract

We study the effect of gamification on retail traders' behavior using a randomized online experiment. Participants with lower financial literacy prefer platforms with hedonic gamification elements, such as confetti and achievement badges. On average, hedonic gamification increases trading volume by 5.17%. However, the difference in trading activity between gamified and non-gamified platforms is driven primarily by self-selection (70%) rather than gamification (30%). Participants who prefer hedonic gamification exhibit noisy trading strategies, while those favoring non-gamified platforms display stronger contrarian behavior. Further, price trend notifications enhance learning for investors with accurate beliefs, but reinforce trading mistakes for those with incorrect beliefs.

Keywords: experimental finance, disposition effect, FinTech, financial literacy, gamification

JEL Classification: C91, G11, G41, G53

*Philipp Chapkovski (chapkovski@gmail.com) is a postdoctoral researcher at the University of Bonn. Mariana Khapko (mariana.khapko@rotman.utoronto.ca) is affiliated with University of Toronto Scarborough and the Rotman School of Management. Marius Zoican (contact author, marius.zoican@rotman.utoronto.ca) is affiliated with University of Toronto Mississauga and the Rotman School of Management. We thank Jason Cai for excellent research assistance. We have greatly benefited from discussions with Elena Asparouhova, Debrah Meloso, Lisa Kramer, Maureen O'Hara, Alessandro Previtero, and Martijn van den Assem, as well as seminar and conference participants at the University of Melbourne, the 2022 Plato Market Innovator (MI3) conference, the 4th Future of Financial Information Conference, and the 2022 Society for Experimental Finance Meeting. Marius Zoican and Mariana Khapko gratefully acknowledge the Social Sciences and Humanities Research Council for an Insight Development Grant (430-2018-00125) and the Canadian Securities Institute Research Foundation (CSIFR) for a research grant. Philipp Chapkovski gratefully acknowledges the generous funding from the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under Germany's Excellence Strategy – EXC 2126/1-390838866.

1 Introduction

> "Technology has provided greater access, but it also raises interesting questions. What does it mean when balloons and confetti are dropping and you have behavioral prompts to get investors to do more transactions?"
>
> – Gary Gensler, Chair of the Securities and Exchange Commission (March 2, 2021)

Does the design of retail-facing trading applications impact the behavior of individual investors? The share of retail volume in US equity markets more than doubled in the past decade, from 10.1% in 2010 to more than 23% in January 2023. As a group, retail traders are now the second largest market segment after high-frequency traders, ahead of hedge funds or bank-affiliated traders. The six largest online brokerages (Fidelity, Vanguard, Charles Schwab, Webull, Robinhood, and Interactive Brokers) have more than 100 million combined users. Between January and December 2021, Robinhood reported a 47% increase in active monthly users (from 11.7M to 17.3M) and a 55% increase in assets under custody (from \$63bn to \$98bn).[1]

What is driving the recent surge in retail trading? Part of the effect can be traced back to the COVID-19 pandemic. A shift in work patterns and entertainment opportunities, doubled by heightened volatility and "fear of missing out," whetted the risk appetite of work-from-home traders. However, we argue that there are structural forces at play – in particular the digitalization and decentralization of asset management: a transition from human advisers in brick-and-mortar institutions to self-managed trading on computer and mobile platforms.

Online brokers are grappling with a zero lower bound on fees, prompting them to seek novel ways to differentiate themselves from competitors. One approach is to offer investors trading apps with sleek interfaces designed to increase trading volume and user engagement with the platform. As a result, these applications are progressively adopting gamification elements, such as vibrant colors, celebratory animations (like confetti), and other prompts designed to encourage users to engage in more frequent trading.

[1] See Wall Street Journal, Individual-Investor Boom Reshapes U.S. Stock Market, August 31, 2020; Reuters, Factbox: The U.S. retail trading frenzy in numbers, January 29, 2021; Robinhood Reports Fourth Quarter and Full Year 2021 Results, January 27, 2022; and Bloomberg, Day Trading Army's Grip on Stock Market Is Tighter Than in Meme Stock Era, February 2, 2023.

Does the gamification of trading apps influence individual investor behavior? The question is of first-order importance for regulators: The retail-driven trading frenzy of GameStop equities in January 2021 prompted Gary Gensler, chair of the U.S. Securities and Exchange Commission (SEC), to raise concerns about the potential impact of "behavioral technology" and gamification on trading app users.[2] Furthermore, in December 2020 Robinhood faced an administrative complaint by the Commonwealth of Massachusetts for "aggressive marketing" deemed not in the best interest of investors. More recently, in April 2022 Verena Ross, chair of the European Securities and Markets Authority (ESMA), expressed concern that gamification techniques in trading apps could lead retail investors to engage in trading behavior without understanding the risks involved.[3]

In this paper, we propose a randomized controlled experiment to assess the behavioral externalities of trading gamification. In particular, we study the impact of gamification strategies on the intensity of retail traders' trading activity, trading mistakes, the magnitude of the disposition effect, and the ease of information processing. The experimental design allows us to provide a nuanced analysis of gamification by distinguishing the impact of gamification elements that convey price-relevant information and those that do not. The experimental approach solves the problem of endogenous platform choice by randomly assigning participants to gamified and non-gamified platforms, which allows for a causal estimation of the impact of trading gamification on investor behavior.

We build an experimental platform in oTree (Chen et al., 2016) starting from the classical investment games in Frydman et al. (2014) and Weber and Camerer (1998). The experiment comprises four rounds of trading, each lasting five minutes, in addition to a brief training round. Participants can buy and sell a risky asset in real time but cannot short sell or hold more than one unit at a time. However, they can borrow cash at a zero interest rate. The asset price process has predictable momentum and follows a Markov chain process with two highly persistent states. Incorporating momentum in our experimental asset price process emphasizes the disposition effect in the data–given that the optimal strategy of a Bayesian investor would display the very opposite behavior–and allows us to highlight its interaction with gamification and information, with further

[2]See Bloomberg, Gensler Targets Broker 'Gamification' After Trading Tumult, March 2, 2021.
[3]See ESMA makes recommendations to improve investor protection, April 29, 2022.

insights provided when momentum is removed.[4]

Participants trade on either a gamified or non-gamified platform in each trading round. To design the gamified platform, we draw inspiration from popular trading apps such as Robinhood, EToro, and Binance. Our gamified platform features two types of gamification elements: *hedonic* and *informational*. Hedonic gamification elements, which relate to the sensory and emotional aspects of user experience, are designed to encourage prolonged rather than productive use of the product (Hirschman and Holbrook, 1982; van der Heijden, 2004). For trading platforms, these elements include reward animations and badges upon completing a certain number of trades. On the contrary, informational gamification elements include notifications about trending stocks and significant price swings.

We conjecture, based on a simple theoretical framework following Frydman and Rangel (2014), that hedonic and informational strategies have a distinct impact on investor behavior. On one hand, achievement badges and animations might encourage excessive trading and suboptimal buy and sell decisions. On the other, price movement notifications may reduce information processing costs and steer investors toward better trading decisions by reducing the disposition effect—particularly by encouraging them to realize losses.

We recruit 958 experimental subjects from Prolific, a subject pool for online experiments, to participate in the trading game on April 11 and April 12, 2023.[5] We build a population-representative sample of the United States and United Kingdom (using census data from these countries), stratified by age, gender, and ethnic group. We administer a 12-question financial literacy quiz based on Fernandes et al. (2014) to participants, and also elicit a self-assessment of their financial knowledge. After the experiment, we inquire about participants' preferences between gamified and non-gamified designs.

Our results reveal that, after controlling for realized profits, individuals with lower financial literacy tend to favor trading platform with hedonic gamification elements such as confetti and achievement badges. Specifically, a one-standard-deviation decrease in the financial quiz score leads

[4]Our price process is almost identical to the one in Frydman et al. (2014), who mention that "*The optimal strategy therefore involves selling winner stocks relatively rarely, and losing stocks more often, thereby generating the reverse of the disposition effect*" (p. 918).

[5]See Prolific's website at `https://prolific.co/`.

to a nine-percentage-point rise in the likelihood of choosing the hedonic platform. At the same time, we find no relationship between financial literacy and participants' inclination towards informational gamification elements such as price trend notifications.

Our first experimental session focuses on hedonic gamification elements such as confetti and badges. On average, hedonic gamification leads to a marginally significant 5.17% increase in trading activity. However, the impact of gamification is more pronounced (a 12.5% increase) for participants who prefer the hedonic design. Our findings suggest that there is a significant selection effect, as participants who prefer hedonic gamification tend to trade 21.4% more than their counterparts even on non-gamified platforms. We estimate that 70% of the gap in trading activity between gamified and non-gamified platforms can be attributed to self-selection (i.e., participant preferences), while the remaining 30% is traced to the direct impact of gamification.

We find no evidence that hedonic gamification leads to an increase in trading mistakes. Nonetheless, we do observe that participants who have a preference for gamified or non-gamified platforms tend to deviate from a Bayesian benchmark in distinct ways. Specifically, those who prefer non-gamified platforms tend to sell the asset after a series of price increases and buy it back after a string of price drops. This behavior aligns with an irrational belief that the stock price follows a mean-reverting process. As a result, participants who favor non-gamified platform trade too little relative to the Bayesian benchmark and exhibit a large disposition effect. Participants who prefer gamified platforms tend to trade more and at seemingly random times. On aggregate, we find that participants with low financial literacy who prefer hedonic gamification tend to have more *noisy* trading strategies, while those who self-select into non-gamified platforms exhibit stronger contrarian behavior, in that their strategy is *biased* relative to a Bayesian trader.

In a separate experimental session, we analyze the impact of information-based gamification. Optimally, participants in our experiment should buy the stock when its price rises and sell it when the price drops, given the momentum embedded in the price process. We document that the impact of price trend notifications depends on the accuracy of traders' beliefs about the price process. For traders with correct beliefs, notifications appear to improve learning by reducing information constraints. These traders are more likely to buy the stock after receiving a price increase alert, but do not realize their losses after receiving a drop alert. In a setting without momentum, where a martingale price process renders notifications uninformative, participants holding correct beliefs cease responding to alerts. This result underscores that informative price notifications can indeed enhance learning. Conversely, notifications reinforce contrarian behavior for traders with inaccurate beliefs, leading to even greater deviations from the Bayesian benchmark. These traders are 31.81% more likely to sell the asset after a positive alert and 37.5% more likely to buy the asset after a negative alert. We also find that price trend notifications amplify the disposition effect, due to traders with incorrect beliefs experiencing a rise in realized gains.

2 Related literature

Digital trading platforms. Our paper fits into a growing literature on digital trading platforms. Closest to our paper, Arnold et al. (2021) find that push notifications alerting investors about large price swings increase risk taking, as measured by leverage. Moss (2022) documents that push Robinhood notifications increase the intensity of retail trading by 25% for 15 minutes after the alert. Kalda et al. (2021) study transaction-level data from two German banks, and find that investors execute riskier trades on smartphones than on other, more traditional platforms. Our study stands out by conducting a controlled experiment that introduces various gamification elements while measuring trading mistakes, beliefs, and behavioral biases such as the disposition effect. Our randomized approach eliminates selection bias and allows us to measure the impact of financial literacy and trading experience on gamification and investor behavior. Overall, our findings provide insights into how gamification affects investor decision-making and trading behavior on digital platforms.

Retail trading. Our paper further contributes to a resurgent literature on retail trading. Previous studies have shown that individual traders often lack information and are susceptible to behavioral biases. This is reinforced by research conducted by Barber and Odean (2000, 2007), which found that retail traders tend to exhibit overconfidence, engage in excessive turnover, and show a preference for small high-beta stocks that capture their attention.

More recent evidence (Kaniel et al., 2008; Kelley and Tetlock, 2013) suggests retail order flow may be a predictor of future stock returns: aggressive trades can predict future news, whereas passive orders are contrarian and provide liquidity. Barber et al. (2022) show that the design of the Robinhood trading app (in particular, the *Top Movers* tab) steers investors' attention to stocks with extreme returns, leading to portfolio underperformance. At the same time, Welch (2022) documents that, in aggregate, retail investors using the Robinhood app performed well between 2018 and 2020. Our paper contributes to this literature by examining how the design of trading platforms impacts the portfolio choices of retail traders.

Gamification and behavior. Our paper relates to research in computer science, marketing, and psychology studying gamification and its impact on consumer actions. Deterding et al. (2011) define gamification as "the use of game design elements in non-game contexts." Hirschman and Holbrook (1982) and Huotari and Hamari (2012) relate gamification to hedonic consumption of multisensory and emotive aspects of the product user experience, generating value beyond its utilitarian role (van der Heijden, 2004). Csikszentmihalyi et al. (2014) emphasize that gamification elements are intrinsically rewarding if they establish clear goals and provide immediate feedback to users. However, the scholarly literature on gamification in finance is relatively scant. Baptista and Oliveira (2017) and Rodrigues et al. (2016) find that customers are more likely to use a banking app if it emphasizes the hedonic element. Further, gamification elements such as achievement badges can yield greater engagement with platforms (Kwon et al., 2015).[6]

Disposition effect experiments. The disposition effect, first identified by Odean (1998), is defined as an empirical pattern wherein traders are more likely to realize profits than losses. We build our experimental design on a series of classical investment games (Weber and Camerer, 1998; Frydman et al., 2014) that study the disposition effect starting from the realization utility model of Barberis and Xiong (2012) and Ingersoll and Jin (2013). We contribute to this strand of experimental

[6] A related strand of literature in behavioral finance studies the impact of emotional state on trading decisions. Existing work shows that positive feelings exacerbate risk-taking (see, e.g., Kuhnen and Knutson, 2011; Andrade et al., 2015) and overconfidence (Breaban and Noussair, 2017) while negative emotions are associated with heightened risk aversion (Kamstra et al., 2003) but potentially lower loss aversion (Campos-Vazquez and Cuilty, 2014).

finance literature by studying the impact of platform gamification strategies on the magnitude of the disposition effect.

FinTech and financial literacy. Finally, our paper relates to a growing literature on financial literacy and technology innovations. While FinTech aims to make financial services more accessible for individuals with low financial literacy, it may also exacerbate existing financial barriers and inequalities, as evidenced by Haran Rosen and Sade (2022). Karlan et al. (2016) highlight that digital finance has the potential to improve products and market conditions, but success requires a nuanced understanding of market failures affecting low-income and low–financial literacy households. To promote financial inclusion, it is important to integrate FinTech with supportive financial and digital literacy programs. Relying solely on simplified behavioral insights may be more effective than traditional financial education methods (Drexler et al., 2014). Confidence in one's financial knowledge, in addition to measured financial literacy, is crucial for making sound investment decisions, as emphasized by Allgood and Walstad (2016), Bannier and Schwarz (2018), and Cupák et al. (2020). In this study, we investigate how trading gamification impacts investor behavior, moderated by both objective and perceived financial literacy.

3 Experimental design

We start by describing the experimental market in Section 3.1, followed by the design of the trading platform and gamification features in Section 3.2. In Section 3.3 we lay out a theoretical decision-making framework that allows us to state the Bayesian benchmark strategies for participants.[7]

3.1 Market design

Our experimental design closely follows Frydman et al. (2014) and Weber and Camerer (1998), who build laboratory markets to study the disposition effect in stock trading (i.e., the investors' tendency to sell winners too early and hold on to loser stocks for too long). In the same spirit, we

[7] In February 2023, following the approval of our registered report at Management Science, we filed a pre-analysis plan which is available online at `https://osf.io/ud3ts/?view_only=91f98723bea34744ad666bde289ebc8e`. The experiment was performed exactly as proposed. We largely follow the empirical analysis described in the pre-analysis plan, enhancing it to include results across different participant subsamples.

focus on individual decision-making in a trading game while abstracting from market clearing and price formation concerns.

Market and endowments. Participants are given the opportunity to trade one virtual stock on a laboratory market over four rounds. Each round consists of 60 trials, indexed by t: each trial corresponds to a stock price update and lasts for five seconds. Asset prices and participants' payoffs are denominated in "experimental dollars" (E$), an artificial laboratory currency, and converted into Canadian dollars at the end of the experiment. The exchange rate between experimental and Canadian dollars is E$1 = CA$0.05.

At the start of each round, each participant is endowed with E$50 and one unit of the stock. The stock has an initial price of E$100, and therefore the total endowment of each participant is equivalent to E$150. The rationale behind having a cash buffer is to absorb stock market losses throughout the round and make it less likely that the limited liability constraint binds.

At any point during the round, each participant can hold at most one unit of the stock. Further, short selling is not allowed. The constraints simplify the participants' strategy space, allowing for a sharper identification of the mechanisms at play. Due to the limited time participants have to make trading decisions, an increase in the number of "rational" trades could reduce the potential for gamification-induced trades and lower the statistical power of our tests. To avoid this, a participant only has to choose whether to buy the stock if they are not already holding it, or whether to sell the stock if they do hold it. While trading, participants are effectively allowed to borrow and carry negative cash balances. However, to compute the end-of-round payoff, any negative balance at the end of the round is subtracted from the value of the stock portfolio.

Following Frydman et al. (2014), trading is disallowed for the first four trials of each round. This allows participants to learn by observing the asset price movements before engaging in trading decisions. From $t = 5$ onward, participants can freely buy and sell the stock at any time, conditional on staying within the position limits.

Asset price. The stock price is updated for every trial following a two-state Markov chain process. In the "good" state (g), the stock price increases with probability 0.55 and decreases with probability

0.45. In the "bad" state (b), the probabilities are reversed: the price has a 45% chance of going up and a 55% chance of falling. The size of price changes is drawn with equal probabilities from the set $\{\text{E\$5}, \text{E\$10}, \text{E\$15}\}$. The magnitude and direction of price changes are drawn independently. Conditional on being in state $i \in \{g, b\}$ at trial t, the stock has an 85% chance of remaining in state i at trial $t+1$ and a 15% chance of switching to state $-i$. Thus, the stock price exhibits momentum and is therefore predictable; price increases (drops) are likely to be followed by further increases (drops).

Participants receive information on the process used to generate prices and the transition probabilities, but we do not disclose the state in any given trial. Instead, each participant has to use the history of prices to infer the current state and make predictions about future returns. To facilitate comparison across experimental subjects, we use the same price histories for all participants.

As a robustness check, we also run an experimental session in which the asset price is a martingale (i.e., there is no momentum). If stock returns exhibit momentum, acting upon gamification elements that highlight information is a good idea, but that might not be the case if prices are a martingale or if they mean-revert. The robustness session without built-in momentum allows us to determine whether certain gamification features, such as price notifications, ameliorate investors' attention constraints or if they simply nudge them into trading.

Participant beliefs. To assess participants' perception of asset pricing trends, we follow Weber and Camerer (1998) and directly elicit beliefs about the current state of the stock. Concretely, for each round we pause trading for 20 seconds before trial $t = 40$ and display the following questions:

How likely is the stock to go up next? and *How confident are you in this assessment?*

followed by a sliding scale that allows participants to select the perceived probability of an uptick in the following trial and a five-point Likert scale to measure confidence.

Moreover, we also obtain participant beliefs prior to trial $t = 1$. At the beginning of each round, absent any price history, the stock is equally likely to be in a good or a bad state. We ask participants "How likely is the stock to go up in the first period?" and provide a sliding scale on which they can select the probability of the stock price going up (denoted by u), as well as the level of confidence in the evaluation. We then use their answer to build a measure of prior beliefs about the stock price as $1 - 2 \times |u - 0.5|$, which is higher if the participant's belief is closer to the correct answer $u = 0.5$.

Treatments. Our experimental design is a mixture of "within" and "between" treatments. Importantly, all participants are exposed to both non-gamified and gamified markets and we measure their performance in both these trading environments. However, each participant is only exposed to one combination of gamification elements; that is, a single version of a gamified market.

In the experiment, following the taxonomy of Gallo (2022) we distinguish between purely hedonic gamification elements—achievement badges, confetti, or congratulatory messages—that aim to increase engagement with the platform on one hand, and on the other hand gamification elements that highlight information, such as price swing notifications. We provide an in-depth discussion on gamification elements and connect our experimental design elements with the gamification strategies of real-life trading platforms considered in Section 3.2 and Online Appendix E. The SEC also enumerates these particular gamification strategies in its August 2021 request for comments.[8]

The four between-subject sessions of the experiment, where each session features a different combination of gamification strategies, are:

1. **Session I**: Non-gamified + Gamified with only hedonic elements of gamification,
2. **Session II**: Non-gamified + Gamified with informational elements (i.e., price notifications),
3. **Session III**: Non-gamified + Gamified with both hedonic and informational elements,
4. **Session IV (robustness)**: Non-gamified + Gamified with only informational elements as in Session II, but the price process is a martingale.

Each participant trades in both non-gamified and gamified platforms, so that (i) we establish a baseline trading behavior at the participant level and (ii) we are able to elicit preferences between gamified and non-gamified designs. At the same time, each participant is exposed to a single type of gamification treatment. That is, the gamification strategies vary between participants. This

[8]See `https://www.sec.gov/rules/other/2021/34-92766.pdf`, pages 7 and 8.

experimental setup allows us to disentangle the effects of hedonic and informational gamification strategies. The robustness session allows decomposing the price notification effect into a "nudge to trade" component (the effect in Session IV) and a "rational attention improvement" component (the positive difference, if any, between the effects in Session II and Session IV).

In addition to the between-treatments variability, there is variability within each experimental session. Each of the four sessions has four trading rounds: two gamified and two non-gamified (in random order). Additionally, the purchase price may be prominently displayed on the platform (high salience) or not (low salience). As in Frydman and Rangel (2014), during high-salience rounds the participants' trading screen displays the purchase price information along with the current asset price and historical price path. In contrast, during low-salience rounds the purchase price is not displayed (while the current price and historical price path information is still available to participants). Varying the emphasis on purchase price information can manipulate the visibility of paper gains and losses, potentially affecting the size of the disposition effect displayed by investors, as demonstrated by Frydman and Rangel (2014). The order of gamified and salient rounds are randomized, and participants split into four blocks such that half of the subjects start with two gamified rounds, whereas other participants start with two non-gamified rounds.

Round structure and timing. To become familiar with the platform, all participants start with a short non-gamified training round ("round 0") consisting of 10 trials or price updates. This training round is discarded in the data analysis.

After the trading game, we ask participants to self-reflect on their trading decisions on different platforms by asking them four direct questions, as given in Online Appendix D. The idea behind directly eliciting participants' preferences is to gain insight into whether gamified platforms have the potential to improve stock market participation. We purposely phrase the self-reflection questions in a reasonably forward-looking manner in order not to rely on realized (perhaps unlucky) outcomes.

Following the self-reflection questions, participants are asked to answer 12 financial literacy questions, given in Online Appendix C. Our quiz questions come from Fernandes et al. (2014), and subsume the three-question measure of financial literacy developed by Lusardi and Mitchell (2011).[9]

[9]We drop one question in Fernandes et al. (2014) that is specific to the US pension system since many of our

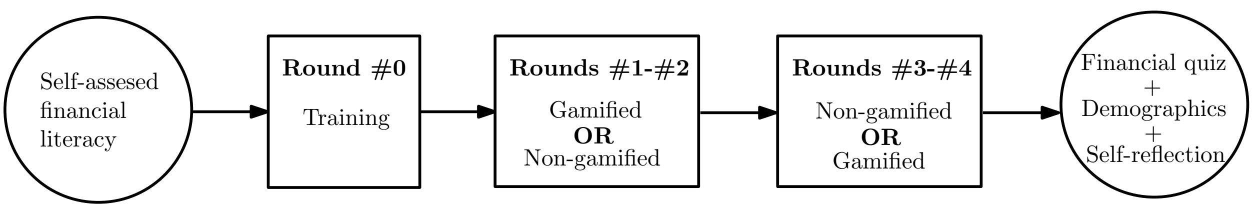
To disentangle between subjective and objective measures of financial literacy, we also ask participants the following question:

> *On a scale from zero to ten, where zero is not at all knowledgeable about personal finance and ten is very knowledgeable about personal finance, what number would you be on the scale?*

The question aims to measure the self-assessed (subjective) level of financial knowledge, and it is identical to the one used in Cupák et al. (2020). We ask this question before the participants start the experiment, so that the answers are not influenced by the monetary performance of the trading game or the subjective difficulty of the quiz.

Figure 1 visualizes the timing of the experiment. The experimental instructions given to participants are reproduced in Online Appendix A. Before the trading starts, participants need to correctly answer five comprehension questions, listed in Online Appendix B. This allows us to make sure that participants indeed understand the experiment before the trading rounds start. Finally, at the end of the experiment all participants are required to fill in a demographic questionnaire.

Figure 1: **Experiment timing**



Payments. Each participant receives a fixed compensation of GB£9 (equivalent to approximately CA$15) per hour. In addition to the fixed amount, participants receive a payment proportional to their performance in the trading game and the financial literacy quiz.

In accordance with standard experimental procedures, the payment round is determined by randomly selecting one of the four trading rounds at the end of the experiment. Participants' earnings are equal to the amount of cash they hold at the end of this randomly chosen payment

experimental participants are not US residents.

round plus the end-of-round price of any stock that they own. The exchange rate is set to E$1 = CA$0.05.

Besides the payment round profit, participants are also rewarded for correct answers in the post-experimental financial literacy quiz. Specifically, each correct answer is rewarded with four experimental dollars, equivalent to CA$0.20. The monetary quiz payoff is subsequently added to the payment round payoff to determine the total payment.

3.2 Gamification strategies and platform design

3.2.1 Gamification strategies in real-world trading apps

As part of the request for comments on digital engagement practices, the SEC defines trading gamification elements to include "social networking tools; games, streaks, and other contests with prizes; points, badges, and leaderboards; notifications; celebrations for trading; visual cues; ideas presented at order placement and other curated lists or features; subscriptions and membership tiers; and chatbots."[10] Following Gallo (2022), we distinguish between three gamification strategies used by financial trading platforms and online brokerages.[11] In Online Appendix E, we provide further details on the gamification strategies used by some of the most popular trading apps in the United States as of July 2022.

1. **Reward animations and badges.** Robinhood, a leading FinTech online brokerage in the United States, shows customers colorful reward animations after each trade. The original animation used celebratory confetti flying across the screen; following widespread criticism—including during a US congressional hearing on February 18, 2021—Robinhood updated the animation to feature floating geometric shapes instead. Platforms such as Binance, the highest-volume cryptocurrency exchange as of May 2022, and the popular social-trading website eToro use achievement badges to reward trading activity.[12]

2. **Lottery incentives.** Some platforms rely on gambling to encourage trading. Coinbase, a

[10]See `https://www.sec.gov/rules/other/2021/34-92766.pdf`, pages 7 and 8.
[11]Gallo (2022) also mentions inadequate disclaimers and disclosures as a form of gamification. We do not study this aspect as it would likely involve using deception in our experimental setup.
[12]See also ForexCrunch: EToro introduces Foursquare Style Badges, January 25, 2011, accessed May 21, 2022.

US-based cryptocurrency exchange, in March 2022 launched a "sweepstakes" program where participants can win large prizes (around US$500,000 in crypto) if they trade at least US$100 on the platform.[13] In Canada, Wealthsimple, a popular FinTech brokerage, offers new accounts a randomly drawn stock worth between CA$5 and CA$4,500 with an average of CA$10.

3. **Emphasis on trending stocks.** Trading apps often provide prominent notifications emphasizing stocks with large price swings, often in the form of push notifications on mobile devices (Chaudhry and Kulkarni, 2021). Evidence suggests that traders are sensitive to such attention-grabbing mechanisms: Arnold et al. (2021) find that push notifications from brokerages incentivize investors to take more risks and increase their leverage. Barber et al. (2022) show that Robinhood traders engage in more attention-induced trading than peer retail investors.

To study the impact of different gamification strategies, we distinguish between reward animations and lottery incentives, on one side, and emphasis on trades on the other side. Reward animations and lottery incentives are not stock-specific: by design they neither contain any information about stock prices and returns, nor do they impact the salience of such information elsewhere on the platform. On the other hand, push notifications draw the investors' attention to stock-specific information—typically a large price swing.

We turn to research in psychology, marketing, and computer science to provide micro-foundations for the value of reward animations and lotteries. Following Huotari and Hamari (2012) and Hamari (2013), we argue that the two gamification strategies provide *hedonic consumption* value for platform users. Hirschman and Holbrook (1982) introduced the concept of hedonic consumption as consumer behavior related to the "multisensory, fantasy, and emotive aspects" of product user experience. Hedonic systems encourage *prolonged* use of the product, in contrast to utilitarian systems designed to maximize *productive* use. In the same spirit, van der Heijden (2004) argues that the value of a hedonic system is driven by the degree to which the user has fun when interacting with the product, for example through a focus on colors, sounds, or animations. Csikszentmihalyi et al. (2014) argue

[13] In contrast to traditional broker-facing exchanges such as NYSE or Nasdaq, cryptocurrency exchanges typically offer retail-friendly online trading platforms.

that clear goals (e.g., entering into a lottery or earning a badge) and immediate feedback (e.g., seeing a reward animation right after a trade) promote "intrinsically rewarding experiential involvement." Dorn and Sengmueller (2009), using survey data for German investors, document that non-pecuniary benefits such as entertainment can explain up to half of the variance in portfolio turnover.

The third gamification strategy prevalent in trading apps, an emphasis on price swings and trends, may also generate hedonic utility to investors by improving product user experience. However, price notifications do not offer clear goals, nor do they provide feedback to investors, casting doubt on their hedonic value. Rather, notifications increase the salience of short-term price movements and therefore carry informational value.

To disentangle the different effects of trading gamification, we leverage the in-between features of our experimental design. Participants in Session I are exposed to design elements with hedonic value, but not to those with informational value. In Sessions II and IV (robustness), the gamified platform only displays price change notifications, but no hedonic elements. Finally, the gamified platform in Session III combines both hedonic and informational gamification features.

3.2.2 Implementation on experimental platform

Badges and reward animations. Table 1 lists the achievement badges and associated messages. Badges are earned upon completing a specified number of trades in a given round. "Unlocking" a badge is accompanied by falling confetti, a congratulatory message, and a animated GIF image.

Table 1: **Achievement badges**

Badge	# trades	$\mathbb{P}$ (badge | optimal play)	Message
Bronze	10	93.66%	Level up! Doing well 👍 GIF image at: `https://bit.ly/3xtGrWk`
Silver	15	73.91%	You belong on the trading floor! 📈 💰 GIF image at: `https://bit.ly/3l8kuqD`
Gold	20	35.59%	You are the money maker! 💰 💰 GIF image at: `https://bit.ly/3n0wbog`
Platinum	25	8.33%	🚀 You are definitely going places! 🙌 GIF image at `https://bit.ly/3cNi6Be`
Diamond	30	0.98%	The Wolf of Wall Street 💎 🤲 GIF image at: `https://bit.ly/3tMKDzE`

To determine the badge thresholds, we simulate optimal play by a Bayesian expected value trader over 10,000 price paths. Given optimal play (that is, buy and sell when the posterior probability of the good state crosses the 0.5 threshold), the median number of trades in one stock over 56 $(= 60 - 4)$ trials is 17, with an interquartile range of 14 to 21 trades.

Price change notification. Another gamification feature we implement in the experiment is the emphasis on trends. To do this, we introduce price change alerts every time the stock price increases or decreases for three trials in a row. We only display a single notification per stock price run to best identify effects empirically (i.e., such that there is no ambiguity whether a trader responds to a three-jumps or a four-jumps notification; this also avoids assigning higher empirical weight to runs with more observations).

Lottery incentives. While some real-life platforms such as Coinbase use lottery-like incentives to increase engagement, we do not implement lotteries on our platform, for two reasons. First, even for small success probabilities, a lottery creates a gap between the expected monetary payoff on the two platforms. Second, we want to limit the number of moving parts on the platform to maximize participant comprehension.

Figure 2 illustrates the different gamification elements. The left panel displays a typical achievement screen, including badges (locked and unlocked), confetti, and congratulatory messages. The right panel illustrates a price change notification.

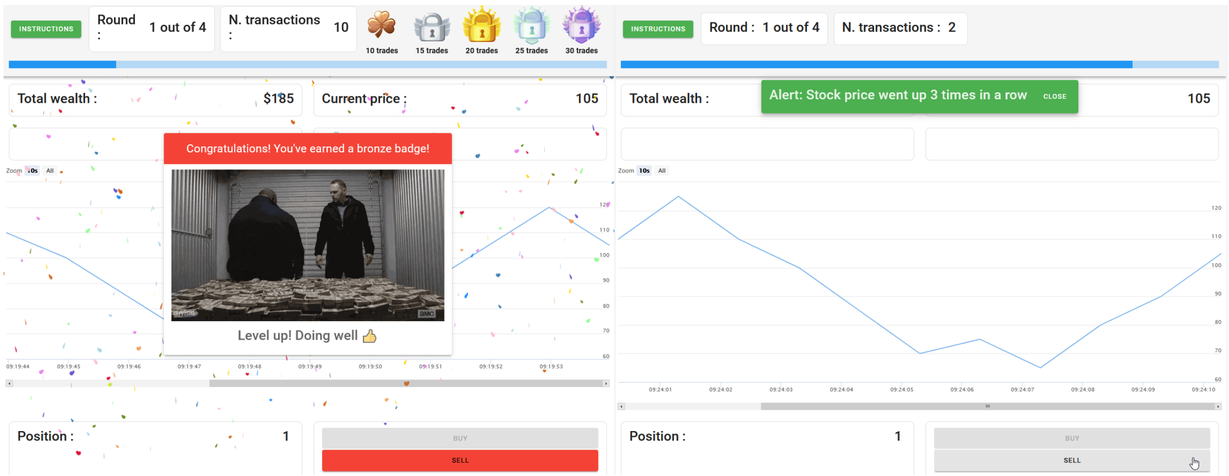
3.3 Theoretical framework

3.3.1 Investor preferences

Frydman et al. (2014) focus separately on two preference specifications: traders either have standard risk-neutral utility and maximize the expected value of their payoffs or they have non-standard preferences such as realization utility as in Barberis and Xiong (2012). We provide below an in-depth discussion of both preference specifications. In this paper, we follow Frydman and Rangel (2014) and assume that investors' utility is a linear combination of the two benchmarks, to which we add

Figure 2: **Trading platform screenshots**

This figure displays two representative screenshots of the gamified trading platform: badges and reward animations (left panel) and price change notifications (right panel). Both platforms include price graphs, information on the current position, total wealth, buy and sell buttons, and a link to instructions.



(a) Badges and rewards

(b) Price movement notification

a hedonic consumption value. This allows us to generate specific predictions on how gamification impacts trader behavior as a function of the intensity of their behavioral biases.

Relative expected value (REV). The *relative expected value* component corresponds to the utility of a risk-neutral trader who maximizes the end-of-round expected payoff. We define REV as in Frydman and Rangel (2014) as the difference between the expected stock price after the next update ($\mathbb{E}p_{t+1}$) and the current stock price p_t. If π_t denotes the Bayesian posterior that the stock is in the good state given its price history up to t, the REV utility component can be written as

$$\begin{aligned}\mathrm{REV}_t &= \mathbb{E}\left(p_{t+1} - p_t \mid p_{\{0,1,\ldots,t\}}\right) \\ &= (2\pi_t - 1)\,(0.85 - 0.15)\,(0.55 - 0.45) \times 10 = 0.7\,(2\pi_t - 1)\,. \qquad (1)\end{aligned}$$

If the stock is in the good state at $t+1$, then the price goes up on average by E\$10 (i.e., the average magnitude of price changes is $(5+10+15)/3 = 10$) with probability 0.55 and drops on average by E\$10 with probability 0.45. The expected price change conditional on state g at $t+1$ is therefore $(0.55 - 0.45) \times 10 =$ E\$1. Similarly, the expected price change given state b at $t+1$ is $-$E\$1. The term $(2\pi_t - 1)(0.85 - 0.15)$ reflects that with probability π_t, the next price change is positive 85% of the time. With probability $1 - \pi_t$, the probability of a price increase at the next trial is only 15%.

Equation (1) highlights the role of beliefs in forecasting price changes. A Bayesian investor expects a price increase at next trial if and only if they believe the stock is more likely to currently be in the state g than state b, that is if $\pi_t > 0.5$. This follows immediately from the fact that states are persistent.

Capital gains (CG). We also allow traders to have linear *realization utility*, as defined in Barberis and Xiong (2012) and Ingersoll and Jin (2013). The main feature of realization utility is that investors experience utility bursts upon realizing gains and losses; that is, at the moment of selling the stocks. The realization utility payoff or capital gain is equal to

$$\mathrm{CG}_t = p_t - c_t, \tag{2}$$

where p_t is the selling price and c_t is the purchase price of the stock (cost basis). If $p_t > c_t$, so that investors realize a gain, they experience positive utility. Otherwise, that is if $p_t \leq c_t$, investors have disutility proportional to the size of their loss. Frydman et al. (2014) find supportive evidence for the realization utility model using neural data from traders' brain activity.

Hedonic consumption (HC). Finally, we assume participants derive utility from the trading process itself. Each executed trade generates a positive utility burst $\tau \geq 0$. The magnitude of the utility burst is a function of whether the platform is gamified or not, with

$$\tau_{\text{gamified}} \geq \tau_{\text{non-gamified}} \geq 0. \tag{3}$$

We interpret τ as a burst of hedonic consumption, in the spirit of Hirschman and Holbrook (1982), from trading on an aesthetically attractive platform. To the extent that the gamified platform is more appealing than the non-gamified one, participants experience larger hedonic utility. We do not make the restrictive assumption that the non-gamified platform induces $\tau = 0$, as it is plausible that participants are likely to enjoy trading regardless of the platform design.

Utility function. The discussion above allows us to formally define investors' utility. Following Frydman and Rangel (2014), we write the utility as a linear combination of the relative expected value (REV), namely the expected price change in equation (1), and the capital gains (CG) or realization utility component. We additionally include the hedonic consumption term and normalize the weights to add up to one. That is, investors put weights ω and $1-\omega$ on the REV and CG utility components, respectively.

Let q_t denote the holdings of the stock at the beginning of each trial t ($q_t \in \{0,1\}$) and $\Delta q_t \equiv q_t - q_{t-1} \in \{-1,0,1\}$ the direction of the trade (sell, do not trade, or buy, respectively). From equation (1), an investor's expected utility can be written as

$$U\left(q_t, \Delta q_t\right) = \omega \times \underbrace{\left(q_t + \Delta q_t\right)\left(2\pi_t - 1\right)\left(\text{Prob}\left(g_{t+1} \mid g_t\right) - \text{Prob}\left(b_{t+1} \mid g_t\right)\right)}_{\text{REV (relative expected value)}} \tag{4}$$
$$+ \left(1-\omega\right) \times \underbrace{\left(p_t - c_t\right)\mathbb{1}_{\Delta q_t = -1}}_{\text{CG (capital gains)}} + \underbrace{\tau\left(\mathbb{1}_{\text{gamified}}\right)\mathbb{1}_{\Delta q_t \neq 0}}_{\text{HC (hedonic consumption)}},$$

where $\mathbb{1}_{(\cdot)}$ is an indicator function taking the value one if the subscript argument is true and zero otherwise. In line with Barberis and Xiong (2012), investors experience realization utility only when selling a stock ($\Delta q = -1$). Hedonic consumption is only realized upon executing a trade, whether a buy or a sell.

The parameter ω is a measure of investor rationality: values closer to one indicate that investors place more weight on maximizing expected utility than on short-lived realization utility bursts.

Bayesian updating. Let $z_t \in \{1,-1\}$ denote the direction of the price change at trial t. Further, let $s_t \in \{g,b\}$ stand for the state of the Markov process. The estimated probability of being in the good state at trial t, that is π_t, evolves as follows:

$$\begin{aligned} &\pi_t\left(\pi_{t-1}, z_t\right) \\ &= \frac{\mathbb{P}\left(z_t \mid s_t = g\right)\mathbb{P}\left(s_t = g \mid \pi_{t-1}\right)}{\mathbb{P}\left(z_t \mid s_t = g\right)\mathbb{P}\left(s_t = g \mid \pi_{t-1}\right) + \mathbb{P}\left(z_t \mid s_t = b\right)\mathbb{P}\left(s_t = b \mid \pi_{t-1}\right)} \\ &= \frac{\left(0.5 + 0.05z_t\right)\left(0.85\pi_{t-1} + 0.15\left(1-\pi_{t-1}\right)\right)}{\left(0.5 + 0.05z_t\right)\left(0.85\pi_{t-1} + 0.15\left(1-\pi_{t-1}\right)\right) + \left(0.5 - 0.05z_t\right)\left(0.15\pi_{t-1} + 0.85\left(1-\pi_{t-1}\right)\right)}, \end{aligned} \tag{5}$$

where $q_0 = 0.5$ is the long-run stationary probability of state g.[14]

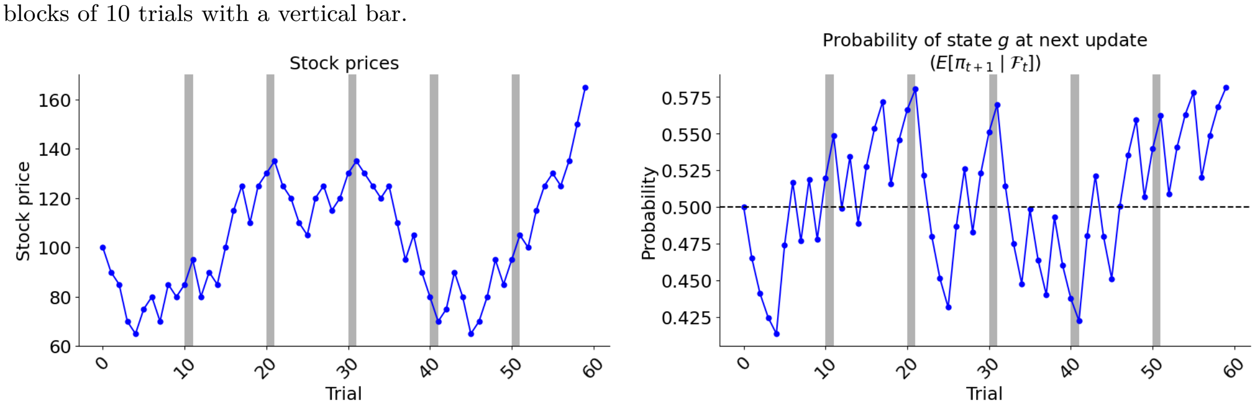
Figure 3 illustrates a simulated price path for the stock (top panel) together with the Bayesian expected probability of an uptick in period $t+1$ conditional on all information up to time t (bottom panel). While investors cannot be expected to perform the computation in (5) in the short time available, Figure 3 highlights a simple heuristic: a run of price increases maps to a higher probability of being in the good state at the next price update; a run of price drops has the opposite effect.

Figure 3: **Simulation of stock price path and good-state probabilities**

The left panel illustrates a potential stock price path generated from Markov chains with state pesistence of 0.85. The initial state is equally likely to be g or b, consistent with the stationary distribution of the Markov chain. The right panel plots the expected uptick probability at trial $t+1$, conditional on all information up to and including trial t (a filtration $\mathcal{F}_t$). That is,

$$\mathbb{E}\left[\pi_{t+1} \mid \mathcal{F}_t\right] = 0.85\pi_t + 0.15\left(1-\pi_t\right), \tag{6}$$

where π_t is computed as in equation (5). To facilitate comparison between the left and right panels, we separate blocks of 10 trials with a vertical bar.



3.3.2 Hedonic consumption and the optimal trading strategy

We turn next to describing the optimal trading strategy. We start from the utility function in (4) and focus on the impact of the hedonic consumption τ on trading decisions.

Buying decisions. First, we analyze the decision to buy the stock. Given the one-unit position limit, investors can only purchase the stock conditional on not owning it already. The decision

[14] We allow for a positive probability of switching between the "good" and "bad" states throughout a single round. This translates to a lower state persistence and consequently to more frequent trades under the optimal Bayesian strategy, since Bayesian participants optimally buy (sell) when the estimated probability of being in the "good" state is higher (lower) than one-half — as we show in Section 3.3.2. Thus, allowing for state transitions within a round enables us to observe violations of the optimal strategy more frequently.

whether to buy boils down to comparing the two branches in equation (7):

$$\begin{cases} U\left(q_t = 0, \Delta q_t = 0\right) = 0, & \text{(do not buy)} \\ U\left(q_t = 0, \Delta q_t = 1\right) = \omega\left(2\pi_t - 1\right)\left(\mathbb{P}\left(g_{t+1} \mid g_t\right) - \mathbb{P}\left(b_{t+1} \mid g_t\right)\right) + \tau. & \text{(buy the stock)} \end{cases} \tag{7}$$

If an investor does not buy the stock, their utility is zero. If they buy it, they obtain the relative expected value utility with weight ω as well as the hedonic consumption τ for executing a trade. There is no realization utility for purchasing the asset. The optimal choice corresponds to a unique probability threshold θ_{buy}. That is, the investor buys a stock if and only if the probability of being in the good state is larger than θ_{buy}, that is if

$$\pi_t > \theta_{\text{buy}} := \frac{1}{2} - \frac{\tau}{\omega}. \tag{8}$$

If investors obtain no intrinsic value for trading (equivalently, for $\tau = 0$), we retrieve the result in Frydman et al. (2014): investors buy a stock if and only if $\pi_t > \frac{1}{2}$. Introducing hedonic value for the trading process widens the probability range for which buying the stock is optimal. In particular, investors are more likely to purchase stocks with negative expected returns (i.e., stocks that are likely to be in the bad state).

Selling decisions. We similarly analyze the optimal selling strategy. Under the no short-selling constraint, investors can only sell the stock if they already own it, that is if $q_t = 1$. To decide whether to sell a stock, investors compare

$$\begin{cases} U\left(q_t = 1, \Delta q_t = 0\right) = \omega\left(2\pi_t - 1\right)\left(\mathbb{P}\left(g_{t+1} \mid g_t\right) - \mathbb{P}\left(b_{t+1} \mid g_t\right)\right), & \text{(do not sell)} \\ U\left(q_t = 1, \Delta q_t = -1\right) = \left(1 - \omega\right)\left(p_t - c_t\right) + \tau. & \text{(sell the stock)} \end{cases} \tag{9}$$

If the investor does not sell the stock, they capture the realized expected value utility. Conversely, if they decide to sell, the investor obtains the realization utility from capital gains (which can be either positive or negative), plus the hedonic consumption τ. The optimal choice maps to a different probability threshold θ_{sell}: investors sell if and only if the probability of being in a good state is low enough; that is

$$\pi_t \leq \theta_{\text{sell}} \equiv \frac{1}{2} + \frac{(1-\omega)(p_t - c_t) + \tau}{\omega}. \tag{10}$$

The optimal strategy for REV investors with no hedonic consumption (i.e., investors with $\omega = 1$ and $\tau = 0$) is to sell the stock if and only if the probability of being in the good state is less than half. If investors care about realized gains and losses ($\omega < 1$), the disposition effect emerges: investors may sell "winner" stocks that are expected to do well in the future and hold on to "loser" stocks that have negative expected returns. Hedonic consumption from trading has an asymmetric impact on the magnitude of the disposition effect. On one hand, investors are even more likely to sell winner stocks, which amplifies the disposition effect. On the other, they are also more likely to sell losing positions, reducing the disposition effect.

3.3.3 Price swing notifications and investor behavior

The discussion in Section 3.3.2 focused on the impact of hedonic gamification strategies with no informational content about stock prices such as reward animations or lotteries for trading. We also introduce another common digital engagement strategy: participants receive notifications about large price swings. The impact of notifications on trading strategies is likely more complex, as they increase the prominence of particular events on the platform.

Our experimental design is well suited to disentangling three potential effects of price change notifications. First, notifications could reduce information processing costs and help participants better forecast asset prices. Second, they might amplify the disposition effect by increasing the salience of gains and losses. Finally, notifications might simply generate hedonic consumption by making the trading platform more appealing. We argue the three channels have distinct implications for the magnitude of the disposition effect on the experimental platform.

Information processing costs. In practice, participants are unlikely to use Bayes' formula to update their probabilities. Frydman et al. (2014) suggest that computing the share of price increases over a recent interval acts as a simple heuristic to forecast the current state. Therefore, participants base their decision on a measure $\tilde{\pi}_t$ which is a noisy estimator of the true π_t.

One hypothesis is that notifications serve as an additional heuristic to aid learning. When investors receive a notification that the stock price went up (down) many times in a row, this is equivalent to a strong signal that the stock is in the good (bad) state, and they update their probabilities upward accordingly:

$$\tilde{\pi}_{\text{update}} = \begin{cases} (1-\lambda)\,\tilde{\pi} + \lambda \times 1 \geq \tilde{\pi} & \text{for price increase notifications} \\ \\ (1-\lambda)\,\tilde{\pi} + \lambda \times 0 \leq \tilde{\pi} & \text{for price decrease notifications} \end{cases} \tag{11}$$

where $\lambda \in [0, 1]$ is the weight investors put on the notification signal. For simplicity, we are assuming investors interpret a price increase notification as a signal that $\pi_t = 1$ and a price drop notification as evidence that $\pi_t = 0$.

If notifications reduce information costs, investors should be less willing to sell stocks that are doing well and more willing to sell stocks that are doing poorly. Using the measures in Odean (1998), the proportion of gains realized (PGR) decreases, while the proportion of losses realized (PLR) is larger. There are two alternative hypotheses. First, notifications may increase the salience of gains and losses. In this case, we should see a stronger disposition effect as PGR increases while PLR drops – investors put more weight on capital gains. Second, if notifications simply provide hedonic value investors would be more willing to sell both winners and losers (both PGR and PLR go up).

4 Results

4.1 Cohort formation

We recruited participants from Prolific, an online subject pool specifically for academic research (Palan and Schitter, 2018). Financial trading apps aim to serve the widest possible clientele; for example, Robinhood's stated mission is to "democratize finance for all". To capture a wide cross-section of the population, we use a representative sample of residents of the United States and the United Kingdom, both of which are anglophone countries with well-developed securities markets. Prolific utilized census data from both countries to construct a stratified sample across age, gender, and ethnicity. Experimental sessions were conducted on April 11 and April 12, 2023 (for the US- and UK-based samples, respectively). Participants required a median of 41 minutes to complete the experiment.

Table 2 breaks down the sample across treatments and subject pools.[15]

Table 2: **Participant sample size across experimental sessions**

Session #	US Participants	UK Participants	Total session
1	157	162	319
2	153	166	323
3	86	77	163
4	82	75	157
Total	478	480	958

Each participant received a fixed amount of GB£6.75 (approximately CA$11.50) for participating in the experiment. This level of fixed compensation offered corresponds to about CA$17.20 per hour. In addition to the fixed amount, participants received a bonus proportional to their performance in a randomly drawn trading round and in the financial literacy quiz. The average and median bonus payments are CA$11.28 and CA$11.25, respectively, with bonuses ranging from CA$1.75 to CA$18.50.

Demographics. After the experiment, each participant completed a short demographics questionnaire. Our sample is gender-balanced, with 479 participants identifying as female (50%), 469 identifying as male (48.95%), and 10 non-binary participants (1%). Age-wise, the median participant is 45 years old, and participant ages range between 19 and 76. By comparison, the average age of Robinhood users is 31.[16] In our sample, 55.21% (529 participants) received some form of undergraduate education and 18.58% (178 subjects) reported having obtained a master's degree, an MBA, or a doctorate. However, only 22.3% of our participants have a formal education in finance, economics, or management (and only 5.9% majored in finance).

[15]For each of the two countries, we aimed for 160 participants (80 participants) in Sessions 1 and 2 (respectively Sessions 3 and 4). To implement this, we assign the first and second of each batch of six participants to Session 1, the third and fourth to Session 2, the fifth to Session 3, and the sixth to Session 4. However, participants can quit the process at any point during the experiment after being allocated to a session. Therefore, in practice the sample sizes can differ slightly from the benchmark. Further, two US participants were erroneously approved by the platform without finishing the experiment. We purge their data from further analysis.

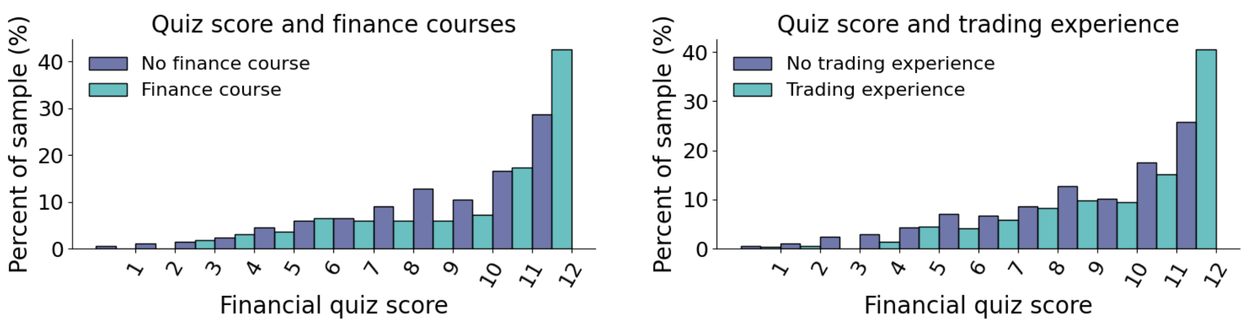
[16]See Reuters: "Young, confident, digitally connected – meet America's new day traders", February 2, 2021.

More than half of our sample report that they have significant trading experience (51.36%) and more than a third (35.28%) assert familiarity with online trading apps. Among the participants with trading experience, almost three quarters (73.9%) trade mainly stocks, with 18.2% focusing on cryptocurrencies and 5.6% on bonds.

We asked our participants about their trading habits. Almost a third of our sample checks their portfolio at least once a week (29.3% of subjects), with 11% executing at least one trade a month. At the other end of the spectrum, 57% of participants check their portfolio less than once a month.

Figure 4: **Financial literacy quiz scores**

This figure illustrates the distribution of financial literacy quiz scores as functions of whether participants were exposed to a formal course in finance and whether they had real-life trading experience before the experiment.



At the end of the experiment, each participant was invited to answer a financial literacy quiz of 12 questions, detailed in Online Appendix C. Each correctly answered question was rewarded with a monetary payment of CA$0.20 (equivalent to one experimental dollar). Figure 4 displays the distribution of quiz scores. The average quiz score is 8.6 points (or 71.6%), with a standard deviation of 2.74 points. The financial literacy score is correlated with whether the participant has taken a formal course in finance (the average score increases to 9.11) as well as with real-life trading experience (average score of 9.41).

4.2 Do novice traders prefer gamified trading platforms?

First, we aim to understand which investors prefer to interact with gamified trading platforms. A prevalent narrative is that novice traders are attracted to online trading platforms—is this due to gamification strategies? Hypothesis 1 tackles the issue of self-selection and conjectures that participants with low levels of financial literacy are more likely to express a preference for the gamified platform, either because they assign more weight to its hedonic value, or because price alerts have a higher marginal value to them, or for a combination of both reasons.

Hypothesis 1. (Revealed preference) *Participants with a lower level of financial literacy are more likely to choose the gamified platform when presented with the option.*

To test Hypothesis 1, for each of Sessions I, II, and III, we estimate linear probability models:

$$d_{\text{choice},j} = \beta_0 + \beta_1 \text{FinLiteracy}_j + \text{Controls} + \text{error}. \tag{12}$$

Here, $d_{\text{choice},j}$ is a dummy encoding participants' responses to Question 1 or Question 2 in Online Appendix D. That is, (1) whether they prefer gamified or non-gamified platforms; (2) whether they feel that they made better decisions on gamified or non-gamified platforms. We recognize that participants may simply prefer the platform design that led to greater success for them. To account for this possibility and estimate participants' preference conditional on their relative performance, we control for the profit difference between gamified and non-gamified rounds.

Table 3 reports the estimation results. A first observation is that only 38% of the participants prefer the hedonic platform over the non-gamified one, relative to 55% of participants who would choose to trade again on the platform with price trend alerts. In line with Hypothesis 1, participants with low financial literacy are more likely to choose the hedonic platform: a one-standard-deviation decrease in the financial quiz score corresponds to a nine percentage point–higher likelihood of choosing the hedonic platform. Table H.1 in Online Appendix H shows further evidence that participants with high financial literacy dislike hedonic gamification features – a one standard deviation increase in quiz score leads to a 11.2% and 13.2% decrease in Likert scores for achievement badges and confetti, respectively. At the same time, we document no significant relationship between financial literacy and the revealed preference for price notification alerts. We conclude that price alert notifications are widely appreciated by a larger cross-section of traders, while hedonic elements appear to be more polarizing and cater to participants with relatively lower levels of financial education.[17]

Table 3: Revealed preferences for trading gamification

This table presents the estimation results of a linear probability model

$$d_{\text{choice},j} = \beta_0 + \beta_1 \text{FinLiteracy}_j + \text{Controls} + \text{error},$$

where $d_{\text{choice},j}$ is the dummy encoding participant answers to Questions 1–3 in Online Appendix D: (1) "*If you can trade again, would you choose a gamified or non-gamified design?*", (2) "*If you can trade again, would you expect to make better decisions on a gamified or non-gamified design?*", and (3) "*If you can trade again, would you prefer to be given an option to choose from a gamified or non-gamified design?*" The explanatory variables include the standardized financial quiz score, the standardized payoff difference between the gamified and non-gamified rounds, the standardized value of the self-assessed financial knowledge, dummies for participant trading experience and whether they took an academic course in finance, the average accuracy of beliefs elicited at the midpoint of each round (computed as the relative distance between the participant's belief that the stock is in a good state and the Bayesian probability of a good state), and finally participant age and gender. Column labels S1, S2, and S3 pertain to experimental Sessions #1, #2, and #3 respectively. The unit of observation is a participant.

	Prefer gamified			Better decisions if gamified			Option to choose	
Session	S1	S2	S3	S1	S2	S3	S1	S2
Constant	0.38***	0.55***	0.40***	0.35***	0.57***	0.40***	0.66***	0.78***
	(6.81)	(9.53)	(4.70)	(6.19)	(10.08)	(4.87)	(11.82)	(16.76)
Financial quiz score	-0.09***	0.01	-0.10**	-0.07**	0.01	-0.09*	-0.02	-0.01
	(-2.91)	(0.42)	(-2.01)	(-2.15)	(0.28)	(-1.80)	(-0.65)	(-0.54)
Payoff difference	0.05**	0.05	-0.02	0.06**	0.03	0.04	0.00	0.03
	(2.03)	(1.37)	(-0.53)	(2.31)	(1.02)	(1.23)	(0.21)	(1.19)
Self-assessed financial literacy	0.01	-0.02	0.03	0.01	-0.04	-0.00	0.02	-0.03
	(0.25)	(-0.60)	(0.66)	(0.31)	(-1.12)	(-0.10)	(0.78)	(-1.13)
Trading experience	0.02	-0.01	-0.02	0.04	0.03	0.01	-0.01	0.04
	(0.26)	(-0.20)	(-0.26)	(0.65)	(0.47)	(0.07)	(-0.16)	(0.65)
Finance course taken	0.08	0.10	0.05	0.10	0.06	0.01	-0.04	0.02
	(0.93)	(1.23)	(0.41)	(1.20)	(0.69)	(0.06)	(-0.47)	(0.39)
Prediction accuracy	-0.02	0.01	-0.07	0.00	0.01	-0.03	-0.03	0.02
	(-0.62)	(0.27)	(-1.59)	(0.08)	(0.37)	(-0.74)	(-1.14)	(0.75)
Age	0.03	0.01	-0.02	0.06	0.01	0.06	-0.04	-0.01
	(0.52)	(0.93)	(-0.34)	(1.23)	(1.30)	(0.88)	(-0.75)	(-0.67)
Gender (female)	0.08	0.08	0.05	0.04	0.05	-0.02	0.07	0.04
	(1.37)	(1.30)	(0.58)	(0.65)	(0.76)	(-0.22)	(1.21)	(0.84)
Observations	291	297	148	291	297	148	291	297
R-squared	0.05	0.02	0.07	0.04	0.01	0.05	0.02	0.02

We further hypothesize that some traders may believe that gamification leads them to make suboptimal decisions, but still find the experience enjoyable and consider it a fair trade-off. This

[17]Table 3 reports estimation results for linear probability models, but we obtain qualitatively identical results when estimating Probit regressions.

kind of behavior may be considered rational and may not be of concern to policymakers. A separate scenario is addiction, where the investor realizes that their financial decisions are being negatively impacted by certain features of the app, acknowledges that the excitement is not worth the financial cost, but is unable to disengage.

In our results, we do not observe a clear indication of an addiction channel. Participants consistently prefer the platform on which they believe to have made better choices: the correlation between the answers to the two self-reflection questions is 80%.[18] To more directly distinguish between a "rational" gamification preference and an addictive one, we also asked participants to indicate a preference between (i) being given the option to choose between two designs or (ii) not being offered a choice and being exposed only to the non-gamified design. From Columns (7) and (8) in Table 3, most of the participants opt to be allowed to choose a gamified platform: that is, 66% of the sample for the hedonic treatment and 78% for the informational treatment. Nevertheless, since participants may rationalize their decisions ex post, our results should not be conclusively interpreted as evidence against an addiction channel.

Figure 5 showcases that the intensity of the preference for hedonic gamification is proportional to financial literacy: The average financial quiz score decreases monotonically in the Likert rating of achievement badges (left panel). We do not document a similar pattern for the treatment featuring information-driven gamification: Participants' rating of price alerts is uncorrelated with their financial quiz score.

4.3 Hedonic gamification and trading behavior

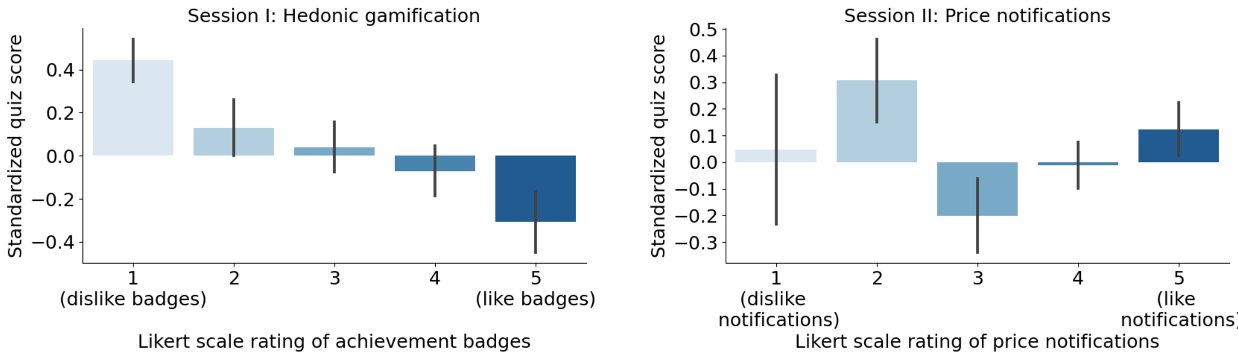
In this section we focus on data from Session I, in which each participant experiences a non-gamified platform as well as a gamified platform with only hedonic elements of gamification (badges and reward animations). We conjecture that reward animations and badges yield an increase in τ, causing participants to trade more on the platform.

A natural measure for the intrinsic value of trading is simply to count executed trades in each

[18]Indeed, 89.55% of the participants who prefer the gamified treatment also state they made better decision in gamified rounds (446 out of 498). Symmetrically, 90.2% of participants who prefer the non-gamified treatment answer that they made better decisions in non-gamified rounds (415 out of 460).

Figure 5: **Preferences for gamification and financial literacy**

This figure illustrates the average standardized financial quiz score across sub-samples of participants, depending on their rating for gamification elements. The left panel focuses on Session I with hedonic gamification elements, whereas the right panel refers to Session II featuring informational gamification.



round. However, the Bayesian benchmark number of trades varies across rounds since the price paths are themselves stochastic. To compare engagement with the platform across rounds, we build a measure of trading activity as the ratio between the realized trade count and the benchmark number of trades. The benchmark number of trades is computed as the number of times the Bayesian "good state" probability π crosses the one-half threshold for player j in round r:

$$\text{TradingActivity}_{j,r} = \frac{\text{Trade count}_{j,r}}{\text{Bayesian trade count}_{j,r}}. \tag{13}$$

Do digital engagement practices, in line with the SEC concerns[19], encourage investors to buy and sell more stocks? Hypothesis 2 aims to establish whether this is true or not in a randomized environment that largely eliminates selection biases and confounding macroeconomic factors (e.g., quantitative easing due to the pandemic).

Hypothesis 2. (Trader engagement) *Participants trade more on the gamified platform than on the non-gamified platform. Further, participants execute a larger number of trades than implied by the benchmark strategy for a Bayesian expected value trader.*

Hypothesis 2 translates to $\beta_0 + \beta_1 > 1$ and $\beta_1 > 0$ in the following linear regression model:

$$\text{TradingActivity}_{j,r} = \beta_0 + \beta_1 d_{\text{game},j,r} + \text{Controls} + \text{error}, \tag{14}$$

[19]See Bloomberg, Trading 'Gamification' Is Huge Concern, SEC Enforcement Chief Says, June 19, 2022.

where $d_{\text{game},j,r}$ is a dummy taking the value one if participant j trades on the gamified platform in round r and zero otherwise. Control variables include participant age, gender, quiz score, self-assessed financial knowledge, dummy variables indicating whether the purchase price is salient, whether the participant has real-life trade experience, whether they have taken a finance course, the accuracy of their mid-round beliefs, and the round-number fixed effects to proxy for experience.

Table 4 displays our estimation results. Overall, the effect of hedonic gamification on trading engagement is modest when considering the entire sample. The use of achievement badges and confetti celebrations results in a marginally significant 5.17% increase in trading activity (equal to 0.03/0.58). However, the effect is much stronger within the subset of participants who are more likely to self-select into gamified trading platforms.[20] When considering participants who prefer the hedonic design, gamification leads to a significant 12.5% increase in trading activity. The impact of gamification is most pronounced for those who highly value achievement badges, with an increase in trade execution of 0.16 (21.33%) in gamified rounds compared to non-gamified ones.[21]

The second part of Hypothesis 2 posits that participants would trade too much relative to the Bayesian risk-neutral strategy. However, our findings imply the opposite: on average, participants execute fewer trades (i.e., $\beta_0 + \beta_1 = 0.62$) than expected under the Bayesian expected value strategy. Nevertheless, as depicted in Figure 6, participants who exhibit a preference for the gamified treatment and rate hedonic elements more favorably tend to trade more, even in non-gamified rounds.

Our findings suggest the presence of a selection effect whereby participants who place a higher value on the hedonic aspects of trading are more likely to opt for the gamified platform. Furthermore, these participants tend to engage in more frequent trading on both gamified and non-gamified platforms. If each participant exclusively traded on their preferred platform design, gamified platforms would have 30% more trades than non-gamified platforms (equivalent to ${}^{(0.73-0.56)}/_{0.56}$). Equation (15) decomposes the difference into the direct impact of gamification and the contribution

[20] We split the sample based on whether participants chose to use the gamified platform or not, rather than their level of financial literacy. This self-selection criterion is more practical for policymakers as it is easier to observe financial market participation and platform choices compared to assessing financial literacy.

[21] In Online Appendix F we test whether the impact of gamification on trading activity is moderated by investor rationality. We find no evidence for such an effect (see Table F.1), while using a number of measures to proxy for rationality: the financial quiz score, initial knowledge self-assessment, overconfidence in financial knowledge, a dummy on whether price and profit are saliently displayed on the platform, or in-game trading experience.

Table 4: Hedonic gamification and trader engagement

This table presents the estimation results for the linear regression model

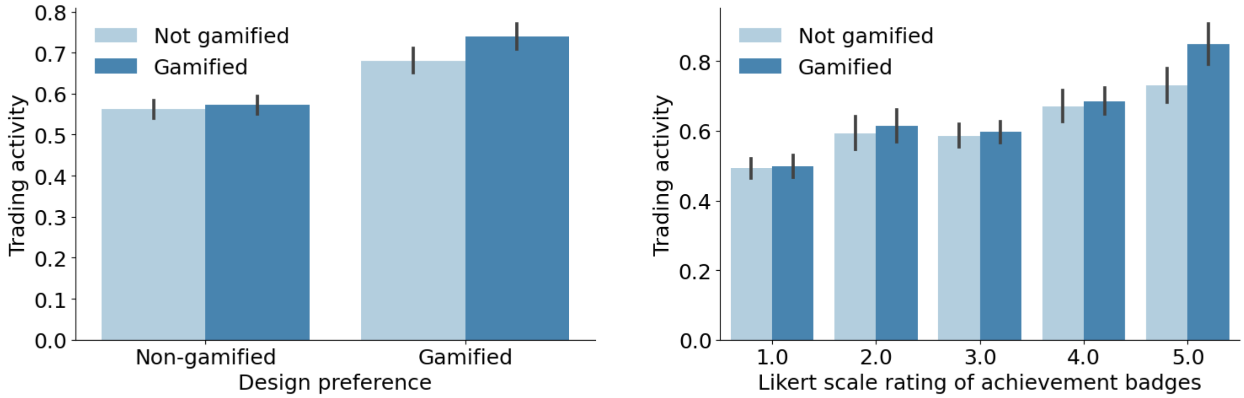
$$\text{TradingActivity}_{j,r} = \beta_0 + \beta_1 d_{\text{game},j,r} + \text{Controls} + \text{error},$$

where j and r run over participants and rounds, respectively. TradingActivity is defined as the ratio between the effective and benchmark number of trades in a given round; $d_{\text{game},j,r}$ is a dummy taking the value one if round r is gamified, and zero else. Controls include a dummy for whether the purchase price is salient in a given round, the standardized financial quiz score, the standardized value of the self-assessed financial knowledge, dummies for participant trading experience and whether the participant took an academic course in finance, the average accuracy of beliefs elicited at the midpoint of each round (computed as the relative distance between the participant's belief that the stock is in a good state and the Bayesian probability of a good state), participant age and gender, and round fixed effects. The unit of observation is a participant-round. Standard errors are clustered by participant.

	Full sample	Gamified preference		Player rating for achievement badges				
		No	Yes	1 (Low)	2	3	4	5 (High)
Gamified	0.03*	0.00	0.08**	0.01	0.00	0.01	0.01	0.16***
	(1.82)	(0.16)	(2.61)	(0.25)	(0.07)	(0.38)	(0.25)	(3.83)
Salient purchase price	-0.01	0.00	-0.02	0.01	0.03	0.01	-0.01	-0.06
	(-0.65)	(0.12)	(-0.54)	(0.48)	(0.64)	(0.39)	(-0.28)	(-1.22)
Age	-0.01	-0.09**	0.11	-0.07	-0.14	0.02	-0.04	0.19*
	(-0.27)	(-2.33)	(1.65)	(-1.42)	(-1.24)	(0.36)	(-0.56)	(1.69)
Gender (female)	-0.03	-0.02	-0.10	-0.02	-0.12	-0.12*	0.08	-0.08
	(-0.78)	(-0.37)	(-1.34)	(-0.29)	(-1.46)	(-1.88)	(0.89)	(-0.52)
Financial quiz score	-0.05**	0.03	-0.11***	0.05	-0.00	-0.02	-0.09*	-0.03
	(-2.12)	(1.06)	(-3.41)	(0.87)	(-0.04)	(-0.46)	(-1.98)	(-0.60)
Self-assessed financial literacy	0.03	0.03	0.02	0.01	-0.08	0.02	0.07	0.04
	(1.53)	(1.36)	(0.47)	(0.30)	(-1.21)	(0.74)	(1.50)	(0.84)
Trading experience	0.11**	0.09*	0.14*	-0.01	0.14*	0.14*	0.24**	-0.02
	(2.38)	(1.72)	(1.79)	(-0.12)	(1.88)	(1.96)	(2.51)	(-0.11)
Finance course taken	-0.00	-0.10	0.09	0.03	0.08	-0.10	-0.26**	0.44**
	(-0.03)	(-1.39)	(0.98)	(0.33)	(0.58)	(-1.01)	(-2.35)	(2.17)
Prediction accuracy	-0.02	-0.00	-0.03	0.01	-0.02	-0.03	-0.01	0.00
	(-1.22)	(-0.28)	(-1.29)	(0.64)	(-0.74)	(-1.15)	(-0.46)	(0.03)
Constant	0.58***	0.53***	0.64***	0.46***	0.58***	0.59***	0.56***	0.75***
	(15.52)	(12.26)	(10.36)	(6.12)	(6.71)	(11.57)	(6.27)	(6.29)
Round FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,063	601	462	228	134	260	246	195
Adjusted R-squared	0.03	0.04	0.07	0.01	0.07	0.04	0.09	0.12

Figure 6: **Trading activity and preferences for gamification**

This figure illustrates the average trading activity measure, defined as in equation (14), across subsamples of participants in Session I. The left panel focuses on participants who either prefer the gamified or the non-gamified design. In the right panel, we split the sample across different ratings for achievement badges.



of the selection effect:

$$\underbrace{\text{TradingActivity}_{G,G}}_{=0.73} - \underbrace{\text{TradingActivity}_{NG,NG}}_{=0.56} = \underbrace{\text{TradingActivity}_{G,NG} - \text{TradingActivity}_{NG,NG}}_{\text{selection effect} \approx 0.68 - 0.56 = 0.12}$$

$$+ \underbrace{\text{TradingActivity}_{G,G} - \text{TradingActivity}_{G,NG}}_{\text{gamification effect} \approx 0.73 - 0.68 = 0.05}, \quad (15)$$

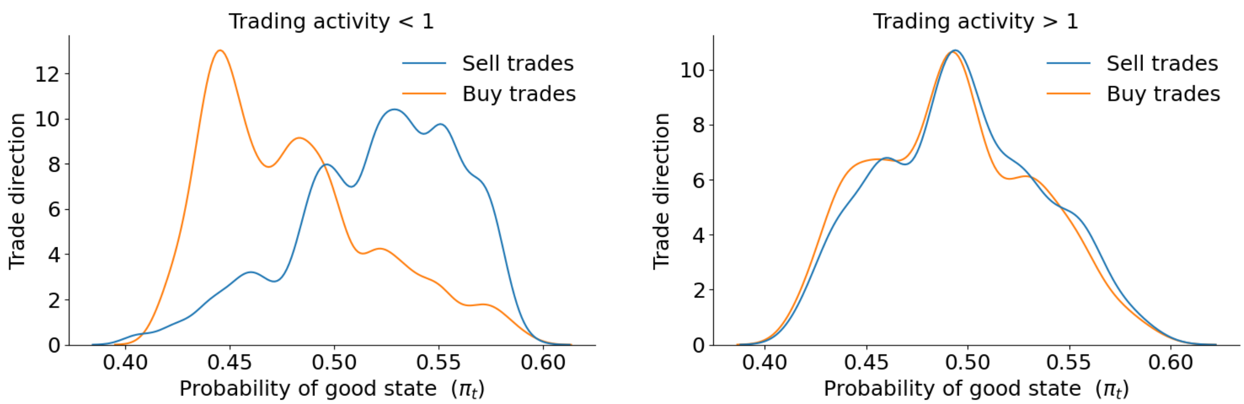
where $\text{TradingActivity}_{i,j}$ is the average trading activity on treatment j for a participant who prefers treatment i.

The results show that the selection effect accounts for over 70% of the difference in the number of trades between gamified and non-gamified platforms, with only 30% directly attributable to the hedonic gamification elements.

To investigate why participants trade less than a Bayesian investor, we further examine their trading behavior. Our theoretical framework in Section 3.3 suggests that participants should buy the stock when the probability of a good state π_t is high enough, and sell it if π_t falls below a certain threshold. Figure 7 shows the empirical distribution of π_t for all buy and sell trades in Session I. Participants who trade less than the Bayesian benchmark (i.e., TradingActivity < 1) tend to act counter to the theoretical prediction. On average, they sell the asset after a series of price increases (when π_t is high) and buy it back after a string of price drops (when π_t is low). This behavior aligns with an irrational belief that the stock price follows a mean-reverting process, as discussed in previous studies (e.g., Weber and Camerer, 1998; Odean, 1998).

Figure 7: **Distribution of π_t by trading activity**

This figure shows the empirical distribution of the good-state probability π_t for buy and sell trades in Session I. The density plots distinguish between participants who trade less than the Bayesian benchmark (left panel) and those who trade more (right panel).



Participants who trade more than the Bayesian benchmark exhibit a weaker pattern. The timing of their buy and sell transactions is only slightly correlated with the good state probability π_t, indicating a more random trading pattern, likely driven by a larger hedonic value of trading.

We recognize that the trade-by-trade threshold, π_t, is inherently noisy. To refine this, we average thresholds each round for every trade made by a single participant. This step reduces the "within" participant standard deviation of π more than twofold from 0.033 to 0.013, providing a clearer, more reliable measure of the true thresholds. To test whether trading gamification affects the timing of trades, we estimate the regression model given by Equation 16:

$$\bar{\theta}_{j,r,d} - \frac{1}{2} = \beta_{0,d} + \beta_1 d_{\text{prefers game},j} + \beta_2 d_{\text{game},j,r} + \beta_3 d_{\text{prefers game},j} \times d_{\text{game},j,r} + \text{Controls} + \text{error}, \quad (16)$$

where, $\bar{\theta}_{j,r,d}$ is the average value of π_t for trades executed by participant j in round r and trade direction d, $d_{\text{game},j,r}$ is a dummy variable that takes the value of one in gamified rounds and zero otherwise, and $d_{\text{prefers game},j}$ is a dummy variable that takes the value of one if participant j states a preference for the gamified treatment.

Table 5 reports the estimation results. We document suboptimal trading decisions for both buy and sell trades. On average, participants tend to buy the asset when the probability of a good state is low, that is $\pi_t \leq 47.30\%$ (i.e., 50% minus 269.53 basis points) and sell the asset when the probability of a good state is high, $\pi_t \geq 52.95\%$ (i.e., 50% plus 295.13 basis points). The effect is 15% to 20% weaker for those participants who prefer the gamified treatment, since on average they execute more trades and their timing appears more random.

Our analysis provides limited evidence that the inclusion of hedonic gamification elements impacts the timing of trades. Table 5 indicates that gamification leads to a 36.28 bps lower bias on sell trades, but only for participants who prefer the gamified treatment (in this context, the term bias refers to a deviation from Bayesian optimal trade thresholds, rather than a cognitive psychological bias). There is no evidence of a significant impact on buy trades.[22]

Interestingly, our experiment shows that suboptimal trading behavior persists even in the absence of gamification. Participants tend to buy at the "bottom" and sell at the "peak" as if prices follow a mean-reverting process. However, this effect is less pronounced for participants who have a larger hedonic value of trading, as they trade more randomly and are thus closer to the Bayesian benchmark.

We turn next to measuring the disposition effect. Following Odean (1998), for each price update we label investors' positions in terms of realized or unrealized gains and losses. If the stock is sold at a higher (lower) price than the purchase price, it counts as a realized gain (loss). If the participant holds the stock in their portfolio at the end of a trial, it is considered a paper gain (loss) if it trades at a higher (lower) price than the purchase price. We sum all realized and paper gains/losses across stocks and trials in round r and compute two ratios:

$$\begin{aligned} PGR_{j,r} &= \frac{\text{Realized gains}}{\text{Realized gains} + \text{Paper gains}} \quad \text{(proportion of gains realized)}, \\ PLR_{j,r} &= \frac{\text{Realized losses}}{\text{Realized losses} + \text{Paper losses}} \quad \text{(proportion of losses realized)}. \end{aligned} \tag{17}$$

Table 5 shows that suboptimal trading leads to a strong disposition effect, as investors realize

[22]We further interact the gamification treatment with measures of investor rationality in Online Appendix F (Table F.2). However, we do not find a significant relationship between gamification and trade timing, even for participants with low levels of financial literacy or trading experience.

Table 5: Trade timing and gamification

This table presents the estimation results for the linear regression model

$$y_{i,t} = \beta_{0,d} + \beta_1 d_{\text{prefers game},j} + \beta_2 d_{\text{game},j,r} + \beta_3 d_{\text{prefers game},j} \times d_{\text{game},j,r} + \text{Controls} + \text{error},$$

where j and r run over participants and rounds, respectively. The dependent variables are (i) the trade bias, measured as the difference between the average probability of a good state upon buy/sell trades and the Bayesian benchmark of $\frac{1}{2}$, that is, $\bar{\theta}_{j,r} - \frac{1}{2}$, and (ii) the proportion of losses and gains realized in round r by participant j, defined as in equation (17). $d_{\text{game},j,r}$ is a dummy taking the value one if round r is gamified for participant j and zero otherwise; $d_{\text{prefers game},j}$ is a dummy taking the value one if participant j prefers the gamified treatment, and zero otherwise. Controls include a dummy for whether the purchase price is salient in a given round, the standardized financial quiz score, the standardized value of the self-assessed financial knowledge, dummies for participant trading experience and whether participants took an academic course in finance, the average accuracy of beliefs elicited at the midpoint of each round (computed as the relative distance between the participant's belief that the stock is in a good state and the Bayesian probability of a good state), participant age and gender, and round fixed effects. The unit of observation is a participant-round. Standard errors are clustered by participant.

	Buy trades bias		Sell trades bias		PLR		PGR	
Constant	-275.07***	-269.53***	294.33***	295.13***	0.09***	0.09***	0.27***	0.26***
	(-11.64)	(-10.44)	(14.01)	(12.93)	(5.43)	(5.13)	(12.56)	(11.46)
Prefers gamified	64.68***	49.77*	-40.44*	-23.58	0.03*	0.03	0.03*	0.03
	(3.00)	(1.92)	(-1.97)	(-0.98)	(1.70)	(1.26)	(1.82)	(1.50)
Gamified × Prefers gamified		18.62		-36.28**		0.01		0.02
		(0.94)		(-2.17)		(0.60)		(0.84)
Gamified × Prefers non-gamified		-11.92		-1.34		-0.00		0.02
		(-0.62)		(-0.08)		(-0.36)		(0.93)
Salient purchase price	-23.05**	-22.95**	-5.13	-5.20	-0.01	-0.01	0.04***	0.04***
	(-2.01)	(-2.00)	(-0.43)	(-0.44)	(-1.21)	(-1.28)	(4.10)	(4.10)
Age	-41.30**	-41.63**	13.76	13.97	-0.01	-0.01	0.00	0.00
	(-2.24)	(-2.25)	(0.76)	(0.77)	(-0.52)	(-0.50)	(0.30)	(0.31)
Gender (female)	-27.86	-27.59	3.14	3.02	-0.01	-0.01	0.01	0.01
	(-1.28)	(-1.26)	(0.15)	(0.15)	(-0.31)	(-0.33)	(0.63)	(0.62)
Financial quiz score	-36.20***	-36.36***	23.89**	24.04**	-0.03***	-0.03***	0.02	0.02
	(-3.25)	(-3.26)	(2.23)	(2.24)	(-3.18)	(-3.23)	(1.57)	(1.58)
Self-assessed financial literacy	16.76	16.84	-21.38*	-21.72*	0.02	0.02	-0.00	-0.00
	(1.42)	(1.43)	(-1.73)	(-1.76)	(1.59)	(1.55)	(-0.16)	(-0.13)
Trading experience	66.37***	66.70***	-54.07**	-54.20**	0.04**	0.04**	0.04*	0.04
	(2.89)	(2.90)	(-2.56)	(-2.57)	(2.46)	(2.43)	(1.66)	(1.64)
Finance course taken	-60.79*	-61.03*	40.57	40.74	-0.00	-0.00	0.01	0.02
	(-1.94)	(-1.95)	(1.28)	(1.28)	(-0.11)	(-0.12)	(0.59)	(0.59)
Prediction accuracy	5.59	5.62	3.71	3.64	-0.00	0.01	-0.01	-0.01
	(0.71)	(0.71)	(0.47)	(0.46)	(-0.45)	(1.20)	(-1.15)	(-1.15)
Round FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,046	1,046	1,063	1,063	1,062	1,062	1,058	1,058
Adjusted R-squared	0.09	0.09	0.07	0.07	0.05	0.04	0.07	0.07

26% of their gains but only 9% of their losses, resulting in a $PGR - PLR$ of 0.15, similar to the results in Frydman et al. (2014). Since the prices exhibit momentum, $PGR - PLR$ under a Bayesian strategy is negative, indicating that it is often optimal to realize losses but not gains. Consistent with Hypothesis 2, we find that participants who prefer the gamified environment are marginally more likely to realize both gains and losses, resulting in little difference in the disposition effect between gamified and non-gamified treatments. As a check, we note that our results on purchase price salience and the disposition effect align with those of Frydman and Rangel (2014): participants are more likely to realize gains in rounds with salient prices, leading to a larger disposition effect.[23]

4.4 Price notifications and trading behavior

Do information-driven gamification elements help investors by increasing the accuracy of their trades and reducing the disposition effect? In this section, we focus on the impact of price change notifications on investor behavior. In particular, we aim to determine whether price change notifications reduce information processing costs for participants, allowing investors to better time their trades. This allows to disentangle the effect of gamification strategies that convey information about stock prices from those that simply increase the enjoyment of trading itself, allowing regulators such as the SEC to specifically target only a subset of harmful gamification practices and encourage the beneficial ones. Hypotheses in this section are tested using the observations in Session II, in which each participant experiences a non-gamified platform as well as a gamified platform with only informational elements of gamification (price alerts).

Hypothesis 3. (Impact of notifications) *Following a price drop notification, participants are more (less) likely to sell (purchase) the stock. Conversely, following a price increase notification, participants are more (less) likely to purchase (sell) the stock.*

To test Hypothesis 3, we zoom in on the tick-by-tick trading activity within each gamified round

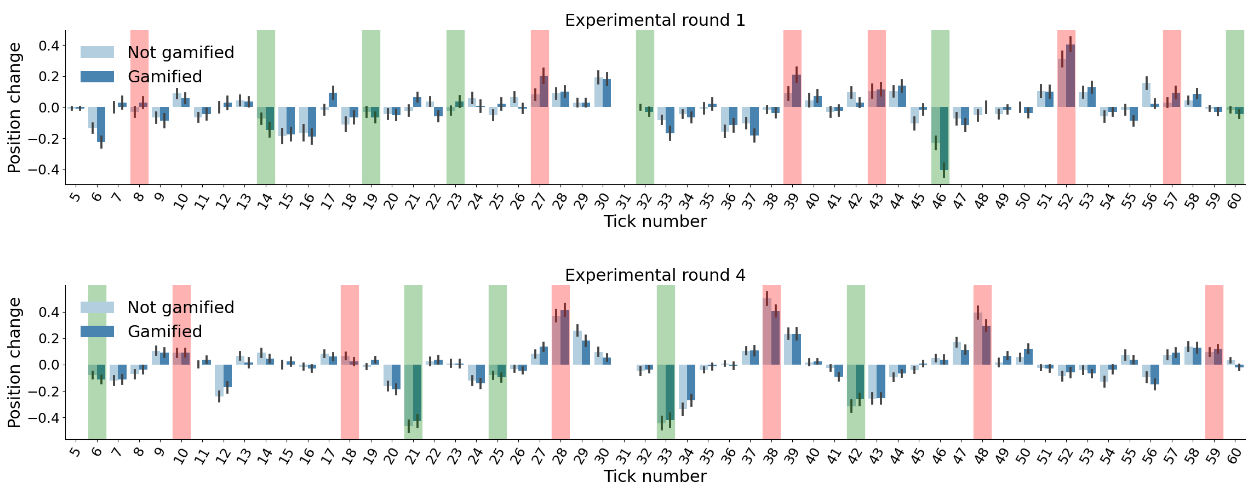
[23]Table 5 documents that the bias on buy trades is significantly larger in salient rounds (first two columns), despite the purchase price not being displayed when participants' holdings are zero. The result is driven by a sharply mean-reverting price path in Round #3, coupled with the restriction that participants hold at most one unit of the stock. Concretely, participants in the salient treatment are more likely to sell the stock and realize their gains at the peak price, in line with (Frydman and Rangel, 2014). Consequently, they are not bound by the one-unit position restriction and can readily buy back the stock several ticks later when the price drops sharply (and π_t is very low).

where the unit of observation is a trial (i.e., a five-second price update) indexed by t. We define two notification dummies: GreenAlert_t and RedAlert_t taking the value one if there was a price jump, respectively drop, notification at trial t.

In Figure 8, we display the average portfolio changes across every tick in the first and last rounds of Session II. We observe significant commonality in participant behavior, with "green alert" ticks resulting in selling activity and "red alert" ticks prompting intense buying activity. This pattern remains consistent across gamified and non-gamified rounds, indicating a tendency among participants to buy the stock cheaply after a run of bad outcomes and sell it after a series of price increases—irrespective of whether they receive a notification or not.

Figure 8: **Tick-by-tick trading decisions and notifications**

This figures illustrates the average position change, across all participants, for every tick in Rounds 1 and 4 from Session 2. A buy trade corresponds to a position change of +1, whereas a sell trade corresponds to a position change of −1. We plot separately the position change for participants in the gamified and non-gamified treatments, respectively. Ticks that correspond to a price increase (drop) notification in the gamified treatment are highlighted in green (red).



Next, we estimate the impact of gamification. Figure 9 (top left panel) shows that price notifications exacerbate participants' contrarian behavior, resulting in even greater deviations from the Bayesian benchmark. In gamified rounds, participants are more inclined to sell (buy) the asset upon receiving a green (red) alert than on the non-gamified platform.

We examine whether the impact of notifications is influenced by an irrational belief in mean-reversion, using mid-round participant beliefs directly elicited on a five-point Likert scale (as in Weber and Camerer, 1998). To match scales, we map Bayesian probabilities π_t to a similar five-point scale. From equation (5), the Bayesian probability is bounded in $\pi_t \in [0.35, 0.65]$.[24] We split the bounded interval in five partitions of equal measure, and assign each partition a value from one to five. The accuracy of beliefs is measured as one minus the normalized distance between the participant's answer and the re-coded Bayesian probability $\mathcal{L}(\pi_t)$,

$$\text{Prediction accuracy} = 1 - \frac{1}{4}\left|\mathcal{L}(\pi_t) - \text{investor belief}\right|. \tag{18}$$

For instance, if a participant's answer indicates the stock is unlikely to be in a good state (e.g., answer of 1 on the 1-5 scale), but the Bayesian probability is $\pi_t = 0.51$ (i.e., a 4 on the "true" scale), the prediction accuracy is computed as $1 - \frac{1}{4}|1-4| = 0.25$.

In Figure 9, we observe a bimodal distribution of beliefs: 44.98% of participant-rounds hold "correct" beliefs (i.e., have a prediction accuracy of one), while 39.08% of participants have a belief accuracy of one-half. The bottom two panels demonstrate that both groups tend to buy and sell the stock following a string of price drops, respectively increases, but notifications have a more subdued effect on participants with correct beliefs.

We estimate a linear probability model to formally test the impact of price notifications on the decision to sell or buy the stock:

$$\begin{aligned} d_{\text{sell},t} = \beta_0 &+ (\beta_1 + \beta_2 d_{\text{game}})\,\text{GreenAlert}_t + (\beta_3 + \beta_4 d_{\text{game}})\,\text{RedAlert}_t \\ &+ \delta_0 \pi_t + \delta_1 (p_t - c_t) + \text{Controls} + \text{error}, \end{aligned} \tag{19}$$

where $d_{\text{sell},t}$ takes the value one if the participant sold the stock at trial t and zero otherwise. The model is estimated over the subset of participants who own the stock at the time of notification. We control for the Bayesian probability of the stock being in a good state as well as for capital gains. Hypothesis 3 implies a negative effect of a "green" alert on selling behavior ($\beta_2 < 0$) and a positive effect of a "red" alert ($\beta_4 > 0$). Alternatively, if notifications reinforce contrarian trading, we expect the opposite signs. We also estimate the model for buying decisions.

[24] To see this, we solve (5) for fixed points over π where $\pi_t = \pi_{t-1}$ and obtain values $\pi = 0.655 \approx 0.65$ for $z_t = 1$ and $\pi = 0.345 \approx 0.35$ for $z_t = -1$.

Figure 9: **Trading decision on notification ticks**

This figure displays the average position change for participants in Session II during "green" and "red" alert ticks, which correspond to price increase and decrease notifications. The figure differentiates between gamified and non-gamified rounds. The top left panel presents average position changes for the full sample, while the bottom panels focus on participant subsamples with belief accuracy smaller than one (left) or equal to one (right). The top right panel shows the distribution of belief accuracy across the full sample.

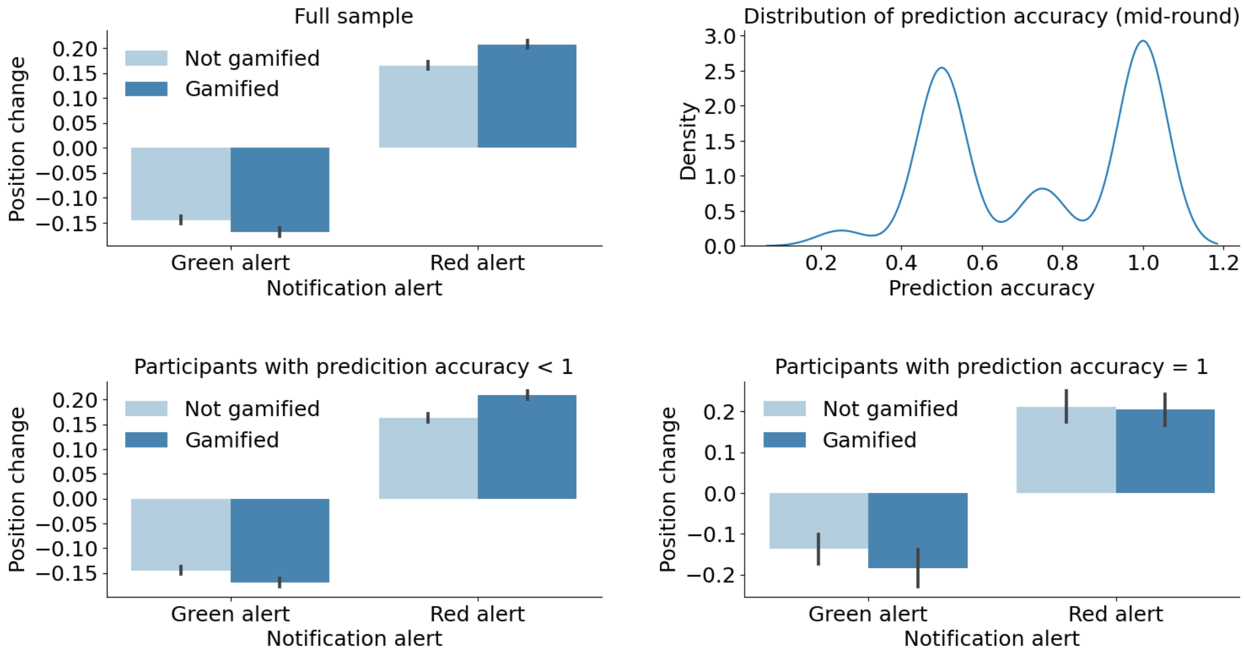


Table 6 shows that price notifications have differential effects on traders depending on the accuracy of their beliefs. In line with Hypothesis 3, participants with correct beliefs are 35.71% (equal to $^{0.05}/_{(0.16-0.02)}$) more likely to buy the asset upon receiving a green alert. However, red alerts do not induce them to realize their losses. On the other hand, for participants with incorrect beliefs, notifications reinforce their contrarian trading behavior and lead to even greater deviations from the Bayesian benchmark. They are 31.81% more likely to sell the asset after a positive alert (computed as $^{0.07}/_{(0.15+0.07)}$) and 37.5% more likely to buy the asset after a negative alert.

We point out two additional results in Table 6. First, in line with the literature on realized utility, we find that capital gains are a strong driver of sell decisions: a one-standard-deviation increase in capital gains translates to an eight-basis-points increase in the propensity to sell the stock. Second, our tick-by-tick analysis confirms that participants are more inclined to sell and less inclined to buy the stock when the probability of the good state is high, which contradicts the

Table 6: Price notifications and trade decisions

The table presents the estimation results for the linear regression model

$$d_{\text{sell},t} = \beta_0 + (\beta_1 + \beta_2 d_{\text{game}})\,\text{GreenAlert}_t + (\beta_3 + \beta_4 d_{\text{game}})\,\text{RedAlert}_t + \delta_0 \pi_t + \delta_1 (p_t - c_t) + \text{Controls} + \text{error},$$

estimated over data from Session II, and across participants with different belief accuracy. The unit of observation is tick-round-participant. GreenAlert_t and RedAlert_t are dummies taking the value one if a price increase (drop) notification is displayed at tick t in the gamified treatment; $d_{\text{game},j,r}$ is a dummy taking the value one if round r is gamified and zero otherwise. Controls include a dummy for whether the purchase price is salient in a given round, the standardized financial quiz score, the standardized value of the self-assessed financial knowledge, standardized capital gains at tick t, dummies for participant trading experience and whether participants took an academic course in finance, the average accuracy of beliefs elicited at the midpoint of each round (computed as the relative distance between the participant's belief that the stock is in a good state and the Bayesian probability of a good state), participant age and gender, and round fixed effects. Standard errors are clustered by participant.

	Full sample		Participants with belief accuracy =1		Participants with belief accuracy <1	
	Buy trades	Sell trades	Buy trades	Sell trades	Buy trades	Sell trades
Green alert	0.01	0.06***	-0.02	0.05***	0.03**	0.07***
	(0.77)	(5.11)	(-1.40)	(2.85)	(2.02)	(3.99)
Green alert tick × gamified	0.03**	0.04**	0.05**	0.02	0.01	0.07**
	(2.09)	(2.52)	(2.18)	(0.96)	(0.55)	(2.57)
Red alert tick	0.16***	0.01*	0.16***	0.00	0.16***	0.03***
	(9.41)	(1.95)	(6.42)	(0.43)	(6.93)	(2.60)
Red alert × gamified	0.07***	0.01	0.03	0.02	0.12***	-0.00
	(3.38)	(1.08)	(0.80)	(1.41)	(3.98)	(-0.34)
Good state probability	-0.07***	0.03***	-0.05***	0.02***	-0.08***	0.03***
	(-16.42)	(8.84)	(-10.94)	(5.42)	(-14.16)	(7.27)
Gamified	0.01*	-0.00	0.03*	0.01	-0.01	-0.01
	(1.85)	(-0.08)	(1.96)	(0.87)	(-0.75)	(-0.84)
Salient purchase price	0.01		-0.00	-0.02**	0.01	0.01
	(1.01)		(-0.25)	(-2.21)	(0.96)	(0.79)
Age	0.00		-0.00	0.00	0.01	0.00
	(0.43)		(-0.51)	(0.96)	(1.10)	(0.62)
Gender (female)	-0.04**		-0.03	-0.01	-0.05***	-0.06***
	(-2.52)		(-1.56)	(-1.01)	(-2.86)	(-3.67)
Financial quiz score	-0.02**		-0.02**	-0.01	-0.02	-0.01*
	(-2.07)		(-2.00)	(-0.79)	(-1.53)	(-1.79)
Self-assessed financial literacy	0.02**		0.01	0.00	0.02*	0.01
	(2.11)		(1.39)	(0.71)	(1.96)	(0.92)
Trading experience	0.00		0.01	-0.00	-0.01	0.01
	(0.11)		(0.43)	(-0.17)	(-0.42)	(0.55)
Finance course taken	-0.02		-0.02	-0.04**	-0.03	-0.05***
	(-1.23)		(-0.74)	(-2.55)	(-1.38)	(-3.19)
Prediction accuracy	-0.00				-0.04***	-0.03***
	(-0.62)				(-2.79)	(-3.20)
Capital gains		0.08***		0.07***		0.08***
		(20.47)		(13.11)		(13.09)
Constant	0.17***	0.15***	0.16***	0.17***	0.16***	0.15***
	(12.61)	(50.58)	(8.03)	(12.01)	(10.58)	(11.79)
Round FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24,553	35,353	10,977	15,903	13,576	19,296
Adjusted R-squared	0.10	0.14	0.08	0.07	0.13	0.10

behavior of a Bayesian trader with realized utility.

Corroborating evidence in Online Appendix F shows that price notifications amplify heterogeneity in beliefs. Table F.3 reveals that participants making above-average forecasts at mid-round tend to further improve their belief accuracy in gamified rounds, whereas participants with below-average forecasts become even more inaccurate.[25] Table F.7 also reveals that participants holding correct beliefs no longer respond to "green alerts" if the price process is a martingale (i.e., in experimental Session IV). This finding suggests that price notifications enhance learning for some traders and are not solely nudging them to trade.

Hypothesis 4. (Notifications and the disposition effect.) *If price notifications enhance learning, the proportion of losses realized, defined as in Odean (1998) and equation (17), is higher on the gamified platform than on the non-gamified platform. At the same time, the proportion of gains realized is lower on the gamified platform.*

Hypothesis 4 proposes that if price notifications enhance information processing, they will reduce the disposition effect by encouraging traders to realize losses and hold on to gains. Conversely, if price notifications reinforce irrational beliefs, we should observe a larger disposition effect in the gamified treatment. To test the hypothesis, we estimate

$$\begin{aligned} PLR_{j,r} &= \beta_0 + \beta_1 d_{\text{game},j,r} + \text{Controls} + \text{error and} \\ PGR_{j,r} &= \beta_0 + \beta_1 d_{\text{game},j,r} + \text{Controls} + \text{error}, \end{aligned} \tag{20}$$

where $PLR_{j,r}$ and $PGR_{j,r}$ are the proportion of gains and losses realized on ticks with price notifications by participant j in round r.

Table 7 presents the estimation results, showing that price notifications amplify the disposition effect for participants holding inaccurate beliefs. Upon receiving a price increase notification, the proportion of gains realized increases by eight percentage points, equivalent to a relative effect of 14.3%. At the same time, gamified price notifications do not impact the magnitude of the disposition

[25] At the same time, we find no evidence that gamification reduces trading noise, as measured by the standard deviation of π_t at the time of a trade (see Table F.5).

effect for participants holding correct beliefs: these traders are more likely to purchase the stock following a "green alert" and do not respond to price drop notifications.

Finally, since many real-life trading applications feature both hedonic and informational gamification, we use data from Session III to study whether there is any interaction between the two types of gamification. Table F.6 in Online Appendix F documents that hedonic gamification elements do not impact the magnitude of learning effects or contrarian trading driven by price notifications.

Table 7: Price notifications and the disposition effect

This table presents the estimation results for the linear regression model

$$y_{j,r} = \beta_0 + \beta_1 d_{\text{game},j,r} + \text{Controls} + \text{error}$$

where j and r run over participants and rounds, respectively. The dependent variables are the proportion of losses and gains realized in round r by participant j, defined as in equation (17); $d_{\text{game},j,r}$ is a dummy taking the value one if round r is gamified for participant j and zero otherwise. Controls include a dummy for whether the purchase price is salient in a given round, the standardized financial quiz score, the standardized value of the self-assessed financial knowledge, dummies for participant trading experience and whether participants took an academic course in finance, the average accuracy of beliefs elicited at the midpoint of each round (computed as the relative distance between the participant's belief that the stock is in a good state and the Bayesian probability of a good state), participant age and gender, and round fixed effects. The unit of observation is a participant-round. Standard errors are clustered by participant.

	Full sample			Participants with belief accuracy = 1			Participants with belief accuracy < 1		
	PLR	PGR	PGR-PLR	PLR	PGR	PGR-PLR	PLR	PGR	PGR-PLR
Gamified	0.00	0.06**	0.05**	0.01	0.06	0.05	-0.01	0.08**	0.09**
	(0.47)	(2.55)	(2.32)	(0.77)	(1.38)	(1.17)	(-0.91)	(2.49)	(2.55)
Salient purchase price	-0.03***	0.01	0.04	-0.03*	0.01	0.05	-0.03*	0.01	0.03
	(-2.67)	(0.43)	(1.46)	(-1.78)	(0.27)	(1.10)	(-1.94)	(0.16)	(0.78)
Age	0.00	-0.00	-0.00	-0.00	-0.01**	-0.01**	0.00	0.01	0.00
	(0.34)	(-0.43)	(-0.69)	(-0.03)	(-1.98)	(-2.36)	(0.65)	(0.66)	(0.53)
Gender (female)	-0.02	-0.04	-0.01	-0.00	0.01	0.02	-0.04*	-0.08**	-0.04
	(-1.37)	(-1.16)	(-0.34)	(-0.22)	(0.37)	(0.43)	(-1.69)	(-1.98)	(-0.91)
Financial quiz score	-0.04***	0.03*	0.07***	-0.04***	0.04*	0.08***	-0.03***	0.02	0.05**
	(-3.77)	(1.69)	(3.50)	(-2.85)	(1.76)	(3.08)	(-2.76)	(0.85)	(2.34)
Self-assessed financial literacy	0.02**	-0.00	-0.02	0.02**	-0.01	-0.03	0.01	0.01	-0.00
	(2.15)	(-0.03)	(-1.04)	(2.01)	(-0.56)	(-1.20)	(1.35)	(0.69)	(-0.19)
Trading experience	-0.00	-0.01	-0.00	-0.01	0.01	0.02	0.00	-0.01	-0.01
	(-0.07)	(-0.19)	(-0.03)	(-0.63)	(0.13)	(0.36)	(0.13)	(-0.24)	(-0.11)
Finance course taken	-0.04**	-0.07	-0.03	-0.04	-0.05	-0.02	-0.05**	-0.08	-0.03
	(-2.42)	(-1.63)	(-0.69)	(-1.64)	(-1.04)	(-0.42)	(-2.06)	(-1.44)	(-0.51)
Prediction accuracy	-0.00	-0.00	-0.00				-0.03**	-0.01	0.03
	(-0.43)	(-0.28)	(-0.01)				(-2.15)	(-0.24)	(0.82)
In-game experience	0.01	-0.07**	-0.09***	0.00	-0.02	-0.02	0.03	-0.12***	-0.15***
	(0.92)	(-2.50)	(-2.67)	(0.13)	(-0.59)	(-0.48)	(1.46)	(-3.13)	(-3.66)
First-tick prediction	0.07***	0.03	-0.04	0.06*	0.15**	0.09	0.06***	-0.05	-0.11*
	(3.60)	(0.59)	(-0.75)	(1.86)	(2.00)	(0.98)	(2.88)	(-0.77)	(-1.65)
Constant	0.06***	0.46***	0.40***	0.07***	0.32***	0.24***	0.03	0.56***	0.53***
	(3.48)	(11.74)	(8.66)	(2.86)	(5.12)	(3.07)	(1.35)	(10.17)	(8.54)
Observations	1,044	959	945	463	423	412	581	536	533
Adjusted R-squared	0.07	0.08	0.11	0.05	0.11	0.12	0.09	0.06	0.09

5 Conclusion

Our study contributes to the spirited policy debate on the impact of trading gamification. As of June 2022, the US Securities and Exchange Commission (SEC) plans to design new rules to "crack down" on behavioral prompts and trading gamification used by online stock brokerages. We provide several insights into the effects of hedonic gamification and price notifications on trading behavior. First, we observe that participants with lower financial literacy tend to self-select into gamified trading platforms with hedonic elements. Second, we find that hedonic gamification can increase engagement with trading platforms, especially among participants who are more inclined to trade even in the absence of gamification. We estimate that the difference between trading activity on gamified and non-gamified platforms can be decomposed into a 70% selection effect and a 30% gamification effect. Third, we do not find any evidence that hedonic gamification leads to greater trading mistakes. Finally, we find that price notifications help participants with correct beliefs to learn better, but for others they reinforce suboptimal contrarian behavior, leading to a higher disposition effect. Overall, our study suggests that gamification and price notifications can have both positive and negative effects on trading behavior, depending on individual differences in financial literacy and accuracy of beliefs.

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Online Appendix to:
Trading Gamification and Investor Behavior

October 2, 2023

A Experimental instructions

Welcome and thank you for participating in the trading experiment! Please read the instructions carefully.

What do I need to do?

After the instructions, you will be directed to an experimental market where you can trade **one virtual stock** over **four trading rounds**. The rounds are independent from each other and each will last for about 5 minutes.

Your **goal is to trade** (that is, buy and sell) in a way that allows you to earn the most money. You can use the information about the observed stock's price changes to help you decide when is a good time to buy or sell.

You will also be asked about **your thoughts on the price** of the stock: Twice during each trading round, trading will be paused at one point for 20 seconds and you will be asked to answer the following two questions:

1. How likely is the stock to go up next?
2. How confident are you in this assessment?

How do I make money?

During each trading round you will observe the stock price changes. These price changes (or price updates) occur every 5 seconds.

Using the information about the price changes, you can make money by choosing smartly when to buy and sell the stock using the BUY and SELL buttons.

The BUY and SELL buttons will not be available for the first 4 price updates. After this initial period of observing but no trading, you will have the opportunity to buy or sell after each subsequent price update.

To help you feel more comfortable with the trading game, the experiment will start with a short **training round** consisting of 10 price updates.

How do I start trading?

At the start of each trading round, you will be given one unit of the stock and have 50 experimental dollars (E$) in cash. Now the trading begins.

How many units of the stock can I buy/sell?

During the trading round, you can only hold 1 or 0 units the stock. If you already own one unit, you will not be able to buy more: you can only choose to sell it. If you do not currently own the stock and want to buy it, you can use your cash balance for the purchase.

If you do not have enough experimental cash for the purchase, you can still buy the stock by running a negative cash balance. Keep in mind that any negative cash balances will be deducted from your final earnings.

You cannot hold negative quantities of the stock. This means that you cannot sell the stock if you do not own it first.

How does the stock price change?

The stock is either in a good state of the economy (think of economic expansion) or in a bad state (think of a recession). In the good state, the stock goes up with 55% chance, and it goes down with 45% chance. In the bad state, the stock goes down with 55% chance and it goes up with 45% chance.

Once it is determined whether the price will go up or down, the size of the price change is always random, and will either be E$5, E$10, or E$15. For example, in the bad state, the stock price will go down with 55% chance, and the amount it goes down by is E$5, E$10, or E$15 with equal chance. Similarly, in the good state the stock price will go up with 55% chance, and the amount it goes up by will either be E$5, E$10, or E$15.

The stock randomly starts in either the good state or bad state, and after each price update, there is an 85% chance of remaining in the same state of the economy and 15% chance the stock switches state (from good to bad or vice versa).

Stock price changes.

	Good state	Bad state
+	55%	45%
-	45%	55%

State changes.

	Good state now	Bad state now
Good state next	85%	15%
Bad state next	15%	85%

How does the trading platform work?

Over the four rounds, you will trade on two different platforms, in random order.

1. A **contemporary** design including:
   - Achievement badges for executing 10, 15, 20, 25, 30 trades. A trade is recorded only if your position in the stock changes between two consecutive price updates – for Sessions I and III.
   - Updated color scheme and user experience – for Sessions I and III.
   - Notifications if the price of the stock moves up or down three times in a row – for Sessions II, III, and IV.
2. A **traditional** trading up design that does not include the elements above.

How do I know how well I did after the experiment?

After you are finished, the computer will select one of the trading rounds at random. This will be your "payment" round: Your earnings at the end of the experiment will be equal to the amount of cash you hold at the end of **the randomly-chosen payment round** plus the **end-of-round** price of the stock if you own it.

$$\text{Earnings} = \text{Cash} + \text{Stock Price} \times \text{Hold Stock}$$

So, think and play in each trading round as if it is the round that counts, because it might be!

Your total compensation will include a participation fee, your experimental earnings, and a bonus based on your performance in the post-experimental quiz. Payment is made through the Prolific platform.

$$\text{Total compensation} = \text{Participation fee} + \text{Earnings} + \text{Quiz bonus}$$

B Comprehension quiz

1. The stock price just went up. At the next price update:
   - (a) The stock is likelier to go up again
   - (b) The stock is likelier to go down
   - (c) The stock is equally likely to go up or down
2. If you do not have enough cash to purchase the stock:
   - (a) You cannot purchase it
   - (b) You can purchase it, but any negative cash balance is subtracted from your final earnings
   - (c) You can purchase it, and any negative cash balance is set to zero at the end of the round
3. Your total bonus payment for the experiment depends on:
   - (a) The sum of payoffs across all rounds
   - (b) Your payoff in a randomly selected round
   - (c) Your payoff in a randomly selected round and your correct answers in the post-experimental quiz
4. When is the trade count updated?
   - (a) If your position in the stock changes between two consecutive price updates.
   - (b) If your position in the stock increases between two consecutive price updates.
   - (c) Every time you click the BUY or SELL buttons, even between two consecutive price updates

C Financial literacy quiz

1. Suppose you had \$100 in a savings account and the interest rate was 3% per year. After 4 years, how much do you think you would have in the account if you left the money to grow?
   - (a) More than \$112
   - (b) Exactly \$112
   - (c) Less than \$112
   - (d) Don't know / Not sure

(e) Prefer not to say

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

    (a) More than today

    (b) Exactly the same as today

    (c) Less than today

    (d) Don't know / Not sure

    (e) Prefer not to say

3. Do you think that the following statement is true or false? "Bonds are normally riskier than stocks."

    (a) True

    (b) False

    (c) Don't know / Not sure

    (d) Prefer not to say

4. A 15-year mortgage typically requires higher monthly payments than a 30-year mortgage, but the total interest paid over the life of the loan will be less.

    (a) True

    (b) False

    (c) Don't know / Not sure

    (d) Prefer not to say

5. Normally, which asset described below displays the highest fluctuations over time?

    (a) Savings accounts

    (b) Stocks

    (c) Bonds

    (d) Don't know / Not sure

    (e) Prefer not to say

6. When an investor spreads his money among different assets, does the risk of losing a lot of money:

    (a) Increase

    (b) Decrease

    (c) Stay the same

    (d) Don't know / Not sure

    (e) Prefer not to say

7. Considering a long time period (for example, 10 or 20 years), which asset described below normally gives the highest return?

(a) Savings accounts
(b) Stocks
(c) Bonds
(d) Don't know / Not sure
(e) Prefer not to say

8. Do you think that the following statement is true or false? "If you were to invest \$1,000 in a stock mutual fund, it would be possible to have less than \$1,000 when you withdraw your money."
   (a) True
   (b) False
   (c) Don't know / Not sure
   (d) Prefer not to say

9. Do you think that the following statement is true or false? "A stock mutual fund combines the money of many investors to buy a variety of stocks."
   (a) True
   (b) False
   (c) Don't know / Not sure
   (d) Prefer not to say

10. Which of the following statements is correct?
    (a) Once one invests in a mutual fund, one cannot withdraw the money in the first year
    (b) Mutual funds can invest in several assets, for example invest in both stocks and bonds
    (c) Mutual funds pay a guaranteed rate of return which depends on their past performance
    (d) None of the above
    (e) Don't know / Not sure
    (f) Prefer not to say

11. Which of the following statements is correct? If somebody buys a bond of firm B:
    (a) She owns a part of firm B
    (b) She has lent money to firm B
    (c) She is liable for the company's debts
    (d) None of the above
    (e) Don't know / Not sure
    (f) Prefer not to say

12. Suppose you owe \$3,000 on your credit card. You pay a minimum payment of \$30 each month. At an annual percentage rate of 12% (or 1% per month), how many years would it take to eliminate your credit card debt if you made no additional new charges?

(a) Less than 5 years
(b) Between 5 and 10 years
(c) Between 10 and 15 years
(d) Never
(e) None of the above
(f) Don't know / Not sure
(g) Prefer not to say

D Self-reflection questions

1. If you can trade again, would you choose Design #1 or Design #2?
   (followed by screenshots of the two platforms, where Design #1 is the non-gamified market and Design #2 is gamified)
2. If you can trade again, would you expect to make better decisions when the market looks as in Design #1 or Design #2?
3. If you could trade again, would you prefer to:
   (a) be given an option to choose between Design #1 and Design #2 or
   (b) not be given the option to choose and trade on the market that looks like Design #1?
4. Please rate the following platform components on a scale from 1 to 5:
   (a) Achievement badges (accompanied by a relevant screenshot) – for Session I;
   (b) Price movement alerts (accompanied by a relevant screenshot) – for Sessions II and IV;
   (a) and (b) – for Session III;

E Gamification elements on trading apps in the United States

Table E.1 lists gamification strategies as employed by U.S.-based online brokers. Non-pecuniary rewards for trade (badges, points, missions) and lottery-like stock and cash giveaways are prevalent for relatively newer brokerages such as Robinhood, Public, Moomoo, or SoFi, or cryptocurrency platforms such as Binance or Crypto.com. In contrast, trading apps belonging to more established institutions such as Charles Schwab, Merrill Lynch, or TD Ameritrade do not include hedonic gamification elements. However, all platforms on our list allow for information-driven gamification elements such as push notifications related to short-term price trends. Figure E.1 illustrates the strategies with concrete examples.

Table E.1: **Gamification strategies on popular trading apps**

In this table we list gamification strategies, or digital engagement practices, on several popular digital trading apps and cryptocurrency exchanges available in the United States. To select the apps, we use the Motley Fool's Best Free Stock Trading Apps for 2022 list (updated July 2022) and the list of online brokers available in the United States on the BrokerChooser website. We add three leading cryptocurrency trading platforms: Binance, Coinbase, and Crypto.com, since cryptocurrency is an asset class heavily dominated by retail traders. The first column, *rewards from trade*, is checked if the platform at any time offered non-pecuniary advantages from trading – such as badges, points, status improvements on its proprietary social network, or entertaining visuals such as falling confetti. The second column, *lottery incentives*, is checked if the platform at any time offered random rewards for opening accounts, referring investors, or trading certain amount. The rewards can consist of stock, cash, or products and services (e.g., sport tickets). We do not consider fixed cash bonuses upon opening an account – by definition, the lottery needs to include an element of randomness. The third column, *trend (push) notifications*, is checked if the mobile app of the platform includes an option to send direct notifications about price movements in selected assets.

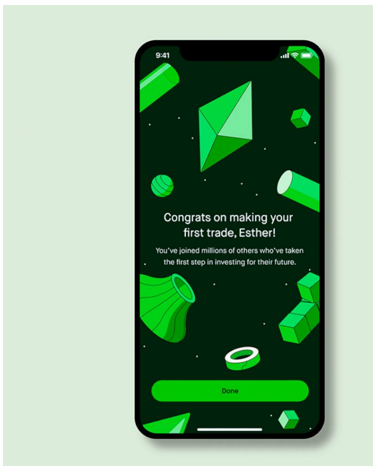
	Platform	Rewards for trade	Lottery incentives	Trend (push) notifications
1	Robinhood	✓ (animation) [a]	✓ (stock giveaway)[b]	✓[c]
2	Public.com	✓ (social)[c]	✓ (stock giveaway)[b]	✓[c]
3	SoFi Invest	✓ (earn points)[c]	✓ (stock giveaway)[b]	✓[c]
4	Moomoo	✓ (badges)[c]	✓ (stock giveaway)[b]	✓[c]
5	Webull	✗	✓ (stock giveaway)[b]	✓[c]
6	AllyInvest	✗	✗	✓[c]
7	eToro	✓ (badges,social) [d]	✗	✓[c]
8	E*Trade	✗	✗	✓[c]
9	Charles Schwab	✗	✗	✓[c]
10	TD thinkorswim	✗	✗	✓[c]
11	Fidelity Spire	✗	✗	✓[c]
12	Merrill Edge	✗	✗	✓[c]
13	Crypto.com	✓ (badges, missions)[c]	✓ (product giveaway)[e]	✓[c]
14	Binance.US	✓ (badges)[f]	✓ (referral giveaway)[g]	✓[c]
15	Coinbase	✗	✓ (stock giveaway)[b]	✓[c]

[a] Associated Press, Robinhood cans the confetti, unveils new celebratory designs, 3/31/2021.
[b] Young & the Invested, How to Get Free Stocks for Signing Up: 15 Apps w/Free Shares, 7/19/2022.
[c] Own website.
[d] ForexCrunch, eToro Introduces Foursquare Style Badges, 1/26/2011.
[e] See, e.g., Crypto.com App UFC 278 Tickets Giveaway.
[f] See, e.g., #IndependenceDayWithBinance: Trade on P2P & Get a Tricolor Profile Badge!.
[g] e.g., Binance, Year of the Bull Promo: $100,000 in BTC to Be Won, 2/10/2021.

Figure E.1: **Trading gamification in practice: examples**

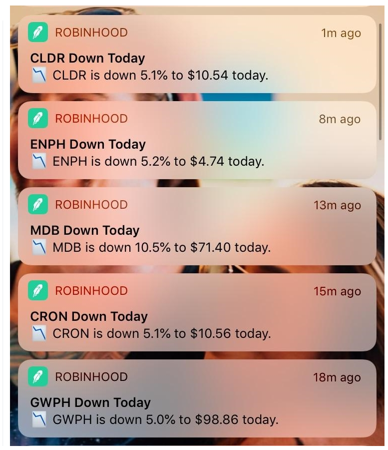
The figure illustrates three examples of trading gamification as implemented by retail-oriented brokerages and exchanges: (a) a reward animation after completing trades on the Robinhood mobile app, (b) a Coinbase announcement of an upcoming lottery for investors who trade $100 on the platform, and (c) a sequence of push notifications emphasizing trending stocks from the Robinhood mobile app. [a]

[a]Sources for images: US News: Robinhood Cans the Confetti, Unveils New Celebratory Designs, March 31, 2021; Coinbase Twitter account; Reddit: r/RobinHood, Binance website.



(a) Reward animations

(b) Lottery incentives



(c) Emphasis on trends

F Additional hypotheses and results

F.1 The impact of gamification and trader rationality

In our theoretical framework, the extent to which hedonic gamification impacts trading behavior is contingent upon the degree of investor rationality. That is, for buy trades, the impact of τ on the distance between the θ_{buy} and 1/2 is decreasing in the relative expected value (REV) utility weight ω, since

$$\frac{\partial^2 \left(\frac{1}{2} - \theta_{\text{buy}}\right)}{\partial\tau\partial\omega} < 0. \tag{F.1}$$

The intuition behind equation (F.1) is that investors who are closer to the expected value benchmark (e.g., investors with better financial literacy) put relatively less weight on the hedonic component of trading. They are less likely to be swayed by these gamification strategies and more likely to maximize their expected value. The result is symmetric for sell trades, since

$$\frac{\partial^2 \left(\theta_{\text{sell}} - \frac{1}{2}\right)}{\partial\tau\partial\omega} = -\frac{1}{\omega^2} < 0. \tag{F.2}$$

Hypothesis F.1. (Gamification and rationality) *The impact of hedonic gamification elements on excessive trading and mistakes is lower for participants who are closer to the expected value utility benchmark—that is, participants with a higher value of ω.*

To account for the noise inherent in measuring investor rationality, we use a number of independent measures for ω to test Hypothesis F.1. First, standardized financial quiz scores are a natural proxy for ω, being a measure of how aligned participants are to standard financial theory. Second, we leverage the result in Frydman et al. (2014) that the salience of purchase price increases the disposition effect. In the context of our model, a more salient purchase price on the gamified platform translates to a lower ω when participants make selling decisions. Third, we argue that ω increases with in-game experience as traders use past payoffs to learn about the optimal strategy (Feng and Seasholes, 2005). In that case, the impact of gamification on trading behavior is larger for participants who are exposed early to the gamified platform (i.e., in rounds #1 and #2). Fourth, we utilize the assessment of participants' prior beliefs regarding the stock price gathered at the start of each round. Finally, we allow participants to self-assess their financial literacy at the beginning of the experiment.

To test Hypothesis F.1, we re-estimate regression models (14) and (16) controlling for the interaction between the gamified treatment and our various measures for the REV weight ω:

$$y_{j,r} = \beta_0 + \beta_1 d_{\text{game},j,r} + \beta_2 \text{REV} + \beta_3 d_{\text{game},j,r} \times \text{REV} + \text{Controls} + \text{error}, \tag{F.3}$$

where the dependent variable $y_{j,r} \in \left\{\text{Trading activity}_{j,r}, \frac{1}{2} - \bar{\theta}^{\text{buy}}_{j,r}, \bar{\theta}^{\text{sell}}_{j,r} - \frac{1}{2}\right\}$ and the REV measure is defined in several alternative ways:

1. the proportion of correct answers in the financial quiz for trader j;
2. a dummy $d_{\text{low-salience}}$ taking value one in low-salience rounds and zero in high-salience rounds;
3. a dummy taking value one if the trader plays the first two rounds on the non-gamified platform;

4. the distance between the participant's estimation of the likelihood of the stock increasing during the first trading period and the objective probability of 0.5, averaged across rounds;
5. overconfidence, measured as the difference between the quiz score and perceived financial literacy.

Hypothesis F.1 implies that $\beta_3 < 0$ across the different measures for investor departures from rationality. That is, the impact of gamification is amplified for traders with stronger behavioral biases, whether induced by the platform design, lack of experience, or deficient financial education.

Table F.1: Trading activity: Interaction between gamification and investor rationality

This table presents the estimation results for the linear regression model

$$\text{Trading activity}_{j,r} = \beta_0 + \beta_1 d_{\text{game},j,r} + \beta_2 \text{REV} + \beta_3 d_{\text{game},j,r} \times \text{REV} + \text{Controls} + \text{error}$$

where j and r run over participants and rounds, respectively. The dependent variable TradingActivity is defined as the ratio between the effective and benchmark number of trades in a given round, while $d_{\text{game},j,r}$ is a dummy taking the value one if round r is gamified for participant j and zero otherwise, and REV is a proxy for the utility weight of the relative expected value. Controls include a dummy for whether the purchase price is salient in a given round, the standardized financial quiz score, the standardized value of the self-assessed financial knowledge, dummies for participant trading experience and whether participants took an academic course in finance, the average accuracy of beliefs elicited at the midpoint of each round (computed as the relative distance between the participant's belief that the stock is in a good state and the Bayesian probability of a good state), participant age and gender, and round fixed effects. The unit of observation is a participant-round. Standard errors are clustered by participant.

	Trading activity									
REV measure	Financial quiz		Low salience		In-game experience		First-tick accuracy		Overconfidence	
Prefer gamified	All	Yes	All	Yes	All	Yes	All	Yes	All	Yes
Gamified	0.03*	0.08**	0.00	0.09**	0.05	-0.02	-0.03	0.00	0.02	0.09**
	(1.74)	(2.61)	(0.04)	(2.13)	(1.09)	(-0.28)	(-0.80)	(0.07)	(0.63)	(2.06)
Gamified × REV	0.01	-0.01	0.06*	-0.02	-0.03	0.21	0.16**	0.18	-0.06	0.04
	(0.51)	(-0.41)	(1.86)	(-0.30)	(-0.35)	(1.36)	(1.98)	(1.16)	(-0.68)	(0.34)
Salient purchase price	-0.01	-0.02	0.02	-0.03	-0.01	-0.02	-0.01	-0.02	-0.01	-0.02
	(-0.65)	(-0.53)	(0.77)	(-0.63)	(-0.66)	(-0.49)	(-0.63)	(-0.54)	(-0.65)	(-0.53)
Age	-0.01	0.11	-0.01	0.11	-0.01	0.10	-0.01	0.11	-0.01	0.11
	(-0.27)	(1.65)	(-0.26)	(1.65)	(-0.24)	(1.56)	(-0.37)	(1.63)	(-0.27)	(1.65)
Gender (female)	-0.03	-0.10	-0.03	-0.10	-0.03	-0.09	-0.04	-0.11	-0.03	-0.10
	(-0.78)	(-1.33)	(-0.77)	(-1.34)	(-0.76)	(-1.21)	(-0.95)	(-1.50)	(-0.78)	(-1.33)
Financial quiz score	-0.06**	-0.11***	-0.05**	-0.11***	-0.05**	-0.12***	-0.04*	-0.11***	-0.06**	-0.11***
	(-2.09)	(-2.91)	(-2.11)	(-3.40)	(-2.12)	(-3.45)	(-1.83)	(-3.31)	(-2.15)	(-3.08)
Self-assessed financial literacy	0.03	0.02	0.03	0.02	0.03	0.01	0.03	0.02	0.04	0.01
	(1.53)	(0.47)	(1.54)	(0.47)	(1.55)	(0.34)	(1.52)	(0.47)	(1.63)	(0.33)
Trading experience	0.11**	0.14*	0.11**	0.14*	0.11**	0.15*	0.11**	0.13*	0.11**	0.14*
	(2.38)	(1.79)	(2.37)	(1.79)	(2.36)	(1.85)	(2.31)	(1.69)	(2.38)	(1.79)
Finance course taken	-0.00	0.09	-0.00	0.09	-0.00	0.09	-0.01	0.08	-0.00	0.09
	(-0.03)	(0.98)	(-0.05)	(0.99)	(-0.03)	(0.87)	(-0.15)	(0.82)	(-0.03)	(0.98)
Standardized values of prediction_accuracy	-0.02	-0.03	-0.02	-0.03	-0.02	-0.03	-0.01	-0.03	-0.02	-0.03
	(-1.22)	(-1.29)	(-1.19)	(-1.29)	(-1.22)	(-1.36)	(-1.02)	(-1.15)	(-1.26)	(-1.30)
Constant	0.58***	0.64***	0.57***	0.65***	0.58***	0.64***	0.59***	0.66***	0.58***	0.64***
	(15.50)	(10.34)	(14.92)	(10.48)	(15.53)	(10.33)	(15.80)	(10.73)	(15.51)	(10.35)
Round FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,063	462	1,063	462	1,063	462	1,053	461	1,063	462
Adjusted R-squared	0.03	0.06	0.03	0.06	0.03	0.08	0.03	0.06	0.03	0.06

However, we do not find any consistent evidence to support the conclusion that REV measures significantly moderate the impact of hedonic gamification. Our findings suggest economically small effects that are statistically insignificant and of inconsistent signs. Tables F.1 and F.2 display the estimation results for regression (F.3), where the dependent variable is either our measure of trading activity or the magnitude of trading bias.

F.2 Price notifications and the accuracy of beliefs

In this section, Hypotheses F.2 and F.3 aim to further investigate whether price change notifications reduce information processing costs for participants, allowing investors to better time their trades. This set of hypotheses is tested using the observations in Session II, in which each participant experiences a non-gamified platform as well as a gamified platform with only informational elements of gamification (price alerts).

Hypothesis F.2. (Accuracy of beliefs) *If notifications reduce information processing costs, then investors' beliefs about the stock are more accurate on the gamified platform with price alerts than on the non-gamified platform. Alternatively, if notifications amplify contrarian trading, then investors' beliefs about the stock should be less accurate on the gamified platform with price alerts than on the non-gamified platform.*

The accuracy of beliefs is measured as in equation (18), namely the normalized absolute distance between the participant's answer and the re-coded Bayesian probability $\mathcal{L}(\pi_t)$,

$$\text{Prediction accuracy}_{j,r} = 1 - \frac{1}{4}\left|\mathcal{L}(\pi_t) - \text{investor belief}\right|. \tag{F.4}$$

Hypothesis F.2 implies that if notifications reduce information processing costs, then $\beta_1 > 0$ in the following regression model:

$$\text{Prediction accuracy}_{j,r} = \beta_0 + \beta_1 d_{\text{game},j,r} + \text{Controls} + \text{error}, \tag{F.5}$$

where $d_{\text{game},j,r}$ is a dummy taking the value one if participant j trades on the gamified platform with price alerts in round r and zero otherwise. Alternatively, if notifications lead to an increase in contrarian trading, then we would expect $\beta_1 < 0$. For robustness, we also estimate (F.5) using the confidence level of the belief to weight the distance.

Table F.3 presents the results, indicating that gamification has differential effects on prediction accuracy. For those participants with below-average prediction accuracy, gamification leads to a decrease in prediction accuracy of 4.08% (equivalent to 0.02/0.49, as shown in Column 5). Conversely, for participants with above-average beliefs, gamification further improves prediction accuracy by 2.15% (i.e., 0.02/0.93, as shown in Column 6). These findings align with the results in Tables 6 and 7 of the main text, indicating that price notifications benefit traders with accurate beliefs, but exacerbate contrarian trading for other market participants. Overall, while the impact of gamification on prediction accuracy is negligible on average, it heightens the heterogeneity in prediction quality across participants. Further, in Table F.4 we show the impact of gamification on beliefs is particularly strong for overconfident participants, where overconfidence is measured as the difference between the perceived financial literacy and the quiz score (both normalized between zero and one).

Table F.2: Trade decisions: Interaction between gamification and investor rationality

This table presents the estimation results for the linear regression model

$$10000 \times \left(\bar{\theta}^{\text{buy/sell}}_{j,r} - \frac{1}{2}\right) = \beta_0 + \beta_1 d_{\text{game},j,r} + \beta_2 \text{REV} + \beta_3 d_{\text{game},j,r} \times \text{REV} + \text{Controls} + \text{error}$$

where j and r run over participants and rounds, respectively. The dependent variable is the trade bias on buy (top panel) and sell (bottom panel) trades, measured as the difference between the average probability of a good state upon buy trades and the Bayesian benchmark of $\frac{1}{2}$; that is, $\bar{\theta}_{j,r} - \frac{1}{2}$; while $d_{\text{game},j,r}$ is a dummy taking the value one if round r is gamified for participant j and zero otherwise, and REV is a proxy for the utility weight of the relative expected value. Controls include a dummy for whether the purchase price is salient in a given round, the standardized financial quiz score, the standardized value of the self-assessed financial knowledge, dummies for participant trading experience and whether participants took an academic course in finance, the average accuracy of beliefs elicited at the midpoint of each round, participant age and gender, and round fixed effects. The unit of observation is a participant-round. Standard errors are clustered by participant.

	Buy trades threshold bias: $10,000 \times (\theta_{\text{buy}} - 0.5)$									
REV measure	Financial quiz		Low salience		In-game experience		First-tick accuracy		Overconfidence	
Prefer gamified	All	Yes	All	Yes	All	Yes	All	Yes	All	Yes
Gamified	1.28	17.44	7.02	55.01**	17.98	33.55	-39.97*	-21.41	10.66	26.19
	(0.09)	(0.89)	(0.40)	(2.00)	(0.69)	(0.91)	(-1.81)	(-0.59)	(0.55)	(1.04)
Gamified × REV	-5.87	1.80	-12.32	-74.58**	-34.66	-34.00	104.38**	91.97	44.44	48.04
	(-0.40)	(0.10)	(-0.50)	(-2.10)	(-0.81)	(-0.55)	(2.36)	(1.29)	(0.85)	(0.67)
Salient purchase price	-23.81**	-22.74	-29.87*	-58.85**	-24.07**	-22.92	-23.56**	-20.99	-23.82**	-22.52
	(-2.07)	(-1.27)	(-1.73)	(-2.37)	(-2.08)	(-1.27)	(-2.02)	(-1.16)	(-2.07)	(-1.26)
Age	-40.81**	33.56	-40.84**	34.36	-39.59**	35.24	-44.24**	31.44	-40.71**	33.63
	(-2.17)	(1.26)	(-2.17)	(1.29)	(-2.11)	(1.30)	(-2.37)	(1.17)	(-2.16)	(1.26)
Gender (female)	-22.95	-53.90*	-23.06	-54.79*	-22.46	-55.45*	-24.95	-56.35*	-22.98	-53.75*
	(-1.04)	(-1.80)	(-1.04)	(-1.83)	(-1.02)	(-1.82)	(-1.13)	(-1.87)	(-1.04)	(-1.79)
Financial quiz score	-39.31***	-58.97***	-42.26***	-58.74***	-42.04***	-57.36***	-37.89***	-56.70***	-37.26***	-52.79***
	(-2.98)	(-3.85)	(-3.86)	(-4.63)	(-3.83)	(-4.41)	(-3.50)	(-4.38)	(-3.02)	(-3.75)
Self-assessed financial literacy	16.95	-2.12	16.89	-2.54	18.43	-1.28	17.91	-2.42	11.97	-7.37
	(1.43)	(-0.14)	(1.43)	(-0.16)	(1.55)	(-0.08)	(1.51)	(-0.16)	(0.88)	(-0.42)
Trading experience	68.60***	90.14***	68.65***	90.75***	67.81***	88.81***	65.80***	87.94***	68.63***	90.21***
	(2.97)	(3.00)	(2.97)	(3.03)	(2.93)	(2.93)	(2.89)	(2.94)	(2.97)	(3.00)
Finance course taken	-54.24*	11.56	-54.07*	13.38	-54.15*	13.07	-60.10*	8.90	-54.30*	11.21
	(-1.69)	(0.27)	(-1.69)	(0.32)	(-1.69)	(0.31)	(-1.84)	(0.21)	(-1.69)	(0.27)
Standardized values of prediction_accuracy	4.85	5.42	4.74	5.26	4.79	5.62	5.19	5.84	5.15	5.34
	(0.62)	(0.55)	(0.60)	(0.53)	(0.61)	(0.57)	(0.65)	(0.59)	(0.65)	(0.54)
Constant	-251.51***	-227.92***	-248.22***	-210.01***	-251.30***	-228.20***	-247.22***	-225.83***	-251.36***	-227.19***
	(-10.81)	(-7.20)	(-10.10)	(-6.38)	(-10.85)	(-7.26)	(-10.82)	(-7.12)	(-10.80)	(-7.17)
Round FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,046	458	1,046	458	1,046	458	1,036	457	1,046	458
Adjusted R-squared	0.08	0.09	0.08	0.10	0.08	0.09	0.08	0.10	0.08	0.09

	Sell trades threshold bias: $10,000 \times (\theta_{\text{sell}} - 0.5)$									
REV measure	Financial quiz		Low salience		In-game experience		First-tick accuracy		Overconfidence	
Prefer gamified	All	Yes	All	Yes	All	Yes	All	Yes	All	Yes
Gamified	-16.32	-39.40**	-3.65	-31.74	-34.36	-47.62	17.78	-7.53	-28.08*	-36.55
	(-1.37)	(-2.35)	(-0.22)	(-1.32)	(-1.42)	(-1.41)	(0.86)	(-0.21)	(-1.73)	(-1.63)
Gamified × REV	8.44	-11.88	-24.56	-13.18	38.02	19.47	-82.57*	-73.27	-55.90	9.97
	(0.64)	(-0.75)	(-1.14)	(-0.44)	(0.92)	(0.33)	(-1.91)	(-1.04)	(-1.17)	(0.13)
Salient purchase price	-4.67	-6.38	-16.58	-13.01	-4.28	-6.48	-3.59	-7.96	-4.60	-6.61
	(-0.39)	(-0.37)	(-1.08)	(-0.56)	(-0.36)	(-0.37)	(-0.30)	(-0.45)	(-0.38)	(-0.38)
Age	13.13	-52.95*	13.00	-52.80*	11.84	-53.91*	15.98	-51.28*	13.02	-52.90*
	(0.72)	(-1.71)	(0.71)	(-1.70)	(0.65)	(-1.73)	(0.87)	(-1.66)	(0.71)	(-1.70)
Gender (female)	0.28	41.98	0.24	41.64	-0.30	42.78	3.14	43.76	0.27	41.87
	(0.01)	(1.33)	(0.01)	(1.32)	(-0.01)	(1.31)	(0.15)	(1.38)	(0.01)	(1.32)
Financial quiz score	23.09*	60.87***	27.17**	54.89***	27.13**	54.62***	24.23**	53.98***	20.97*	56.12***
	(1.77)	(3.50)	(2.50)	(3.68)	(2.51)	(3.65)	(2.22)	(3.60)	(1.71)	(3.17)
Self-assessed financial literacy	-21.73*	-8.66	-21.85*	-8.83	-23.37*	-9.22	-22.53*	-8.53	-15.45	-9.86
	(-1.76)	(-0.49)	(-1.77)	(-0.49)	(-1.86)	(-0.51)	(-1.82)	(-0.48)	(-1.14)	(-0.50)
Trading experience	-54.77**	-63.13**	-54.45**	-63.10**	-53.83**	-62.42**	-52.33**	-61.52**	-54.80**	-63.20**
	(-2.59)	(-2.23)	(-2.58)	(-2.23)	(-2.56)	(-2.19)	(-2.49)	(-2.17)	(-2.59)	(-2.23)
Finance course taken	36.22	-6.84	36.61	-6.21	36.18	-7.40	44.22	-4.53	36.30	-6.61
	(1.14)	(-0.16)	(1.15)	(-0.14)	(1.14)	(-0.17)	(1.38)	(-0.10)	(1.14)	(-0.15)
Standardized values of prediction_accuracy	4.10	18.95*	4.00	18.89*	4.17	18.79*	3.79	18.64*	3.72	18.90*
	(0.51)	(1.78)	(0.50)	(1.79)	(0.52)	(1.77)	(0.47)	(1.75)	(0.46)	(1.79)
Constant	287.01***	265.32***	292.50***	268.13***	286.65***	265.08***	281.52***	263.42***	286.78***	265.13***
	(13.65)	(8.49)	(13.62)	(8.53)	(13.72)	(8.48)	(13.50)	(8.34)	(13.66)	(8.49)
Round FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,063	462	1,063	462	1,063	462	1,053	461	1,063	462
Adjusted R-squared	0.07	0.10	0.07	0.10	0.07	0.10	0.07	0.10	0.07	0.10

Table F.3: Gamification and the accuracy of beliefs

This table presents the estimation results for the linear regression model

$$\text{Prediction accuracy}_{j,r} = \beta_0 + \beta_1 d_{\text{game},j,r} + \text{Controls} + \text{error},$$

where j and r run over participants and rounds, respectively. The dependent variable is the prediction accuracy in round r by participant j, defined as in equation (F.5); $d_{\text{game},j,r}$ is a dummy taking the value one if round r is gamified for participant j and zero otherwise. Controls include a dummy for whether the purchase price is salient in a given round, the standardized financial quiz score, the standardized value of the self-assessed financial knowledge, dummies for participant trading experience and whether participants took an academic course in finance, the average accuracy of beliefs elicited at the midpoint of each round (computed as the relative distance between the participant's belief that the stock is in a good state and the Bayesian probability of a good state), participant age and gender, and round fixed effects. The unit of observation is a participant-round. Standard errors are clustered by participant.

	Prediction accuracy					
	Not weighted			Confidence-weighted		
		Prediction accuracy			Prediction accuracy	
	Full sample	Below mean	Above mean	Full sample	Below mean	Above mean
Gamified	0.01	-0.01*	0.01	0.01	-0.02**	0.02**
	(0.76)	(-1.87)	(1.28)	(0.59)	(-2.05)	(2.25)
Salient purchase price	0.02	-0.01	0.01	0.02	-0.01	0.01
	(1.31)	(-0.75)	(0.97)	(1.09)	(-0.53)	(0.91)
Age	0.00	0.00*	0.00	0.00	0.00*	0.00
	(0.85)	(1.67)	(1.27)	(0.40)	(1.84)	(1.58)
Gender (female)	0.04***	0.01	0.03***	0.04***	0.02	0.03**
	(2.91)	(0.91)	(2.64)	(2.76)	(1.56)	(2.50)
Financial quiz score	0.00	-0.00	0.01	0.00	-0.00	0.01
	(0.39)	(-0.51)	(1.04)	(0.02)	(-0.37)	(1.05)
Self-assessed financial literacy	-0.00	0.00	-0.00	-0.00	0.00	-0.00
	(-0.30)	(0.25)	(-0.27)	(-0.57)	(0.52)	(-0.53)
Trading experience	-0.02	0.00	-0.01	-0.01	0.00	-0.01
	(-1.09)	(0.13)	(-0.64)	(-0.61)	(0.27)	(-0.46)
Finance course taken	0.01	-0.01	-0.00	0.00	-0.01	-0.01
	(0.51)	(-0.72)	(-0.10)	(0.09)	(-0.54)	(-0.60)
In-game experience	-0.02	-0.00	-0.03***	-0.02	-0.00	-0.04***
	(-1.36)	(-0.24)	(-3.52)	(-1.46)	(-0.59)	(-4.34)
First-tick prediction	-0.02	-0.03**	0.04**	-0.02	-0.04***	0.02
	(-0.95)	(-2.39)	(2.22)	(-0.81)	(-2.59)	(0.97)
Constant	0.74***	0.50***	0.93***	0.72***	0.49***	0.93***
	(37.72)	(53.33)	(66.05)	(32.84)	(38.82)	(56.87)
Round FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,058	452	606	1,027	446	581
Adjusted R-squared	0.26	0.02	0.08	0.28	0.05	0.09

Table F.4: Overconfidence and the impact of price notifications on belief accuracy

This table presents the estimation results for the linear regression model

$$y_{j,r} = \beta_0 + \beta_1 d_{\text{game},j,r} + \beta_2 d_{\text{session III},j} + \beta_3 d_{\text{game},j,r} \times d_{\text{session III},j} + \text{Controls} + \text{error},$$

where j and r run over participants and rounds, respectively. The dependent variable is the prediction accuracy in round r by participant j, defined as in equation (F.5) and weighted by the confidence of the prediction; $d_{\text{game},j,r}$ is a dummy taking the value one if round r is gamified for participant j and zero otherwise. Controls include a dummy for whether the purchase price is salient in a given round, the standardized financial quiz score, the standardized value of the self-assessed financial knowledge, dummies for participant trading experience and whether participants took an academic course in finance, the average accuracy of beliefs elicited at the midpoint of each round (computed as the relative distance between the participant's belief that the stock is in a good state and the Bayesian probability of a good state), participant age and gender, and round fixed effects. The first three columns use the full sample of Session II observations. Further, we split the sample across participants with high (above mean) and low (below mean) measure of overconfidence, where overconfidence is measured as the difference between the quiz score and perceived financial literacy. The unit of observation is a participant-round. Standard errors are clustered by participant.

	Full sample		High overconfidence		Low overconfidence	
Prediction accuracy	Below mean	Above mean	Below mean	Above mean	Below mean	Above mean
Gamified	-0.02**	0.02**	-0.05***	0.04***	0.01	-0.00
	(-2.05)	(2.25)	(-4.05)	(2.90)	(0.58)	(-0.34)
Salient purchase price	-0.01	0.01	-0.00	-0.00	-0.01	0.02
	(-0.53)	(0.91)	(-0.11)	(-0.23)	(-0.52)	(1.42)
Age	0.00*	0.00	0.01	0.00	0.00	0.00
	(1.84)	(1.58)	(1.10)	(0.33)	(1.30)	(1.51)
Gender (female)	0.02	0.03**	-0.00	0.04**	0.03**	0.02
	(1.56)	(2.50)	(-0.20)	(2.34)	(2.40)	(1.44)
Financial quiz score	-0.00	0.01	-0.00	-0.01	0.01	0.01
	(-0.37)	(1.05)	(-0.40)	(-0.64)	(0.50)	(0.95)
Self-assessed financial literacy	0.00	-0.00	-0.01	0.01	0.01	-0.00
	(0.52)	(-0.53)	(-1.08)	(0.63)	(1.53)	(-0.42)
Trading experience	0.00	-0.01	0.00	0.00	-0.00	-0.01
	(0.27)	(-0.46)	(0.16)	(0.23)	(-0.23)	(-0.54)
Finance course taken	-0.01	-0.01	-0.02	-0.01	0.01	0.00
	(-0.54)	(-0.60)	(-1.04)	(-0.79)	(0.41)	(0.02)
In-game experience	-0.00	-0.04***	-0.01	-0.05***	0.01	-0.03**
	(-0.59)	(-4.34)	(-0.97)	(-3.66)	(0.97)	(-2.26)
First-tick prediction	-0.04***	0.02	-0.04*	-0.01	-0.05*	0.04
	(-2.59)	(0.97)	(-1.77)	(-0.47)	(-1.84)	(1.33)
Constant	0.49***	0.93***	0.53***	0.92***	0.47***	0.93***
	(38.82)	(56.87)	(33.15)	(36.77)	(19.24)	(38.91)
Round FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	446	581	199	257	247	324
Adjusted R-squared	0.05	0.09	0.11	0.15	0.06	0.06

Hypothesis F.3. (Trading noise) *The standard deviation of $\theta^{buy/sell}$ across trades within the same round is lower for the gamified platform than for the non-gamified platform.*

From equations (8) and (10), investors optimally follow a probability threshold strategy to execute their trades: i.e., they buy (sell) when the stock is sufficiently likely to be in the good (bad) state. Conditional on the hedonic value of the platform and the weight on the REV utility component, the threshold should be constant across all trades. However, if participants' estimate of π_t is noisy due to imperfect heuristics, their trading choices will also reflect the noise. That is, there is variance in the trading thresholds $\theta^{\text{buy/sell}}$ that goes beyond the conditioning factors above.

Theoretically, the variance of the threshold $\theta^{\text{buy/sell}}$ reflects information about investors' precision in estimating π_t. Everything else held constant, if notifications help investors to forecast the stock price, we expect the variance of $\theta^{\text{buy/sell}}$ to be lower in the gamified treatment with price alerts. This is because participants are better able to forecast future price changes and to make more consistent choices across time.

Suppose a participant intends to follow the optimal Bayesian strategy and would like to buy a stock whenever the probability of a good state exceeds 0.5, that is if $\pi_t \geq \theta_{\text{buy}} = 0.5$. In practice, however, participants cannot precisely compute π_t in real time, which leads to noise in their trading decisions. For instance, the good state probabilities over a sample of four buy trades could be $\theta_{t,\text{buy}} \in \{0.48, 0.52, 0.49, 0.53\}$. Our hypothesis is that price notifications reduce participants' costs of computing the good-state probability, leading to a lower variance of $\theta_{t,\text{buy}}$. This argument also holds symmetrically for sell trades and is valid even if participants derive hedonic utility from trading (which shifts the mean of θ_t but does not affect its variance).

That is, we test if $\beta_1 < 0$ in the following model

$$\text{st.dev.} \left(\theta^{\text{buy/sell}}\right)_{j,r} = \beta_0 + \beta_1 d_{\text{game},j,r} + \text{Controls} + \text{error}, \tag{F.6}$$

where $d_{\text{game},j,r}$ is a dummy taking the value one if participant j trades on the gamified platform with price alerts in round r and zero otherwise. The dependent variable is computed as the standard deviation of π_t for each buy, respectively sell, trade for participant j in a given experimental round r:

$$\text{st.dev.} \left(\theta^{\text{buy/sell}}\right)_{j,r} = \begin{cases} \sqrt{\frac{1}{(\#\text{ buys for } j)-1} \sum_{t \in \text{buy trades of } j} \left(\pi_{r,t} - \bar{\theta}^{\text{buy}}_{j,r}\right)^2}, & \text{for buy trades,} \\ \sqrt{\frac{1}{(\#\text{ sells for } j)-1} \sum_{t \in \text{sell trades of } j} \left(\pi_{r,t} - \bar{\theta}^{\text{sell}}_{j,r}\right)^2}, & \text{for sell trades.} \end{cases} \tag{F.7}$$

Importantly, the controls in model (F.6) should include our proxies for REV weight, which generate variation in ω across rounds and participants: the financial quiz score, a dummy for high-salience rounds, a dummy for participants who trade on the gamified platform in the first two rounds, the distance between perceived and real financial literacy, and the measure of participant beliefs about the stock price assessed before the first trial.

Table F.5 presents the results from estimating model F.6. Our findings do not provide empirical support for Hypothesis F.3. Specifically, gamification has a negligible impact on the variability of buy and sell thresholds, accounting for approximately 3% of the unconditional standard deviation. Furthermore, this impact is not statistically significant across any of the tested specifications, including those for the subsample of participant-rounds that made inaccurate predictions. Notably, participants who achieved higher financial quiz scores and those who had completed academic finance courses tend to introduce less noise in their trading decisions.

Table F.5: Gamification and trading noise

This table presents the estimation results for the linear regression model

$$\text{st.dev.}\left(\theta^{\text{buy/sell}}\right)_{j,r} = \beta_0 + \beta_1 d_{\text{game},j,r} + \text{Controls} + \text{error}$$

where j and r run over participants and rounds, respectively. The dependent variable is the standard deviation of π_t at the time of buy/sell trades in round r by participant j, defined as in equation (F.7); $d_{\text{game},j,r}$ is a dummy taking the value one if round r is gamified for participant j and zero otherwise. Controls include a dummy for whether the purchase price is salient in a given round, the standardized financial quiz score, the standardized value of the self-assessed financial knowledge, dummies for participant trading experience and whether participants took an academic course in finance, the average accuracy of beliefs elicited at the midpoint of each round (computed as the relative distance between the participant's belief that the stock is in a good state and the Bayesian probability of a good state), participant age and gender, and round fixed effects. The unit of observation is a participant-round. Standard errors are clustered by participant.

	Full sample				Prediction accuracy < 1			
	St. dev. θ_{buy}		St. dev. θ_{sell}		St. dev. θ_{buy}		St. dev. θ_{sell}	
Gamified	0.08	0.07	0.05	0.05	-0.00	-0.01	-0.05	-0.06
	(0.80)	(0.76)	(0.54)	(0.51)	(-0.02)	(-0.09)	(-0.38)	(-0.49)
Salient purchase price		0.08		-0.15		0.14		0.03
		(0.84)		(-1.58)		(1.00)		(0.23)
Age		0.02		-0.01		0.03		-0.01
		(0.88)		(-0.36)		(1.13)		(-0.70)
Gender (female)		-0.10		-0.05		-0.25*		-0.09
		(-0.75)		(-0.37)		(-1.67)		(-0.58)
Financial quiz score		-0.16**		-0.12*		-0.16*		-0.09
		(-2.23)		(-1.92)		(-1.76)		(-1.04)
Self-assessed financial literacy		0.12		0.03		0.06		0.02
		(1.65)		(0.43)		(0.65)		(0.22)
Trading experience		-0.10		0.10		-0.17		0.17
		(-0.63)		(0.71)		(-0.93)		(1.06)
Finance course taken		-0.02		-0.35**		0.01		-0.47**
		(-0.13)		(-2.11)		(0.05)		(-2.53)
Standardized values of prediction_accuracy		-0.09		-0.06		-0.23*		-0.16
		(-1.54)		(-1.07)		(-1.72)		(-1.23)
In-game experience		-0.01		-0.04		-0.07		-0.02
		(-0.07)		(-0.33)		(-0.48)		(-0.14)
Constant	2.66***	2.72***	2.88***	2.99***	2.54***	2.52***	2.74***	2.62***
	(32.91)	(17.67)	(35.41)	(21.37)	(27.19)	(12.15)	(28.29)	(14.75)
Round FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	955	950	981	976	527	527	541	541
Adjusted R-squared	0.12	0.14	0.11	0.12	0.10	0.12	0.15	0.15

F.3 Interaction effects and robustness

In this section, we focus on the robustness experimental Sessions III and IV, which deviate from the original design by either (i) introducing multiple types of gamification or (ii) altering the nature of the price process.

Disposition effect and beliefs. Using observations from Session III, which exposes participants to both hedonic and informational aspects of gamification, we investigate how the two types of gamification features interact with each other. On one hand, the hedonic features of gamification can enhance learning by better engaging investors and thereby lowering attention costs. On the other, the badges and notifications on the screen might be perceived as distracting and increase attention costs for investors. In the model, this corresponds to the hedonic elements leading to either a higher or a lower λ, the weight investors put on the notification signal.

We test for these effects by comparing participants' trading decisions, trading noise, and the accuracy of beliefs in Sessions II and III. That is, we test for a difference in the coefficients between two sessions by including an interaction term in the following regression model:

$$y_{j,r} = \beta_0 + \beta_1 d_{\text{game},j,r} + \beta_2 d_{\text{session III},j} + \beta_3 d_{\text{game},j,r} \times d_{\text{session III},j} + \text{Controls} + \text{error}, \tag{F.8}$$

where $d_{\text{session III},j}$ is the dummy variable taking the value one for participants in Session III and zero otherwise, and $y_{j,r} \in \{\text{PLR}_{j,r}, \text{PGR}_{j,r}, \Delta_{j,r}\}$.

We report the results in Table F.6 and document that there is no significant interaction between price notifications and hedonic gamification elements. That is, the coefficient β_3 is not significantly different from zero for any of the dependent variables we consider: the proportion of gains and losses realized, and the accuracy of prediction. These findings imply that the impacts of the two forms of gamification are distinct and independent of one another. Policymakers should consider addressing their effects separately.

Martingale prices. We finally turn to studying data from Session IV to delve deeper into the influence of price notifications on investor behavior. Since prices follow a random walk in Session IV, the informational content of gamification is zero. Do participants still respond to "informational" gamification?

We re-estimate the model used to test Hypothesis 3 across observations in both Sessions II and IV, separately for buy and sell trades:

$$\begin{aligned} d_{\text{sell/buy},t} = \alpha &+ \left[(\beta_1 + \beta_2 d_{\text{game}}) \times d_{\text{Session II}} + (\beta_3 + \beta_4 d_{\text{game}}) \times d_{\text{Session IV}}\right] \text{GreenAlert}_t + \\ &+ \left[(\gamma_1 + \gamma_2 d_{\text{game}}) \times d_{\text{Session II}} + (\gamma_3 + \gamma_4 d_{\text{game}}) \times d_{\text{Session IV}}\right] \text{RedAlert}_t + \text{Controls} + \text{error}. \end{aligned} \tag{F.9}$$

Table F.7 shows that participants in both Sessions II and IV exhibit irrational behavior by trading as if the price process is mean-reverting: They sell the asset after a run of price increases and buy it back after a string of price drops. Participants with perfect prediction accuracy do not respond to gamified price increase notifications in the martingale session. The lack of response in Session IV is rational, as the price process is not predictable. This confirms that price alert notifications aid learning for participants with correct beliefs. However, gamification amplifies deviations from the expected value benchmark for participants with low prediction accuracy, hindering learning in both sessions. These results suggest that gamification does not improve learning for traders with low prediction accuracy.

Table F.6: Interaction between price notifications and hedonic gamification

This table presents the estimation results for the linear regression model

$$y_{j,r} = \beta_0 + \beta_1 d_{\text{game},j,r} + \beta_2 d_{\text{session III},j} + \beta_3 d_{\text{game},j,r} \times d_{\text{session III},j} + \text{Controls} + \text{error},$$

where j and r run over participants and rounds, respectively. The dependent variable is either (i) the proportion of losses realized; (ii) the proportion of gains realized; or (iii) the prediction accuracy in round r by participant j, defined as in equation (F.5); $d_{\text{game},j,r}$ is a dummy taking the value one if round r is gamified for participant j and zero otherwise, while $d_{\text{session III},j}$ is a dummy taking value one for participants in experimental Session III. Controls include a dummy for whether the purchase price is salient in a given round, the standardized financial quiz score, the standardized value of the self-assessed financial knowledge, dummies for participant trading experience and whether participants took an academic course in finance, the average accuracy of beliefs elicited at the midpoint of each round (computed as the relative distance between the participant's belief that the stock is in a good state and the Bayesian probability of a good state), participant age and gender, and round fixed effects. The unit of observation is a participant-round. Standard errors are clustered by participant.

	PLR		PGR		Prediction accuracy	
Prediction accuracy	Below mean	Above mean	Below mean	Above mean	Below mean	Above mean
Gamified	0.01	0.00	0.08**	0.03	-0.02**	0.02**
	(0.44)	(0.16)	(2.21)	(0.94)	(-2.05)	(2.55)
Gamified $\times d_{\text{session III}}$	0.01	0.02	-0.08	-0.03	0.02	-0.02
	(0.43)	(0.56)	(-1.12)	(-0.58)	(1.43)	(-1.16)
$d_{\text{session III}}$	0.02	0.02	0.05	0.02	-0.01	0.00
	(1.05)	(0.82)	(1.11)	(0.55)	(-1.01)	(0.34)
Salient purchase price	-0.02*	-0.03***	0.05	0.02	-0.00	0.00
	(-1.77)	(-2.87)	(1.46)	(0.70)	(-0.56)	(0.61)
Age	0.00	-0.00	0.00	-0.00	0.00	0.00*
	(0.56)	(-0.26)	(0.42)	(-0.35)	(1.61)	(1.70)
Gender (female)	-0.02	-0.01	-0.02	-0.04	0.01	0.02**
	(-0.82)	(-0.49)	(-0.75)	(-1.23)	(1.33)	(2.40)
Financial quiz score	-0.04***	-0.03**	0.03	0.02	0.00	0.00
	(-2.97)	(-2.54)	(1.44)	(1.37)	(1.23)	(0.64)
Self-assessed financial literacy	0.02*	0.01	0.02	0.03	-0.01	-0.01
	(1.68)	(0.84)	(1.07)	(1.61)	(-0.96)	(-1.09)
Trading experience	0.01	-0.03**	0.02	-0.03	0.01	0.01
	(0.55)	(-1.98)	(0.42)	(-0.98)	(1.00)	(1.21)
Finance course taken	-0.02	0.01	-0.08**	-0.03	-0.00	-0.01
	(-1.00)	(0.33)	(-1.98)	(-0.77)	(-0.38)	(-0.84)
Prediction accuracy	0.01	0.03**	0.02	-0.01		
	(0.26)	(2.06)	(0.29)	(-0.26)		
In-game experience	0.02	0.00	-0.08***	-0.09***	-0.00	-0.03***
	(1.00)	(0.35)	(-2.59)	(-2.96)	(-0.18)	(-2.90)
First-tick prediction	0.06***	0.06***	-0.05	0.12**	-0.05***	-0.01
	(2.86)	(2.63)	(-0.84)	(2.15)	(-3.45)	(-0.50)
Constant	0.05*	0.06**	0.51***	0.43***	0.49***	0.93***
	(1.71)	(2.51)	(7.59)	(7.71)	(44.60)	(59.26)
Round FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	670	886	623	810	660	876
Adjusted R-squared	0.08	0.05	0.04	0.10	0.05	0.04

Table F.7: Price notifications and trade decisions: Martingale prices

The table presents the estimation results for the linear regression model in (F.3), estimated over data from Sessions II and IV, and across participants with different belief accuracy. The unit of observation is tick-round-participant. GreenAlert_t and RedAlert_t are dummies taking the value one if a price increase (drop) notification is displayed at tick t in the gamified treatment; $d_{\text{game},j,r}$ is a dummy taking the value one if round r is gamified and zero otherwise. Controls include a dummy for whether the purchase price is salient in a given round, the standardized financial quiz score, the standardized value of the self-assessed financial knowledge, standardized capital gains at tick t, dummies for participant trading experience and whether participants took an academic course in finance, the average accuracy of beliefs elicited at the midpoint of each round (computed as the relative distance between the participant's belief that the stock is in a good state and the Bayesian probability of a good state), participant age and gender, and round fixed effects. Standard errors are clustered by participant.

	Full sample		Participants with belief accuracy =1		Participants with belief accuracy <1	
	Buy trades	Sell trades	Buy trades	Sell trades	Buy trades	Sell trades
Green alert (Session II)	0.00	0.06***	-0.02	0.05***	0.02	0.06***
	(0.29)	(4.42)	(-1.53)	(2.62)	(1.55)	(3.39)
Green alert (Session IV)	-0.07***	0.06***	-0.03	0.11***	-0.08***	0.06***
	(-5.56)	(3.32)	(-0.71)	(2.75)	(-6.32)	(2.84)
Red alert (Session II)	0.16***	0.01	0.16***	-0.00	0.15***	0.02
	(9.12)	(0.95)	(6.34)	(-0.05)	(6.71)	(1.50)
Red alert (Session IV)	0.07***	0.01	0.08*	-0.01	0.07***	0.01
	(3.46)	(0.60)	(1.72)	(-0.14)	(3.12)	(0.80)
Green alert × gamified × Session II	0.03***	0.05***	0.06**	0.03	0.01	0.07***
	(2.64)	(2.77)	(2.49)	(1.06)	(0.57)	(2.72)
Green alert × gamified × Session IV	0.01	0.09***	-0.03	-0.01	0.03	0.10***
	(0.80)	(3.82)	(-0.41)	(-0.11)	(1.50)	(4.31)
Red alert × gamified × Session II	0.08***	0.01	0.04	0.02	0.12***	-0.00
	(3.72)	(1.36)	(1.05)	(1.46)	(4.04)	(-0.12)
Red alert × gamified × Session IV	0.05*	-0.02	0.06	0.04	0.06*	-0.03
	(1.71)	(-1.07)	(0.90)	(0.72)	(1.71)	(-1.30)
Good state probability	-0.07***	0.03***	-0.05***	0.02***	-0.08***	0.04***
	(-16.53)	(9.00)	(-11.01)	(5.53)	(-14.19)	(8.59)
Capital gains		0.07***		0.07***		0.07***
		(22.46)		(15.24)		(18.67)
Salient purchase price	0.01**	-0.00	0.00	-0.02**	0.02**	0.00
	(2.31)	(-0.61)	(0.08)	(-2.43)	(2.05)	(0.66)
Age	0.00	0.01	-0.00	0.01	0.01	0.01
	(0.79)	(1.09)	(-0.17)	(1.09)	(1.25)	(0.97)
Gender (female)	-0.02	-0.03**	-0.01	-0.00	-0.02	-0.04***
	(-1.28)	(-2.49)	(-0.31)	(-0.27)	(-1.39)	(-2.88)
Financial quiz score	-0.03***	-0.02**	-0.02	-0.00	-0.03***	-0.02***
	(-3.22)	(-2.55)	(-1.54)	(-0.77)	(-3.02)	(-2.64)
Self-assessed financial literacy	0.02***	0.01***	0.02	0.01	0.03***	0.02***
	(3.49)	(2.88)	(1.63)	(1.04)	(3.50)	(3.08)
Trading experience	-0.01	-0.01	-0.02	-0.02	-0.01	-0.00
	(-0.54)	(-0.67)	(-0.74)	(-1.26)	(-0.32)	(-0.24)
Finance course taken	0.01	-0.01	-0.00	-0.03**	0.01	-0.01
	(0.45)	(-0.82)	(-0.06)	(-1.97)	(0.42)	(-0.47)
Prediction accuracy	-0.01	-0.01			-0.01	-0.01
	(-1.28)	(-1.41)			(-1.33)	(-0.88)
Gamified	0.01	-0.00	0.02	0.01	-0.00	-0.00
	(1.00)	(-0.18)	(1.57)	(0.66)	(-0.26)	(-0.59)
Constant	0.16***	0.17***	0.16***	0.17***	0.16***	0.17***
	(12.98)	(16.84)	(8.87)	(13.11)	(9.82)	(12.65)
Round FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	37,248	51,064	12,857	18,111	24,391	32,953
Adjusted R-squared	0.08	0.07	0.07	0.07	0.09	0.08

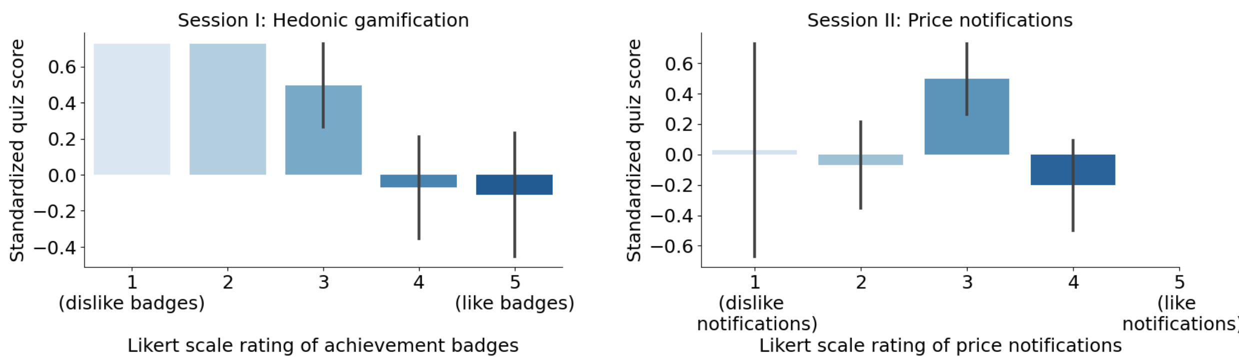
G Additional experimental sessions at University of Toronto (UofT)

As an additional robustness check, we assigned the experiment as a take-home assignment to a small sample (71 participants) of third-year undergraduate finance students at the University of Toronto. Students did not receive a monetary compensation for the task, but completing the experiment was rewarded with 5% of the final grade for a course on investments. Figures G.1 through G.4 replicate four key graphs in the main paper using student data. We conclude that our main results carry over to this sample. In particular:

1. Figure G.1 shows that the UofT participants who prefer the hedonic gamified platform tend to obtain lower scores on the financial literacy quiz. There is no evidence of this effect on the gamified platform with price notifications.

Figure G.1: **Preferences for gamification and financial literacy: UofT sample**

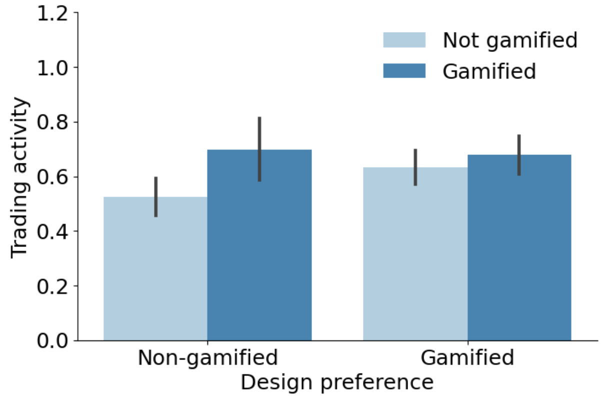
This figure illustrates the average standardized financial quiz score across subsamples of participants. The left panel focuses on Session I with hedonic gamification elements, whereas the right panel refers to Session II featuring informational gamification.

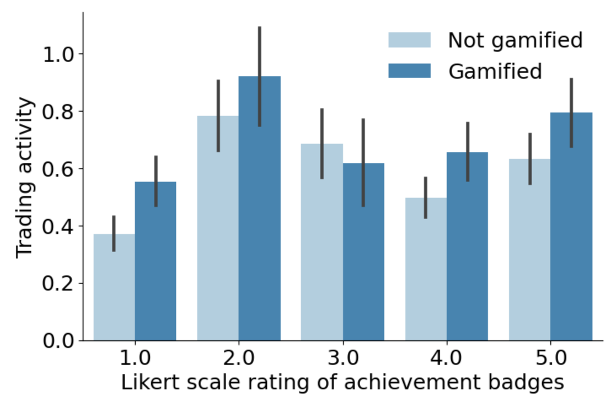


2. Figure G.2 shows that (i) on average, participants trade less than under the Bayesian benchmark, and that (ii) hedonic gamification leads to an increase in trading activity. Unlike the results in the main paper, however, even participants who prefer the non-gamified platform seem to trade more in a gamified environment.

Figure G.2: **Trading activity and preferences for gamification: UofT sample**

This figure illustrates the average trading activity measure, defined as in equation (14), across subsamples of participants in Session I. The left panel focuses on participants who either prefer the gamified or the non-gamified design. In the right panel, we split the sample across different ratings for achievement badges.

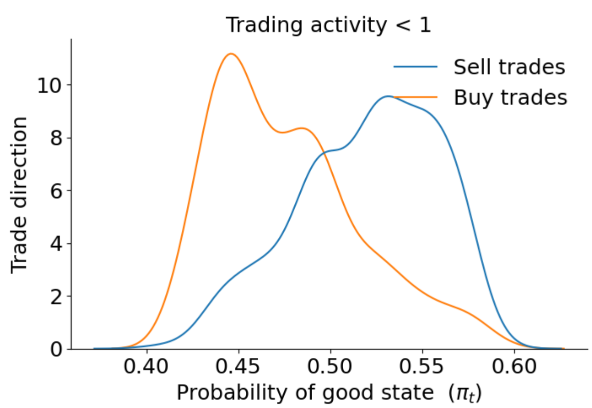


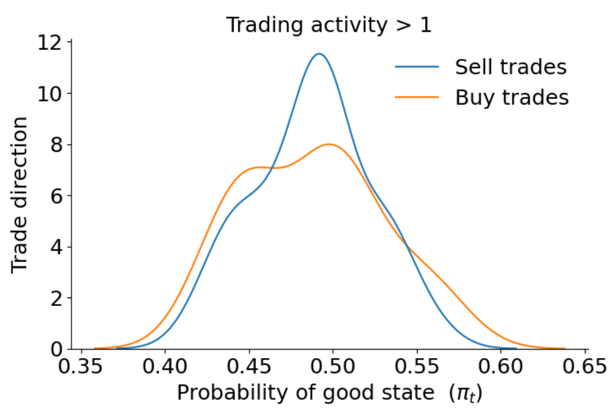


3. Figure G.3 shows that participants in the UofT session follow very similar trading strategies to those in the main representative sample. That is, students who trade less than a Bayesian benchmark tend to sell an asset after a series of price increases (when π_t is high) and buy it back after a string of price drops (when π_t is low). On the other hand, students who trade more than the Bayesian benchmark exhibit a more random trading pattern. This behavior may be driven by a larger hedonic value of trading.

Figure G.3: **Distribution of π_t by trading activity: UofT sample**

This figure shows the empirical distribution of the good-state probability π_t for buy and sell trades in Session I. The density plots distinguish between participants who trade less than the Bayesian benchmark (left panel) and those who trade more (right panel).



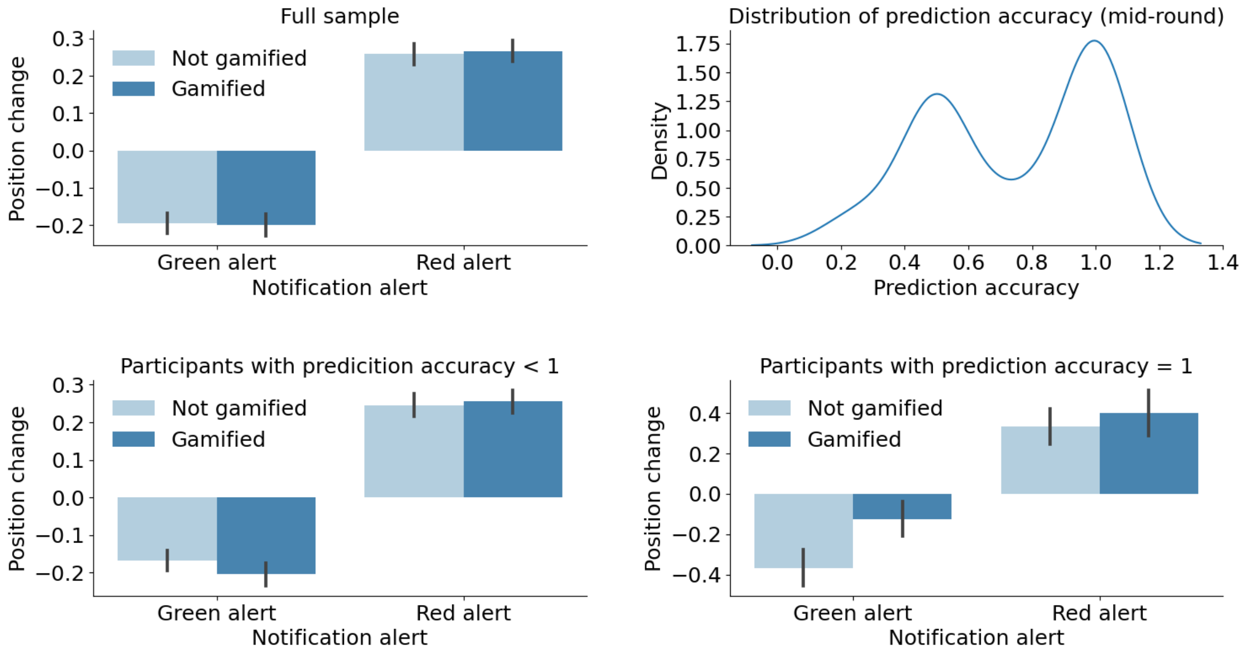


4. Finally, Figure G.4 illustrates that UofT students exhibit the same bimodal distribution of mid-round beliefs as participants in the main session. Those participants who hold correct beliefs (i.e., a prediction accuracy equal to one) learn from price notifications: they are less likely to sell the asset following a green alert in the gamified treatment. In contrast, participants with inaccurate beliefs (prediction

accuracy smaller than one) are more likely to sell the asset following a upward trend notification in the gamified treatment, suggesting that price alerts tend to reinforce contrarian behavior. These results are consistent with our main findings in the paper.

Figure G.4: **Trading decision on notification ticks: UofT sample**

This figure displays the average position change for participants in Session II during “green” and “red” alert ticks, which correspond to price increase and decrease notifications. The figure differentiates between gamified and non-gamified rounds. The top left panel presents average position changes for the full sample, while the bottom panels focus on participant subsamples with belief accuracy smaller than one (left) or equal to one (right). The top right panel shows the distribution of belief accuracy across the full sample.



H Additional robustness checks

Table H.1 shows evidence that participants with high financial literacy dislike hedonic gamification features – a one standard deviation increase in quiz score leads to a 11.2% and 13.2% decrease in Likert scores for achievement badges and confetti, respectively.

Table H.1: Gamification ratings and financial literacy

This table presents the estimation results of a regression model

$$\text{Likert}_{j,k} = \beta_0 + \beta_1 \text{FinLiteracy}_j + \text{Controls} + \text{error},$$

where $\text{Likert}_{j,k}$ is the Likert rating (on a scale from 1 to 5) for a given gamification element k: either achievement badges, confetti upon trade execution, or price notifications. The explanatory variables include the standardized financial quiz score, the standardized payoff difference between the gamified and non-gamified rounds, the standardized value of the self-assessed financial knowledge, dummies for participant trading experience and whether they took an academic course in finance, the average accuracy of beliefs elicited at the midpoint of each round (computed as the relative distance between the participant's belief that the stock is in a good state and the Bayesian probability of a good state), and finally participant age and gender. The unit of observation is a participant.

	Likert rating for gamification strategy					
	Badges		Confetti		Price notifications	
	(1)	(2)	(3)	(4)	(5)	(6)
Financial quiz score	-0.34***	-0.32***	-0.32***	-0.34***	-0.04	-0.02
	(-5.38)	(-4.17)	(-4.92)	(-4.51)	(-0.85)	(-0.35)
Age		0.05		0.20*		0.02
		(0.42)		(1.68)		(1.01)
Gender (female)		0.20		0.27**		0.15
		(1.54)		(1.99)		(1.57)
Self-assesed financial literacy		0.02		0.06		0.06
		(0.22)		(0.68)		(1.17)
Trading experience		-0.10		-0.06		-0.15
		(-0.67)		(-0.38)		(-1.29)
Finance course taken		0.04		0.31		0.21
		(0.21)		(1.63)		(1.49)
Prediction accuracy		-0.06		-0.12*		-0.10**
		(-0.94)		(-1.67)		(-2.12)
Payoff difference		0.08		0.07		0.09*
		(1.39)		(1.17)		(1.93)
Constant	2.90***	2.85***	2.71***	2.57***	3.72***	3.69***
	(46.64)	(22.59)	(40.81)	(19.33)	(80.77)	(41.54)
Round FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	480	439	480	439	633	593
Adjusted R-squared	0.06	0.05	0.04	0.06	0.00	0.01

One plausible concern is that the self-assessment of financial knowledge is elicited on an ordinal scale, yet we use it as a cardinal-scale variable throughout the analysis. This can introduce biases, since ordinal scale labels may be interpreted inconsistently across participants (Hubbard and Evans, 2010). For robustness, Tables H.2 through H.6 replicate the analysis in Tables 3 through 7, replacing the cardinal measure of financial knowledge self-assessment with a dummy taking the value one if the self-assessment is above average and zero else. All results are robust to this alternative specification.

Table H.2: Revealed preferences for trading gamification (using self-assessed literacy dummy)

This table presents the estimation results of a linear probability model

$$d_{\text{choice},j} = \beta_0 + \beta_1 \text{FinLiteracy}_j + \text{Controls} + \text{error},$$

where $d_{\text{choice},j}$ is the dummy encoding participant answers to Questions 1–3 in Online Appendix D: (1) "*If you can trade again, would you choose a gamified or non-gamified design?*", (2) "*If you can trade again, would you expect to make better decisions on a gamified or non-gamified design?*", and (3) "*If you can trade again, would you prefer to be given an option to choose from a gamified or non-gamified design?*" The explanatory variables include the standardized financial quiz score, the standardized payoff difference between the gamified and non-gamified rounds, the standardized value of the self-assessed financial knowledge, dummies for participant trading experience and whether they took an academic course in finance, the average accuracy of beliefs elicited at the midpoint of each round (computed as the relative distance between the participant's belief that the stock is in a good state and the Bayesian probability of a good state), and finally participant age and gender. Column labels S1, S2, and S3 pertain to experimental Sessions #1, #2, and #3 respectively. The unit of observation is a participant.

	Prefer gamified			Better decisions if gamified			Option to choose	
Session	S1	S2	S3	S1	S2	S3	S1	S2
Constant	0.37***	0.59***	0.38***	0.35***	0.64***	0.42***	0.65***	0.84***
	(6.13)	(9.62)	(4.28)	(5.69)	(10.69)	(5.00)	(10.83)	(18.04)
Financial quiz score	-0.09***	0.02	-0.09*	-0.07**	0.01	-0.08*	-0.02	-0.01
	(-2.93)	(0.51)	(-1.91)	(-2.12)	(0.39)	(-1.71)	(-0.60)	(-0.43)
Payoff difference	0.05**	0.05	-0.02	0.06**	0.03	0.05	0.00	0.02
	(2.02)	(1.37)	(-0.50)	(2.28)	(0.98)	(1.25)	(0.13)	(1.17)
$d_{\text{self-assessed literacy}}$	0.02	-0.10	0.02	-0.00	-0.15**	-0.06	0.02	-0.13***
	(0.38)	(-1.53)	(0.26)	(-0.03)	(-2.46)	(-0.66)	(0.30)	(-2.72)
Trading experience	0.02	-0.01	-0.01	0.05	0.04	0.02	0.00	0.05
	(0.25)	(-0.08)	(-0.13)	(0.77)	(0.63)	(0.18)	(0.02)	(0.86)
Finance course taken	0.08	0.10	0.05	0.11	0.06	0.01	-0.03	0.03
	(0.90)	(1.27)	(0.47)	(1.26)	(0.73)	(0.11)	(-0.38)	(0.46)
Prediction accuracy	-0.02	0.01	-0.07	0.00	0.01	-0.03	-0.03	0.02
	(-0.61)	(0.28)	(-1.64)	(0.08)	(0.38)	(-0.77)	(-1.13)	(0.76)
Age	0.03	0.01	-0.02	0.06	0.01	0.06	-0.04	-0.01
	(0.51)	(0.89)	(-0.25)	(1.26)	(1.21)	(1.00)	(-0.69)	(-0.76)
Gender (female)	0.08	0.08	0.05	0.04	0.05	-0.02	0.07	0.04
	(1.39)	(1.29)	(0.54)	(0.63)	(0.77)	(-0.19)	(1.20)	(0.83)
Observations	291	297	148	291	297	148	291	297
R-squared	0.05	0.03	0.06	0.04	0.03	0.05	0.01	0.04

Table H.3: Hedonic gamification and trader engagement (using self-assessed literacy dummy)

This table presents the estimation results for the linear regression model

$$\text{TradingActivity}_{j,r} = \beta_0 + \beta_1 d_{\text{game},j,r} + \text{Controls} + \text{error},$$

where j and r run over participants and rounds, respectively. TradingActivity is defined as the ratio between the effective and benchmark number of trades in a given round; $d_{\text{game},j,r}$ is a dummy taking the value one if round r is gamified, and zero else. Controls include a dummy for whether the purchase price is salient in a given round, the standardized financial quiz score, the standardized value of the self-assessed financial knowledge, dummies for participant trading experience and whether the participant took an academic course in finance, the average accuracy of beliefs elicited at the midpoint of each round (computed as the relative distance between the participant's belief that the stock is in a good state and the Bayesian probability of a good state), participant age and gender, and round fixed effects. The unit of observation is a participant-round. Standard errors are clustered by participant.

	Full sample	Gamified preference		Player rating for achievement badges				
		No	Yes	1 (Low)	2	3	4	5 (High)
Gamified	0.03*	0.00	0.08**	0.01	0.02	0.01	0.01	0.16***
	(1.77)	(0.20)	(2.54)	(0.28)	(0.30)	(0.40)	(0.28)	(3.66)
Salient purchase price	-0.01	0.00	-0.02	0.01	0.02	0.01	-0.01	-0.06
	(-0.64)	(0.07)	(-0.52)	(0.50)	(0.55)	(0.36)	(-0.29)	(-1.28)
Age	-0.01	-0.09**	0.12*	-0.08	-0.14	0.02	-0.03	0.22*
	(-0.19)	(-2.45)	(1.73)	(-1.56)	(-1.20)	(0.37)	(-0.49)	(1.82)
Gender (female)	-0.03	-0.01	-0.10	-0.01	-0.14	-0.12*	0.10	-0.10
	(-0.74)	(-0.23)	(-1.38)	(-0.21)	(-1.64)	(-1.78)	(1.15)	(-0.64)
Financial quiz score	-0.05**	0.03	-0.11***	0.04	-0.00	-0.02	-0.09*	-0.03
	(-2.05)	(1.03)	(-3.28)	(0.78)	(-0.02)	(-0.45)	(-1.88)	(-0.49)
$d_{\text{self-assessed literacy}}$	0.03	0.09*	-0.07	0.08	-0.07	0.08	0.09	-0.18
	(0.64)	(1.78)	(-0.89)	(1.01)	(-0.84)	(1.07)	(0.94)	(-1.35)
Trading experience	0.12***	0.09*	0.17**	-0.02	0.12	0.13*	0.26***	0.05
	(2.60)	(1.66)	(2.10)	(-0.21)	(1.50)	(1.88)	(2.68)	(0.26)
Finance course taken	0.01	-0.10	0.13	0.01	0.09	-0.10	-0.26**	0.54***
	(0.09)	(-1.48)	(1.33)	(0.12)	(0.79)	(-1.06)	(-2.26)	(3.07)
Standardized values of prediction_accuracy	-0.02	-0.00	-0.03	0.01	-0.02	-0.03	-0.01	-0.01
	(-1.20)	(-0.32)	(-1.38)	(0.58)	(-0.71)	(-1.19)	(-0.50)	(-0.19)
Constant	0.56***	0.49***	0.66***	0.43***	0.62***	0.56***	0.49***	0.79***
	(13.44)	(10.75)	(9.24)	(5.06)	(6.23)	(8.50)	(6.27)	(5.09)
Round FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,063	601	462	228	134	260	246	195
Adjusted R-squared	0.03	0.05	0.07	0.02	0.05	0.05	0.08	0.14

Table H.4: Trade timing and gamification (using self-assessed literacy dummy)

This table presents the estimation results for the linear regression model

$$y_{i,t} = \beta_{0,d} + \beta_1 d_{\text{prefers game},j} + \beta_2 d_{\text{game},j,r} + \beta_3 d_{\text{prefers game},j} \times d_{\text{game},j,r} + \text{Controls} + \text{error},$$

where j and r run over participants and rounds, respectively. The dependent variables are (i) the trade bias, measured as the difference between the average probability of a good state upon buy/sell trades and the Bayesian benchmark of $\frac{1}{2}$, that is, $\bar{\theta}_{j,r} - \frac{1}{2}$, and (ii) the proportion of losses and gains realized in round r by participant j, defined as in equation (17). $d_{\text{game},j,r}$ is a dummy taking the value one if round r is gamified for participant j and zero otherwise; $d_{\text{prefers game},j}$ is a dummy taking the value one if participant j prefers the gamified treatment, and zero otherwise. Controls include a dummy for whether the purchase price is salient in a given round, the standardized financial quiz score, the standardized value of the self-assessed financial knowledge, dummies for participant trading experience and whether participants took an academic course in finance, the average accuracy of beliefs elicited at the midpoint of each round (computed as the relative distance between the participant's belief that the stock is in a good state and the Bayesian probability of a good state), participant age and gender, and round fixed effects. The unit of observation is a participant-round. Standard errors are clustered by participant.

	Buy trades bias		Sell trades bias		PLR		PGR	
Constant	-279.90***	-274.06***	311.81***	312.79***	0.08***	0.08***	0.27***	0.27***
	(-11.87)	(-10.62)	(14.97)	(13.72)	(4.82)	(4.58)	(12.25)	(11.06)
Prefers gamified	64.86***	50.16*	-39.97*	-23.45	0.03*	0.03	0.03*	0.03
	(3.00)	(1.94)	(-1.93)	(-0.98)	(1.68)	(1.26)	(1.84)	(1.51)
Gamified × Prefers gamified		17.49		-35.43**		0.01		0.02
		(0.89)		(-2.11)		(0.54)		(0.83)
Gamified × Prefers non-gamified		-12.62		-1.22		-0.00		0.02
		(-0.65)		(-0.07)		(-0.37)		(0.92)
Salient purchase price	-22.69**	-22.60**	-5.11	-5.19	-0.01	-0.01	0.04***	0.04***
	(-1.98)	(-1.97)	(-0.43)	(-0.44)	(-1.20)	(-1.27)	(4.11)	(4.11)
Age	-38.65**	-38.97**	12.85	13.04	-0.01	-0.01	0.01	0.01
	(-2.09)	(-2.10)	(0.70)	(0.71)	(-0.44)	(-0.42)	(0.36)	(0.37)
Gender (female)	-29.43	-29.15	1.58	1.45	-0.00	-0.01	0.01	0.01
	(-1.34)	(-1.33)	(0.08)	(0.07)	(-0.27)	(-0.30)	(0.54)	(0.54)
Financial quiz score	-34.41***	-34.57***	23.23**	23.36**	-0.03***	-0.03***	0.02	0.02
	(-3.06)	(-3.07)	(2.14)	(2.16)	(-3.14)	(-3.18)	(1.62)	(1.63)
$d_{\text{self-assessed literacy}}$	-3.28	-3.23	-29.36	-29.71	0.02	0.02	-0.01	-0.01
	(-0.16)	(-0.15)	(-1.44)	(-1.45)	(0.87)	(0.82)	(-0.71)	(-0.69)
Trading experience	78.05***	78.42***	-60.28***	-60.53***	0.05***	0.05***	0.04*	0.04*
	(3.34)	(3.35)	(-2.81)	(-2.81)	(2.75)	(2.73)	(1.88)	(1.87)
Finance course taken	-52.00*	-52.22*	37.85	37.95	0.00	-0.00	0.02	0.02
	(-1.69)	(-1.69)	(1.22)	(1.23)	(0.01)	(-0.00)	(0.70)	(0.70)
Prediction accurac	6.01	6.04	3.58	3.51	-0.00	0.01	-0.01	-0.01
	(0.75)	(0.76)	(0.45)	(0.44)	(-0.42)	(1.22)	(-1.13)	(-1.13)
Round FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,046	1,046	1,063	1,063	1,062	1,062	1,058	1,058
Adjusted R-squared	0.09	0.09	0.07	0.07	0.05	0.04	0.07	0.07

Table H.5: Price notifications and trade decisions (using self-assessed literacy dummy)

The table presents the estimation results for the linear regression model

$$d_{\text{sell},t} = \beta_0 + (\beta_1 + \beta_2 d_{\text{game}})\,\text{GreenAlert}_t + (\beta_3 + \beta_4 d_{\text{game}})\,\text{RedAlert}_t + \delta_0 \pi_t + \delta_1 (p_t - c_t) + \text{Controls} + \text{error},$$

estimated over data from Session II, and across participants with different belief accuracy. The unit of observation is tick-round-participant. GreenAlert_t and RedAlert_t are dummies taking the value one if a price increase (drop) notification is displayed at tick t in the gamified treatment; $d_{\text{game},j,r}$ is a dummy taking the value one if round r is gamified and zero otherwise. Controls include a dummy for whether the purchase price is salient in a given round, the standardized financial quiz score, the standardized value of the self-assessed financial knowledge, standardized capital gains at tick t, dummies for participant trading experience and whether participants took an academic course in finance, the average accuracy of beliefs elicited at the midpoint of each round (computed as the relative distance between the participant's belief that the stock is in a good state and the Bayesian probability of a good state), participant age and gender, and round fixed effects. Standard errors are clustered by participant.

	Full sample		Participants with belief accuracy =1		Participants with belief accuracy <1	
	Buy trades	Sell trades	Buy trades	Sell trades	Buy trades	Sell trades
Green alert	0.01	0.06***	-0.02	0.05***	0.03**	0.07***
	(0.77)	(5.11)	(-1.44)	(2.87)	(2.02)	(3.99)
Green alert × gamified	0.03**	0.04**	0.05**	0.02	0.01	0.07**
	(2.13)	(2.52)	(2.23)	(0.95)	(0.57)	(2.57)
Red alert	0.16***	0.01*	0.16***	0.00	0.16***	0.03**
	(9.41)	(1.95)	(6.45)	(0.41)	(6.92)	(2.59)
Red alert × gamified	0.07***	0.01	0.03	0.02	0.12***	-0.00
	(3.38)	(1.08)	(0.79)	(1.42)	(3.98)	(-0.33)
Good state probability	-0.07***	0.03***	-0.05***	0.02***	-0.08***	0.03***
	(-16.50)	(8.84)	(-10.96)	(5.46)	(-14.24)	(7.27)
Gamified	0.01*	-0.00	0.03*	0.01	-0.01	-0.01
	(1.90)	(-0.08)	(1.97)	(0.84)	(-0.84)	(-0.85)
Salient purchase price	0.01		-0.00	-0.02**	0.01	0.01
	(0.96)		(-0.21)	(-2.12)	(0.97)	(0.76)
Age	0.00		-0.00	0.00	0.01	0.00
	(0.46)		(-0.44)	(1.05)	(1.10)	(0.68)
Gender (female)	-0.04***		-0.03	-0.01	-0.05***	-0.06***
	(-2.63)		(-1.58)	(-1.03)	(-2.92)	(-3.76)
Financial quiz score	-0.02**		-0.02**	-0.01	-0.01	-0.01*
	(-2.08)		(-2.05)	(-0.95)	(-1.49)	(-1.87)
$d_{\text{self-assessed literacy}}$	0.04**		0.04**	0.02**	0.03	0.02
	(2.28)		(2.49)	(2.11)	(1.63)	(1.34)
Trading experience	0.00		0.01	-0.01	-0.01	0.01
	(0.22)		(0.36)	(-0.43)	(-0.25)	(0.49)
Finance course taken	-0.02		-0.02	-0.04**	-0.03	-0.06***
	(-1.23)		(-0.72)	(-2.56)	(-1.39)	(-3.28)
Prediction accuracy	-0.00				-0.04***	-0.03***
	(-0.60)				(-2.82)	(-3.18)
Capital gains		0.08***		0.07***		0.08***
		(20.47)		(13.24)		(13.13)
Constant	0.16***	0.15***	0.15***	0.16***	0.14***	0.14***
	(10.70)	(50.58)	(8.06)	(12.01)	(8.03)	(9.28)
Round FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24,553	35,353	10,977	15,903	13,576	19,296
Adjusted R-squared	0.10	0.14	0.08	0.07	0.13	0.10

Table H.6: Price notifications and the disposition effect (using self-assessed literacy dummy)

This table presents the estimation results for the linear regression model

$$y_{j,r} = \beta_0 + \beta_1 d_{\text{game},j,r} + \text{Controls} + \text{error}$$

where j and r run over participants and rounds, respectively. The dependent variables are the proportion of losses and gains realized in round r by participant j, defined as in equation (17); $d_{\text{game},j,r}$ is a dummy taking the value one if round r is gamified for participant j and zero otherwise. Controls include a dummy for whether the purchase price is salient in a given round, the standardized financial quiz score, the standardized value of the self-assessed financial knowledge, dummies for participant trading experience and whether participants took an academic course in finance, the average accuracy of beliefs elicited at the midpoint of each round (computed as the relative distance between the participant's belief that the stock is in a good state and the Bayesian probability of a good state), participant age and gender, and round fixed effects. The unit of observation is a participant-round. Standard errors are clustered by participant.

	Full sample			Participants with belief accuracy = 1			Participants with belief accuracy < 1		
	PLR	PGR	PGR-PLR	PLR	PGR	PGR-PLR	PLR	PGR	PGR-PLR
Gamified	0.00	0.06**	0.05**	0.01	0.05	0.05	-0.01	0.08**	0.09***
	(0.47)	(2.54)	(2.30)	(0.84)	(1.32)	(1.09)	(-1.05)	(2.53)	(2.61)
Salient purchase price	-0.03***	0.01	0.04	-0.03*	0.01	0.05	-0.02*	0.00	0.03
	(-2.69)	(0.44)	(1.48)	(-1.77)	(0.31)	(1.14)	(-1.89)	(0.13)	(0.73)
Age	0.00	-0.00	-0.00	0.00	-0.01*	-0.01**	0.00	0.01	0.00
	(0.31)	(-0.36)	(-0.61)	(0.00)	(-1.95)	(-2.37)	(0.58)	(0.77)	(0.69)
Gender (female)	-0.03	-0.03	-0.00	-0.01	0.02	0.03	-0.04*	-0.08**	-0.03
	(-1.62)	(-1.09)	(-0.14)	(-0.44)	(0.49)	(0.63)	(-1.84)	(-2.01)	(-0.82)
Financial quiz score	-0.04***	0.03	0.06***	-0.04***	0.04*	0.08***	-0.03***	0.02	0.04**
	(-3.68)	(1.54)	(3.32)	(-2.88)	(1.67)	(3.01)	(-2.61)	(0.74)	(2.14)
$d_{\text{self-assessed literacy}}$	0.02	0.03	0.01	0.04**	-0.00	-0.05	0.00	0.07*	0.05
	(1.09)	(1.16)	(0.27)	(2.08)	(-0.05)	(-0.93)	(0.05)	(1.73)	(1.18)
Trading experience	0.01	-0.02	-0.02	-0.01	-0.00	0.01	0.01	-0.02	-0.02
	(0.27)	(-0.48)	(-0.43)	(-0.48)	(-0.05)	(0.17)	(0.42)	(-0.43)	(-0.43)
Finance course taken	-0.04**	-0.07*	-0.04	-0.04	-0.06	-0.03	-0.05**	-0.08	-0.03
	(-2.31)	(-1.69)	(-0.76)	(-1.50)	(-1.08)	(-0.50)	(-2.01)	(-1.52)	(-0.59)
Prediction accuracy	-0.00	-0.00	0.00				-0.03**	-0.01	0.03
	(-0.45)	(-0.29)	(0.02)				(-2.16)	(-0.32)	(0.76)
In-game experience	0.01	-0.07**	-0.09***	-0.00	-0.02	-0.02	0.03	-0.12***	-0.15***
	(0.78)	(-2.55)	(-2.66)	(-0.00)	(-0.56)	(-0.43)	(1.45)	(-3.28)	(-3.80)
First-tick prediction	0.07***	0.02	-0.05	0.06*	0.15*	0.10	0.06***	-0.05	-0.12*
	(3.60)	(0.46)	(-0.86)	(1.67)	(1.94)	(1.04)	(3.01)	(-0.83)	(-1.74)
Constant	0.05***	0.45***	0.41***	0.06**	0.32***	0.26***	0.03	0.53***	0.51***
	(2.81)	(11.37)	(8.76)	(2.19)	(5.23)	(3.36)	(1.16)	(9.78)	(8.72)
Observations	1,044	959	945	463	423	412	581	536	533
Adjusted R-squared	0.06	0.09	0.11	0.05	0.11	0.12	0.08	0.06	0.10

Finally, we investigate whether any particular question in our 12-item quiz is more likely to drive the empirical results on financial literacy. In the left panel of Figure H.1, we show that the pairwise correlation between any two individual answers is always positive, and relatively stable with values between 0.12 and 0.34. We construct 12 "jack-knifed" financial quiz scores for each participant: that is, we discard one by one the answers to individuals question and recompute the score over the remaining 11 questions. The correlation between jack-knifed quiz score (right panel on Figure H.1) are very high — always in excess of 0.96. Therefore, we conclude that no individual questions is likely to drive the results. In Table H.7, we replicate the first column in Table 3 — showing that high-score participants are less likely to prefer gamified platforms — using the jack-knife financial quiz scores. The results remain quantitatively and qualitatively robust.

Figure H.1: **Correlation between financial quiz answers**

This figure plots a heat map of correlation coefficients between (i) individual answers to the 12 financial literacy quiz questions, in the left panel, and (ii) jack-knifed financial literacy scores computed by discarding one individual question at a time — in the right panel.

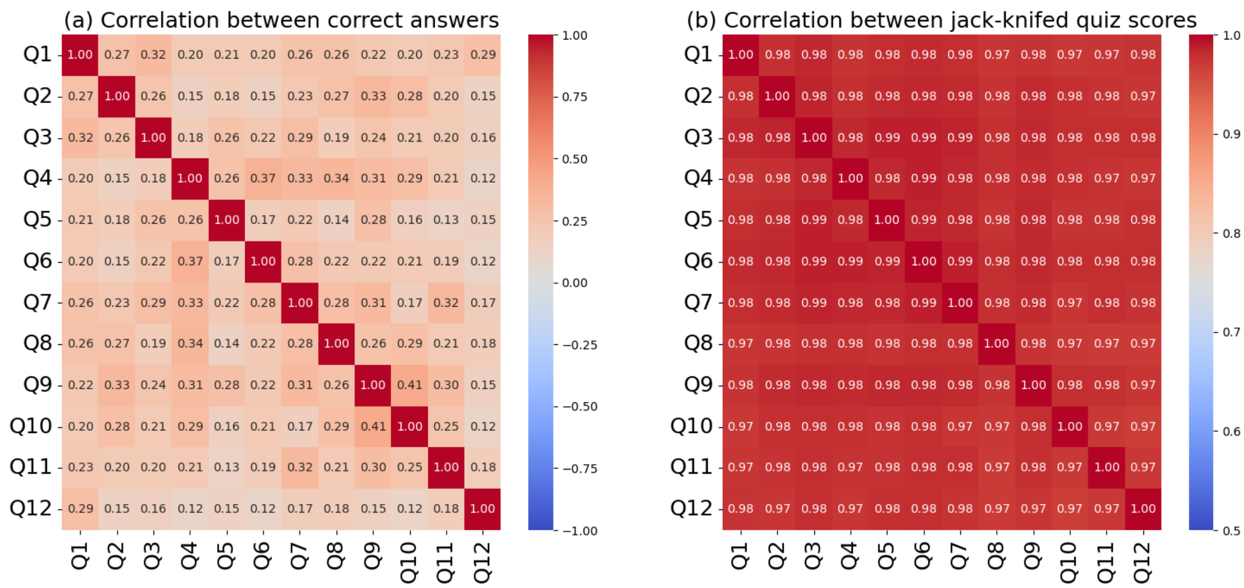


Table H.7: Revealed preferences for trading gamification: Financial quiz jack-knife

This table presents the estimation results of a linear probability model

$$d_{\text{choice},j} = \beta_0 + \beta_1 \text{FinLiteracy}_j + \text{Controls} + \text{error},$$

where $d_{\text{choice},j}$ is the dummy encoding Session I participant answers to Questions 1 in Online Appendix D: "*If you can trade again, would you choose a gamified or non-gamified design?*." The explanatory variables include the standardized jack-knife financial quiz score, the standardized payoff difference between the gamified and non-gamified rounds, the standardized value of the self-assessed financial knowledge, dummies for participant trading experience and whether they took an academic course in finance, the average accuracy of beliefs elicited at the midpoint of each round (computed as the relative distance between the participant's belief that the stock is in a good state and the Bayesian probability of a good state), and finally participant age and gender. The financial quiz score in column QX in the table is computed while ignoring answers to question X. The unit of observation is a participant.

	Full	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12
Constant	0.38***	0.38***	0.38***	0.38***	0.38***	0.38***	0.38***	0.38***	0.38***	0.38***	0.39***	0.38***	0.38***
	(6.81)	(6.77)	(6.74)	(6.75)	(6.82)	(6.85)	(6.81)	(6.80)	(6.83)	(6.81)	(6.87)	(6.88)	(6.76)
Financial quiz score	-0.09***	-0.09***	-0.09***	-0.09***	-0.09***	-0.10***	-0.09***	-0.09***	-0.09***	-0.09***	-0.08***	-0.09***	-0.09***
	(-2.91)	(-2.87)	(-2.91)	(-2.97)	(-2.75)	(-3.08)	(-2.82)	(-2.84)	(-3.05)	(-3.00)	(-2.61)	(-2.92)	(-2.67)
Payoff difference	0.05**	0.05**	0.05**	0.05**	0.05**	0.05**	0.05**	0.05**	0.05**	0.05**	0.05**	0.05**	0.05**
	(2.03)	(2.01)	(2.05)	(2.09)	(2.02)	(2.08)	(2.00)	(2.02)	(2.04)	(2.07)	(2.01)	(2.01)	(1.98)
Self-assessed financial literacy	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	(0.25)	(0.21)	(0.23)	(0.26)	(0.25)	(0.29)	(0.24)	(0.24)	(0.24)	(0.29)	(0.19)	(0.26)	(0.22)
Trading experience	0.02	0.02	0.02	0.02	0.01	0.02	0.02	0.02	0.02	0.02	0.01	0.02	0.01
	(0.26)	(0.27)	(0.28)	(0.28)	(0.20)	(0.29)	(0.25)	(0.26)	(0.27)	(0.24)	(0.10)	(0.24)	(0.21)
Finance course taken	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.07	0.08	0.08
	(0.93)	(0.93)	(0.91)	(0.95)	(0.90)	(0.92)	(0.92)	(0.93)	(0.91)	(0.95)	(0.87)	(0.93)	(0.94)
Prediction accuracy	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02
	(-0.62)	(-0.64)	(-0.62)	(-0.61)	(-0.60)	(-0.58)	(-0.61)	(-0.61)	(-0.59)	(-0.67)	(-0.69)	(-0.62)	(-0.58)
Age	0.03	0.02	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.03	0.02	0.03	0.03
	(0.52)	(0.46)	(0.52)	(0.51)	(0.50)	(0.56)	(0.50)	(0.57)	(0.48)	(0.51)	(0.46)	(0.51)	(0.51)
Gender (female)	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08
	(1.37)	(1.39)	(1.38)	(1.38)	(1.39)	(1.30)	(1.39)	(1.39)	(1.37)	(1.37)	(1.35)	(1.34)	(1.39)
Observations	291	291	291	291	291	291	291	291	291	291	291	291	291
R-squared	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05