Trading gamification and investor behavior: Registered Report Version

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Abstract

We propose a randomized online experiment to study the impact of trading platform gamification on retail traders' behavior. Participants can trade a virtual asset on a laboratory platform, which is either gamified or not. We conjecture that gamification strategies with pure entertainment value (i.e., achievement badges) lead to excessive trading activity and a bias toward risk-taking. However, information-driven gamified elements such as price swing notifications enhance investor learning and reduce noise in trading decisions, potentially alleviating the disposition effect. We further test whether financial literacy and trading experience moderate the negative impact of entertainment-driven gamification strategies.

Keywords: experiment, FinTech, financial literacy, gamification, disposition effect
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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 on U.S. equity markets more than doubled over the past decade, from 10.1% in 2010 to more than 25% in July and August 2020. As a group, retail traders are now the second-largest market segment after market-makers and individual high-frequency traders, but larger than quantitative investors (15.9%), hedge funds (9%), or bank-affiliated traders (5.8%). The largest six online brokerages (Fidelity, Vanguard, Charles Schwab, Webull, Robinhood, and Interactive Brokers) have more than 100 million users combined. Between January and December 2021, Robinhood reported a 47% jump in monthly active users (from 11.7M to 17.3M) and a 55% increase in assets under custody (from \$63bn to \$98bn).[1]

What drives 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 the computer and mobile platforms.

Competition between U.S. online brokerages is strong. On October 1st, 2019, Charles Schwab eliminated trading fees on equities, exchange-traded funds, and options. A "race to zero" swiftly ensued, as competitors TD Ameritrade Holding Corp. and E*Trade Financial Corp matched the move within a week. Newer market entrants, such as Robinhood, were already offering zero-commission trading at the time. As competition on fees reaches a zero lower bound, online brokers need to find new ways to differentiate: for example, by offering investors sleek interfaces aimed to stimulate trading volume and engagement with the platform. The resulting trading apps are increasingly gamified, featuring bright flashing colors, reward animations such as confetti to celebrate a trade, and other behavioral prompts.

Does the gamification[2] of trading apps influence individual investor behavior? The question is of first-order importance for regulators: the January 2021 retail-driven trading surge in Gamestop equities prompted Gary Gensler, chair of the U.S. Securities and Exchange Commission (SEC)

[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; and Robinhood Reports Fourth Quarter and Full Year 2021 Results from January 27, 2022.

[2] Gamification can be defined as the use of elements (and design) of games in non-game contexts (Deterding et al., 2011).

to publicly raise concerns about "behavioral technology" and gamification of trading apps.[3] In December 2020, the Commonwealth of Massachusetts filed an administrative complaint against Robinhood for "aggressive marketing" that goes against the investors' best interest. The European Securities and Markets Authority (ESMA) chair Verena Ross expressed concern in April 2022 that "gamification techniques in trading apps [...] may cause retail investors to engage in trading behaviour without understanding the risks involved."[4]

In this paper, we propose a randomized controlled experiment to assess behavioral externalities of trading gamification. In particular, we first study the impact of gamification strategies on the intensity of retail traders' trading activity, trading mistakes and risk-taking, the magnitude of the disposition effect bias, and the ease of information processing. The experimental design allows us to provide a nuanced analysis of gamification; that is, tease out the impact of gamification elements that convey substantial information and those that do not. Second, we analyze the potential of financial education and trading experience to alleviate or aggravate the externalities related to trading gamification. Finally, we investigate whether gamification can potentially improve stock market participation rates.

Empirically identifying the impact of gamification on investor behaviour is challenging since, for example, investors might self-select into gamified trading apps. The experimental approach allows us to avoid endogeneity problems by randomly assigning participants to gamified and non-gamified platforms.

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). Participants trade a risky asset on a laboratory market over four rounds lasting five minutes each, in addition to a short training round at the start of the experiment. They can buy and sell the asset in real time, but cannot short sell it or hold more than one unit (they can, however, borrow cash at zero interest rate). The asset price process has predictable momentum as it follows a Markov chain process with two highly persistent states, which allows us to solve for the optimal strategy of a Bayesian investor who maximizes her expected terminal wealth.

In each round, participants trade either on a gamified or a non-gamified platform. To design the gamified platform, we draw upon the user interface of real-world trading apps and platforms such as Robinhood, EToro, Binance, or Coinbase. We distinguish between two classes of gamification elements: *hedonic* and *informational*. Building upon the psychology and computer science literature (Hirschman and Holbrook, 1982; Huotari and Hamari, 2012; van der Heijden, 2004), we define hedonic gamification strategies as related to the "multisensory, fantasy, and emotive aspects" of user experience – aspects that encourage prolonged rather than a productive use of the product. As applied to trading platforms, hedonic elements include reward animations and badges upon completing a number of trades. On the other hand, informational gamification strategies include

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

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 the one hand, achievement badges and animations encourage excessive trading, risk-taking behaviour, and sub-optimal buy and sell decisions. On the other hand, price movement notifications may reduce information processing costs, enhance learning, and steer investors toward better trading decisions by reducing the disposition effect – particularly by encouraging them to realize losses. We measure investor learning both directly by eliciting beliefs about the next asset price movement as well as indirectly by studying trading decisions. On aggregate, we conjecture that hedonic aspects of trading apps introduce a *bias* in investors' trading decisions, whereas informational elements reduce the *noise* in buy and sell choices. To cleanly distinguish between the impact of hedonic and informational elements, we randomly assign participants to different experimental sessions with each session subjected to a distinct combination of gamification features.

Is trading app gameful design more likely to sway young and inexperienced investors? Our simple theoretical framework suggests that the impact of gamification is stronger for traders who are further away from the benchmark of a Bayesian expected value investor. We proxy the distance from the rational benchmark in five separate ways. First, we ask participants to complete a 12-question financial literacy quiz based on Fernandes et al. (2014). Second, we manipulate the intensity of the disposition effect across rounds by varying the salience of paper gains and losses (as in Frydman and Rangel, 2014). Third, we vary the in-game trading experience, by randomizing the order in which participants play on gamified and non-gamified platforms. Fourth, we elicit participants' beliefs at the beginning of each trading round. Finally, we allow participants to self-assess their financial literacy at the beginning of the experiment.

We recruit 1,040 experimental subjects from Prolific, a subject pool for online experiments, to participate in the trading game.[5] We build a population-representative sample as our benchmark for the United States and the United Kingdom populations (using census data from both countries), stratified over age, gender, and ethnic group.

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 "attention triggers", that is push notifications from brokers alerting investors about large price swings, increase risk taking as measured by leverage. In the same spirit, Kalda et al. (2021) study transaction-level data from two German banks, and find that investors execute riskier trades on smartphones than other, more traditional, platforms. In the United States, Fedyk (2022) finds that investment patterns on Robinhood, a leading digital

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

platform, can be largely explained by attention-inducing trading in response to extreme price swings or earnings announcements. Moss (2022) documents that push notifications on Robinhood increase trading intensity from retail traders by 25% over 15 minutes following the alert. Chaudhry and Kulkarni (2021) build a comprehensive qualitative analysis of the user interfaces of the most popular investment platforms in the United States. We complement these two recent studies by introducing different elements of trading gamification in a controlled experimental setting with clearly specified price dynamics. The setup allows us to precisely quantify trading mistakes, measure investor beliefs, and study the impact of gamification on well-documented biases such as the disposition effect. Importantly, the randomized experiment allows us to eliminate selection bias (i.e., which traders self-select to use a broker that sends push notifications) as well as control for brokers' endogenous decision of which stocks to send messages about and when. Finally, we are able to measure the impact of financial literacy and trading experience on gamification and investor behavior.

Retail trading. Our paper further contributes to a resurgent literature on retail trading (see Barber and Odean, 2013, for a comprehensive survey of the earlier literature). Early studies find that individual traders are typically uninformed and subject to behavioural biases. Barber and Odean (2000, 2007) show that retail traders are typically over-confident, have excessive turnover, and tilt their portfolio towards small, high-beta stocks that grab their attention. Odean (1998) and Grinblatt and Keloharju (2001) document a disposition effect, wherein retail investors tend to realize gains too soon and hold on to losses for too long. Using Taiwanese data, Barber et al. (2008) estimate a 3.8% annual performance penalty for individual portfolios.

More recent evidence (Kaniel et al., 2008; Kelley and Tetlock, 2013) suggests retail order flow may be able to predict future stock returns: aggressive trades can predict future news, whereas passive orders are contrarian and provide liquidity. Boehmer et al. (2021) provide empirical support to these findings, building a modern measure of retail trading that exploits the fact that most retail order flow on U.S. markets is internalized or sold to wholesalers. Barber et al. (2021) show that the design of the Robinhood trading app (i.e., the *Top Movers* tab) steers investors' attention to stocks with extreme returns, leading to portfolio underperformance. However, Welch (2021) documents that, on aggregate, retail investors using the Robinhood app performed well between 2018 and 2020. Finally, Gargano and Rossi (2018) show that retail portfolio performance is positively related trading in attention-grabbing stocks. Our paper contributes to this literature by examining how the design of trading platforms impacts the portfolio choices of retail traders.

Gamification and behavior. We relate 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 – which generate value beyond its utilitarian use (van der Heijden, 2004). Csikszentmihalyi et al. (2014) emphasizes that gamification elements are intrinsically rewarding if they establish clear goals and provide immediate feedback to users. 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]

In behavioral economics, gamification is usually linked to nudges, which Thaler and Sunstein (2009) define as "*any aspect of choice architecture that alters people's behaviour in a predictable way without forbidding any options or significantly changing their economic incentives.*" A growing literature shows that nudges can be effective in financial settings. Thaler and Benartzi (2004) document that a prescriptive savings program, where employees commit to allocating future salary increases towards retirement, leads to a three-fold increase in the average savings rate. Payzan-LeNestour and Bossaerts (2014) find that participants optimally learn about asset payoffs only when nudged to pay attention to changes in payoff distributions. Agarwal et al. (2014) finds that nudging credit card owners to pay off balances in 36 months has a small impact on the share of accounts that make the 36-month payment value. We contribute to this literature by showing how gamification nudges can impact the investment behaviour of retail traders, particularly on digital platforms.

Disposition effect experiments. The disposition effect, first identified by Odean (1998), is defined as an empirical pattern where 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; Frydman and Rangel, 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 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. Klapper and Lusardi (2020) estimate that only a third of adults around the globe are financially literate. Recent research at the intersection of computer science and finance documents that FinTech advances have the potential to improve literacy (e.g., Rodrigues et al., 2017; Samonte et al., 2017). For example, the U.S. Federal Reserve Bank of Boston introduced digital games to improve financial literacy. One such app, SavingsQuest, used an animated pig that danced every time the user engaged in savings – Maynard and McGlazer (2017) show that the gamified app increased savings rate by 25%. Klein (2022) argues that trading on digital platforms

[6] A related strand of literature in behavioural finance studies the impact of emotional state on trading decisions. Existing work shows that positive feelings exacerbate risk-taking (Isen and Patrick, 1983; Kuhnen and Knutson, 2011; Andrade et al., 2015) and overconfidence (Ifcher and Zarghamee, 2014; Breaban and Noussair, 2017) and negative emotions are associated with heightened risk-aversion (Bosman and Riedl, 2003; Lerner and Keltner, 2001; Kamstra et al., 2003) but potentially lower loss aversion (Campos-Vazquez and Cuilty, 2014).

can offer incentives for investors to self-educate on financial topics. FinTech can be particularly instrumental in boosting financial literacy in developing countries: Kass-Hanna et al. (2022) find that mobile-driven digital financial services in South Asia and Sub-Saharan Africa are crucial to building financial resilience. Demirgüç-Kunt et al. (2020) argue that mobile banking can reduce barriers for disadvantaged groups with low financial literacy. Using data from Japan, Yoshino et al. (2020) document that higher financial literacy leads to an increased usage of FinTech services, but is negatively correlated with holdings of cryptocurrencies (although the evidence on financial literacy and crypto holding is mixed, see Fujiki, 2021).

While the introduction of FinTech is often intended to lower financial hurdles for individuals with low financial literacy, it is important to recognize that these same advancements could potentially exacerbate existing financial barriers and inequalities for this population. For example, Haran Rosen and Sade (2022) found that the introduction of a free government online service aimed at increasing attention to inactive retirement accounts still resulted in limited attention, particularly among those with low financial literacy and socioeconomic status. 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. Karlan et al. (2016) also caution that, in the context of FinTech innovations, relying on simplified behavioral insights, such as providing practical guidelines, may be more effective than traditional financial education methods, as demonstrated by Drexler et al. (2014). Finally, Allgood and Walstad (2016), Bannier and Schwarz (2018), and Cupák et al. (2020) emphasize the role of confidence in one's own financial knowledge, in addition to measured financial literacy, particularly when it comes to making investment decisions. We complement this literature by focusing on how objective and perceived financial literacy moderate the impact of trading gamification on investor behavior.

3 Experimental design

We start by describing the experimental market in Section 3.1, followed by the design of the trading platform and gamification strategies in Section 3.2. Next, in Section 3.3 we lay out a theoretical decision-making framework that allows us to state the optimal strategies for participants. Guided by the theory, we pin down specific predictions on how trading gamification impacts trading behaviour (Section 4) that we subsequently test in Section 5.

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 focus on individual decision-making in a trading game, and abstract 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 5 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 disallowed. The constraints simplify the participants' strategy space, allowing for sharper identification of the mechanisms at play. A participant only has to choose whether to buy the stock if she is not already holding it, or whether to sell the stock if she holds it. While trading, participants are allowed to effectively 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 4 trials of each round. The first few trials allow 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 updates 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 independently drawn. 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 $-i$. Stock price exhibits momentum and is therefore predictable – price increases (drops) are likely to be followed by further increases (drops).[7]

[7]The assumption allows us to build an environment where it is easier to measure the disposition effect. Frydman et al. (2014) 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). It is therefore more straightforward to measure disposition effect as deviations from the optimal strategy of a rational agent. Further, a price process with changing states actually simplifies the heuristics for participants: a stock that did poorly in the recent past is more

Table 1 enumerates the transition probabilities in the Markov chain.

Table 1: Transition probabilities in the stock Markov chain

State	g_{t+1}	b_{t+1}
g_t	0.85	0.15
b_t	0.15	0.85

Participants receive information about 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, like 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 on the current state of the stock. Concretely, for each round before trial $t = 40$ we pause trading for 20 seconds and display the following questions:

> How likely is the stock to go up next?
> 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 additionally elicit participant beliefs before trial $t = 1$. At the beginning of each round, absent any price history, the stock is equally likely to be in a good or in 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 assessment. 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 answert $u = 0.5$.

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

likely to continue to do poorly, and vice-versa.

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 and 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 in Section 3.2 and Appendix D. 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 only informational elements of gamification (i.e., price notifications).

3. **Session III**: Non-gamified + Gamified with both hedonic and informational elements of gamification.

4. **Session IV (robustness)**: Non-gamified + Gamified with only informational elements of gamification as in Session II, but the price process is a martingale.

Each participant trades in both non-gamified and gamified platforms, such that (i) we establish a baseline trading behaviour 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 only one type of gamification treatment. That is, the gamification strategies vary between participants. This experimental setup allows us to disentangle between 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 an "rational attention improvement" component (the positive difference, if any, between the effect 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). Further, as in Frydman and Rangel (2014), the purchase price of the stock is prominently displayed on the platform (salient) in two of the four rounds and not displayed in the other two. Varying the emphasis on purchase price information can manipulate the visibility of paper gains and losses, affecting the size of the disposition effect displayed by investors, as demonstrated by Frydman and Rangel (2014).

We detail the round structure below.

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

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. Each participant is then equally likely to be allocated to either of four "blocks", labelled A through D. The purpose of the blocks is to randomize the order in which participants are exposed to the treatments. Participants in blocks A and B start with two gamified rounds, whereas other participants start with two non-gamified rounds. Similarly, participants in blocks B and D start with a round where the purchase price is salient, then alternate between high- and low-salience rounds. During high-salience rounds, 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).

Table 2 describes the block design, round-by-round. Salience in Table 2 refers to whether the purchase price is prominently displayed on the platform or not.

Table 2: **Sequence of trading rounds**

Round	Block A		Block B		Block C		Block D	
	Gamified	Salience	Gamified	Salience	Gamified	Salience	Gamified	Salience
0	No	Low	No	Low	No	Low	No	Low
1	Yes	Low	Yes	High	No	Low	No	High
2	Yes	High	Yes	Low	No	High	No	Low
3	No	Low	No	High	Yes	Low	Yes	High
4	No	High	No	Low	Yes	High	Yes	Low

After the trading game, we ask participants to self-reflect on their trading decisions on different platforms by asking them four direct questions, as stated in 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, as stated in 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]

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

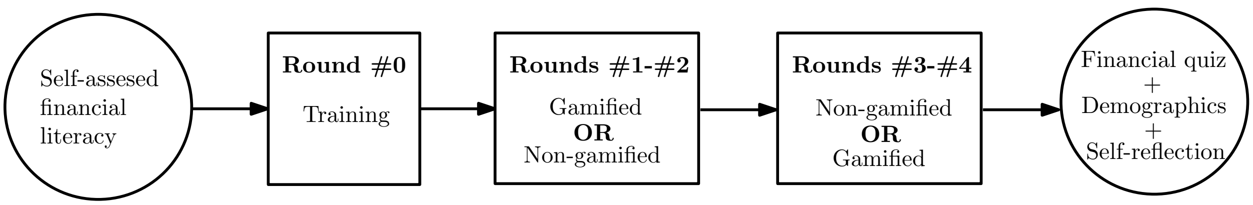
[9] We drop one question in Fernandes et al. (2014) that is specific to the U.S. pension system since many of our experimental participants are not U.S. residents.

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, such 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 Appendix A. Before the trading starts, participants need to correctly answer five comprehension questions, listed in 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. We expect each participant to receive a fixed compensation of 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 the 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 round plus the end-of-round price of any stock that they own.

Besides the payment round profit, participants are also rewarded for correct answers in the post-experimental financial literacy quiz. Namely, 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

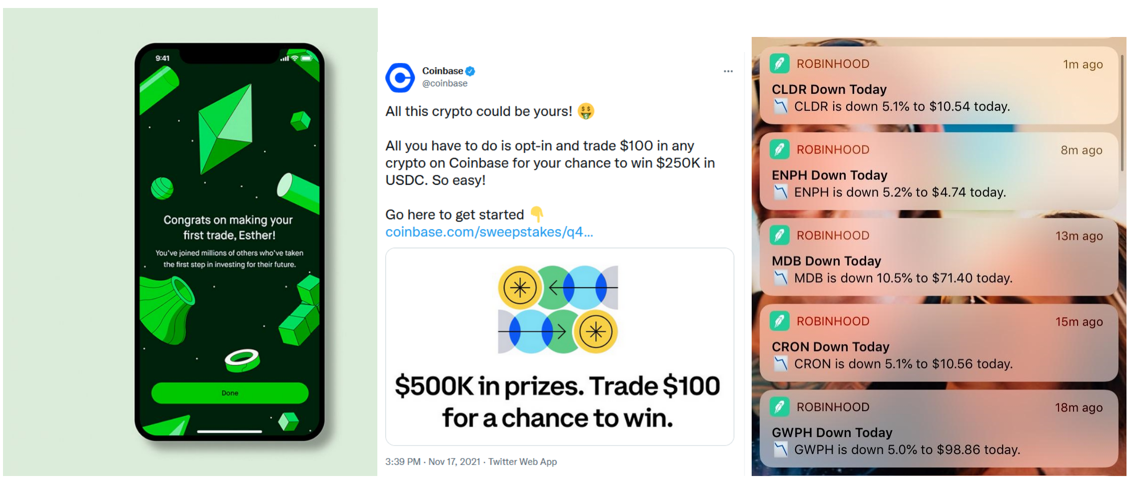
3.2.1 Gamification strategies in real-world trading apps

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] Figure 2 illustrates the strategies with concrete examples. In 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.

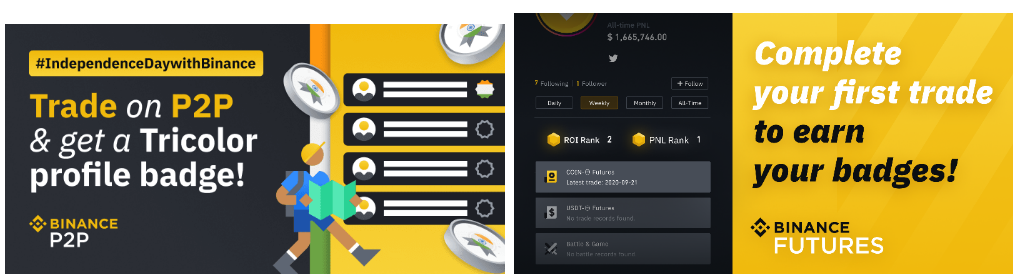
Figure 2: **Trading gamification in practice: examples**

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 upcoming lottery for investors who trade $100 on the platform, (c) a sequence of push notifications emphasizing trending stocks from the Robinhood mobile app, and (d) advertisements for badge-winning opportunities by trading on Binance.[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, and Binance Twitter account.



(a) Reward animations (b) Lottery incentives (c) Emphasis on trends



(d) Achievement badges

1. **Reward animations and badges.** Robinhood, a leading FinTech online brokerage in the U.S., shows customers colorful reward animations after each trade. The original animation used celebratory confetti flying across the screen; following widespread criticism – including

[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.

during a U.S. 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, or 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 U.S.-based cryptocurrency exchange, launched in March 2022 a "sweepstakes" program where participants can win large prices (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 with a value between CA$5 and CA$4,500 with an average of CA$10.

3. **Emphasis on trending stocks.** Trading apps often provide noticeable 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 risk and increase their leverage. Barber et al. (2021) 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 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) introduce the concept of hedonic consumption as consumer behavior related to the "multisensory, fantasy, and emotive aspects" of product user experience.[14] 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 experiences fun when interacting with the product – through, for example, a focus on colors, sounds, animations. Csikszentmihalyi et al. (2014)

[12] See also ForexCrunch: EToro introduces Foursquare Style Badges, 25 January 2011, accessed 21 May, 2022.

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

[14] Alba and Williams (2013, p. 4) provide an extensive list of psychometric investigations supporting the idea that consumption can be distinguished along the lines of utilitarian (cognitive) versus hedonic (emotional).

argue that clear goals (i.e., entering into a lottery or earning a badge) and immediate feedback (i.e., seeing a reward animation right after a trade) promote "intrinsically rewarding experiential involvement." Dorn and Sengmueller (2009) use survey data for German investors and 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 over their hedonic value. Rather, notifications increase the salience of short-term price movements and therefore carry informational value.

Table 3: **Elements of gamification**

	Gamification strategy	Hedonic value	Informational value
1	Reward animations	✓	✗
2	Lottery incentives	✓	✗
3	Emphasis on trends	✓	✓

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 4 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.

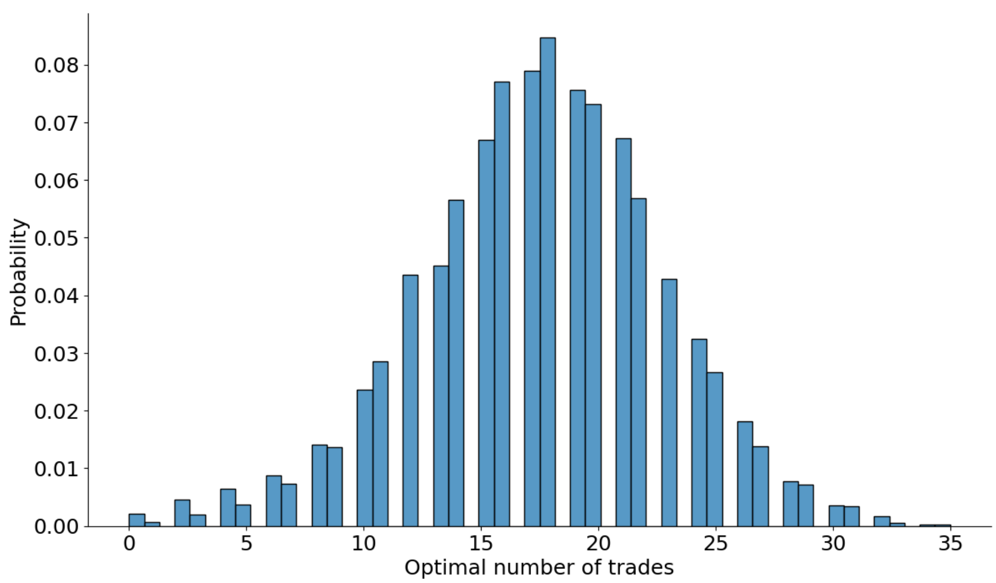
Table 4: **Achievement badges**

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 inter-quartile range of 14 to 21 trades.

Figure 3: **Distribution of optimal trade count**

The figure illustrates the distribution of the optimal number of trades in a given stock over 56 price updates and 10,000 simulations.



Price change notification. Another gamification feature we implement in the experiment is the emphasis on trends. Namely, 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 the three jumps notification or the four jumps notification; also so that we do not assign 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 4 illustrates the different gamification elements. The top panel displays a typical achievement screen, including badges (locked and unlocked), confetti, and congratulatory messages. The bottom 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: i.e., 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 a hedonic consumption value. This allows us to generate specific predictions on how gamification impacts trader behaviour as a function of the intensity of their behavioral biases.

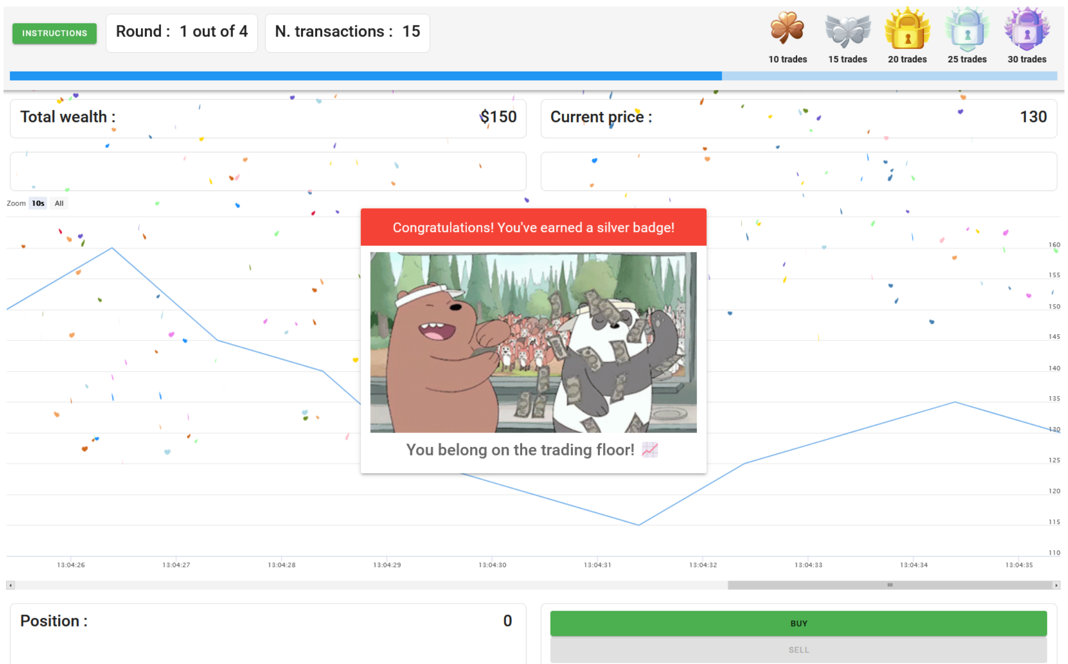
Relative expected value (REV). The *relative expected value* component corresponds to the utility of a risk-neutral trader who maximizes the end-of-round expected payoff. We define REV as in Frydman and Rangel (2014) as the difference between the expected stock price after the next update ($\mathbb{E}p_{t+1}$) 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

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

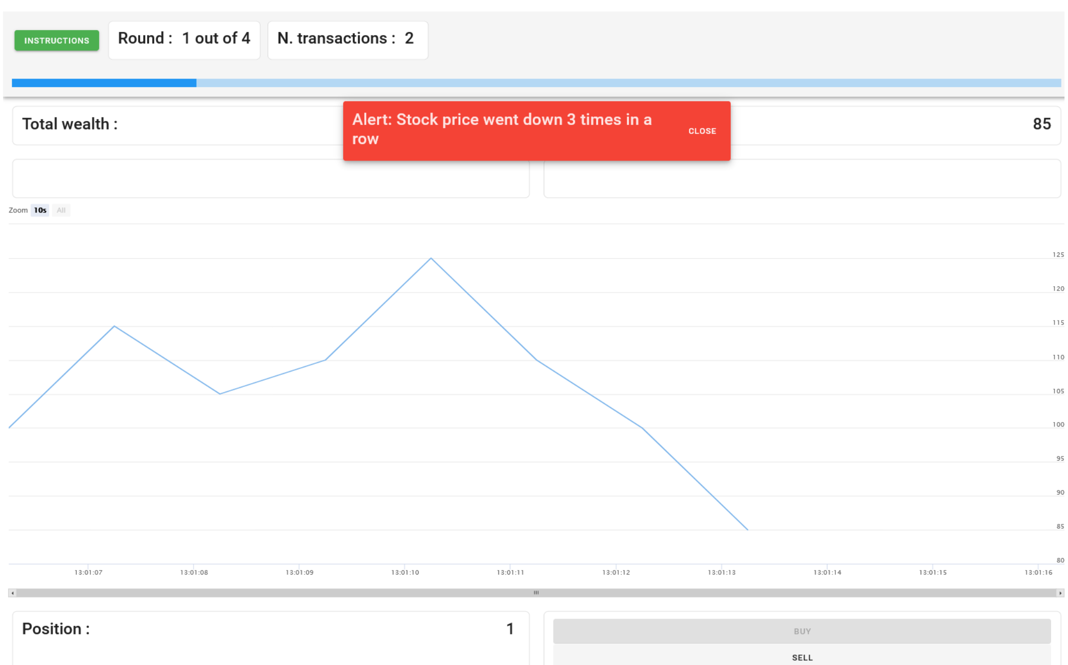
If the stock is in the good state at $t+1$, then the price goes up on average by E\$10 (i.e., the average magnitude of price changes is $(5+10+15)/3 = 10$) with probability 0.55 and drops on average

Figure 4: **Trading platform screenshots**

This figures displays two representative screenshots gamified trading platform: badges and reward animations (top panel) and price change notifications (bottom 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

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 she believes 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 $p_t > c_t$, that is investors realize a gain, they experience positive utility. Otherwise, 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 who self-select into a trading experiment are likely to experience fun from 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) – that is, the expected price change in equation (1) and the capital gains (CG) or the realization utility component. We additionally include the hedonic consumption term and restrict 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), the investor expected utility can be written as

$$U\left(q_t, \Delta q_t\right) = \omega \times \underbrace{\left(q_t + \Delta q_t\right)\left(2\pi_t - 1\right)\left(\operatorname{Prob}\left(g_{t+1} \mid g_t\right) - \operatorname{Prob}\left(b_{t+1} \mid g_t\right)\right)}_{\text{REV (relative expected value)}} \tag{4}$$

$$+ (1-\omega) \times \underbrace{\left(p_t - c_t\right)\mathbb{1}_{\Delta q_t = -1}}_{\text{CG (capital gains)}} + \underbrace{\tau\left(\mathbb{1}_{\text{gamified}}\right)\mathbb{1}_{\Delta q_t \neq 0}}_{\text{HC (hedonic consumption)}},$$

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 – either 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. We use five strategies to control ω in the lab and provide converging evidence in the spirit of Bergman et al. (2020). First, Barberis and Xiong (2012, p. 252) note that realization utility "is likely to play a larger role when the purchase price is more salient." Indeed, Frydman and Rangel (2014) find experimental evidence that removing information on purchasing prices reduces the disposition effect by 25%.[15] Therefore, we induce a lower ω by increasing the salience of the purchase price on the experimental platform. Our second strategy is to proxy ω by financial literacy as measured by the financial quiz score: we argue that participants with higher exposure to markets are more likely to think in expected value terms and less prone to biases (Lusardi and Mitchell, 2014). Third, we proxy ω with in-game experience: we conjecture participants use past payoffs to learn about the profit-maximizing strategy and therefore ω increases with experience (Feng and Seasholes, 2005, provide evidence that trading experience reduces the disposition effect). Forth, to proxy for ω we use a measure of prior beliefs derived from surveying participants' perceptions before trial $t = 1$. Finally, we use the distance between the financial quiz score and the perceived financial literacy as elicited at the beginning of the experiment.[16]

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

[15] Also, Frydman and Wang (2020) provide supportive empirical evidence on the impact of purchase price salience on the disposition effect using a natural experiment with Chinese brokerage data.

[16] Following Menkveld et al. (2022), we also use the first principal component of the five measures as a proxy for investor rationality.

good state at trial t, that is π_t, evolves as follows:

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

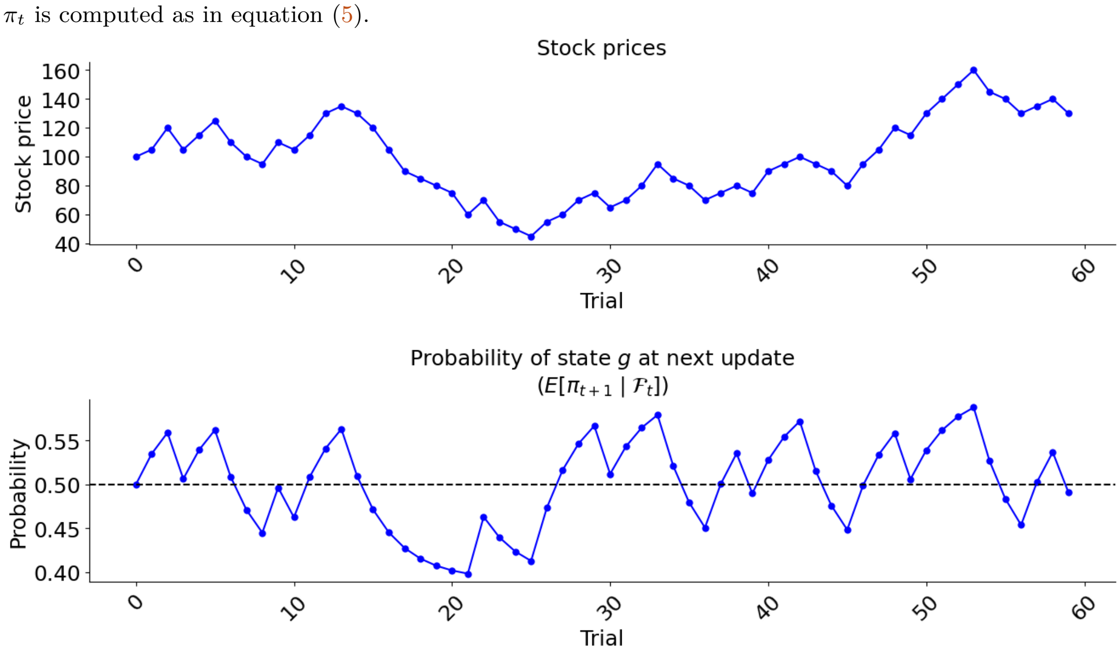
where $q_0 = 0.5$ is the long-run stationary probability of state g. Figure 5 illustrates a simulated price path for the stock (top panel) together with the Bayesian expected probability of an uptick in period $t+1$ conditional on all information up to time t (bottom panel). While investors cannot be expected to perform the computation in (5) in the short time available, Figure 5 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 5: **Simulation of stock price path and good-state probabilities**

The top panel illustrates potential stock price paths generated from Markov chains with transition probabilities as enumerated in Table 1. The initial state is equally likely to be g or b, consistent with the stationary distribution of the two Markov chains. The bottom 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).



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 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, her utility is zero. If she buys it, she obtains 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

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

If investors have 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). The impact on τ on the distance between the θ_{buy} and one half decreases in the REV weight ω, since

$$\frac{\partial^2\left(\frac{1}{2} - \theta_{\text{buy}}\right)}{\partial\tau\partial\omega} < 0. \tag{9}$$

The intuition behind (9) 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.

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

$$\begin{cases} U\left(q_t = 1, \Delta q_t = 0\right) = \omega\left(2\pi_t - 1\right)\left(\mathbb{P}\left(g_{t+1} \mid g_t\right) - \mathbb{P}\left(b_{t+1} \mid g_t\right)\right) & \text{(do not sell)} \\ U\left(q_t = 1, \Delta q_t = -1\right) = \left(1 - \omega\right)\left(p_t - c_t\right) + \tau. & \text{(sell the stock)} \end{cases} \tag{10}$$

If the investor does not sell the stock, she captures the realized expected value utility. Conversely, if she decides 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 the probability of being in a good state is low enough, that is if

$$\pi_t \leq \theta_{\text{sell}} \equiv \frac{1}{2} + \frac{(1-\omega)(p_t - c_t) + \tau}{\omega}. \tag{11}$$

The optimal strategy for REV investors with no hedonic consumption (that is, 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 the one hand, investors are even more likely to sell winner stocks, which amplifies the bias. Nevertheless, they are also more likely to sell losing positions, which reduces the disposition. As for buying choices, the impact of τ on the probability threshold is lower for investors who assign a larger weight to the REV benchmark, since

$$\frac{\partial^2 \left(\theta_{\text{sell}} - \frac{1}{2}\right)}{\partial \tau \partial \omega} = -\frac{1}{\omega^2} < 0. \tag{12}$$

3.3.3 Price swing notifications and investor behavior

The discussion in Section 3.3.2 focuses 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 disentangle between 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.

Reduce information processing costs. In practice, participants are unlikely to use Bayes' formula to update their probabilities. Frydman et al. (2014) suggests that computing the share of price increases over a recent interval is a simple heuristic to forecast the current state. Therefore, participants guide 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 upwards accordingly:

$$\tilde{\pi}_{\text{update}} = \begin{cases} (1-\lambda)\,\tilde{\pi} + \lambda \times 1 \geq \tilde{\pi} & \text{for price increase notifications} \\ (1-\lambda)\,\tilde{\pi} + \lambda \times 0 \leq \tilde{\pi} & \text{for price decrease notifications,} \end{cases} \tag{13}$$

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

4 Hypothesis development and econometric methodology

4.1 Do participants trade too much on gamified platforms?

Hypotheses 1 to 3 relate to the impact of "hedonic trading." This set of hypotheses is tested using the observations in 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 – leading participants to trade too much relative to an optimal benchmark and have predictable biases in timing their transactions.

Hypothesis 1. (Trader engagement) *Participants execute an excessive number of trades on the gamified platform with hedonic elements of gamification, relative to the optimal trade count for a Bayesian expected value trader. Further, investors execute relatively more trades on the gamified platform than on the non-gamified platform.*

A natural measure for the intrinsic value of trading is to simply count executed trades in each round. However, the optimal number of trades varies across rounds since the price paths are themselves stochastic. To test Hypothesis 1, we build a measure of excessive trading as the ratio between the realized trade count and the optimal number of trades. The optimal 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:

$$\text{ExcessiveTrading}_{j,r} = \frac{\text{Trade count}_{j,r}}{\text{Optimal trade count}_{j,r}}. \tag{14}$$

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

$$\text{ExcessiveTrading}_{j,r} = \beta_0 + \beta_1 d_{\text{game},j,r} + \text{Controls} + \text{error}, \tag{15}$$

where d_{game} 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, real-life trading experience, a dummy indicating whether the purchase price is salient or not, and the round number to proxy for experience.

Hypothesis 2. (Trading biases) *Let $\bar{\theta}^{buy/sell}$ denote the estimated probability thresholds that trigger a trade, for both buy and sell transactions, defined as*

$$\bar{\theta}^{buy/sell}_{j,r} = \begin{cases} \frac{1}{\#\ buys\ for\ j} \sum_{t \in buy\ trades\ of\ j} \pi_{r,t}, & for\ buy\ trades\ , \\ \frac{1}{\#\ sells\ for\ j} \sum_{t \in sell\ trades\ of\ j} \pi_{r,t}, & for\ sell\ trades\ . \end{cases} \tag{16}$$

We conjecture that $\bar{\theta}^{buy} \leq \frac{1}{2}$ and $\bar{\theta}^{sell} > \frac{1}{2}$. Further, the buy probability threshold $\bar{\theta}^{buy}$ is smaller on the gamified platform than on the non-gamified platform, while the opposite is true for the sell probability threshold $\bar{\theta}^{sell}$.

We turn next to quantifying trading biases, from the perspective of a Bayesian investor. Equations (8) and (11) suggest that investors follow a biased probability threshold strategy when buying and selling stocks. We empirically measure the threshold as in equation (16), by taking the average value of π_t for each buy, respectively sell, trade for participant j in a given experimental round r. The rationale for averaging is to reduce the measurement noise since investors likely use an imperfect heuristic proxy for the true π_t on a trade-by-trade basis.

Hypothesis 2 implies that, from the perspective of a rational expected value trader, participants make sub-optimal trading decisions. On the gamified platform with only hedonic elements of gamification, participants are more willing to purchase a stock with a negative expected return next period (since $\bar{\theta}^{\text{buy}} \leq \frac{1}{2}$), as well as to sell a stock with positive expected return ($\bar{\theta}^{\text{sell}} > \frac{1}{2}$). Risk-averse and risk-neutral investors do not optimally take positions in risky stocks with negative returns. An important consequence of Hypotheses 2 is that hedonic elements of gamification trigger investors to behave as if they were effectively risk-loving. We estimate

$$\bar{\theta}^{\text{buy/sell}}_{j,r} - \frac{1}{2} = d_{\text{buy/sell}} \left(\beta_0 + \beta_1 d_{\text{game},j,r} \right) + \text{Controls} + \text{error}, \tag{17}$$

where $d_{\text{buy/sell}}$ is a dummy taking value one for sells and minus one for buys. Hypothesis 2 immediately maps to $\beta_0 > 0$ and $\beta_1 > 0$ in equation (17). For sell decisions, we include capital gains as an additional control (i.e., the difference between the current price and the purchase price).

Hypothesis 3. (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.*

Equations (9) and (12) imply that a higher weight on the expected value (REV) component of utility translates to a lower impact of gamification on trading decisions. The impact of gamification on trading decisions depends on how close investors' preferences are to the expected value benchmark. More rational traders assign a relatively lower weight to the hedonic elements of the platform. They are less likely to be swayed by these gamification strategies and more likely to maximize their expected value.

To provide converging evidence in the spirit of Bergman et al. (2020), we use a number of independent measures for ω to capture departures from rationality in the lab. First, standardized financial quiz scores are a natural proxy for ω – 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 3, we re-estimate regression models (15) and (17) where we control for the interaction between the gamified treatment and our different measures for the REV weight ω:

$$y_{j,r} = \beta_0 + \beta_1 d_{\text{game},j,r} + \beta_2 \text{REV} + \beta_3 d_{\text{game},j,r} \times \text{REV} + \text{Controls} + \text{error}, \tag{18}$$

where the dependent variable $y_{j,r} \in \left\{ \text{ExcessiveTrading}_{j,r}, \frac{1}{2} - \bar{\theta}^{\text{buy}}_{j,r}, \bar{\theta}^{\text{sell}}_{j,r} - \frac{1}{2} \right\}$ 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 $d_{\text{experience}}$ taking value one if the trader plays the first two rounds on the non-gamified platform and zero otherwise;
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. the difference between the financial quiz score and the perceived financial literacy as elicited at the beginning of the experiment;
6. the first principal component of the above.

Hypothesis 3 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 – either induced by the platform design, lack of experience, or deficient financial education.

4.2 Do participants learn better on gamified platforms?

In this section, Hypotheses 4 to 6 focus on the potential positive impact of trading gamification. In particular, we aim to determine 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 4. (Trading noise) *The variance 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 (11), 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.

To test Hypotheses 2 and 3, we average out the noise across all trades in a given round since we are primarily interested in the magnitude of the bias. Nevertheless, the variance of the threshold $\theta^{\text{buy/sell}}$ reflects information about the 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 make fewer mistakes. That is, we test if $\beta_1 < 0$ in the following model

$$\text{var}\left(\theta^{\text{buy/sell}}\right)_{j,r} = \beta_0 + \beta_1 d_{\text{game},j,r} + \text{Controls} + \text{error}, \tag{19}$$

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 variance of π_t for each buy, respectively sell, trade for participant j in a given experimental round r:

$$\text{var}\left(\theta^{\text{buy/sell}}\right)_{j,r} = \begin{cases} \frac{1}{(\#\text{ buys for } j)-1} \sum_{t \in \text{buy trades of } j} \left(\pi_{r,t} - \bar{\theta}^{\text{buy}}_{j,r}\right)^2, & \text{for buy trades,} \\ \frac{1}{(\#\text{ sells for } j)-1} \sum_{t \in \text{sell trades of } j} \left(\pi_{r,t} - \bar{\theta}^{\text{sell}}_{j,r}\right)^2, & \text{for sell trades.} \end{cases} \tag{20}$$

Importantly, the controls in model (19) 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.

Hypothesis 5. (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.*

We directly elicit participant beliefs in the middle of each round about the subsequent stock price change following Weber and Camerer (1998). For simplicity, beliefs are coded on a five-point Likert scale ranging from a low to a high probability that the stock is in the "good" Markov state. To match scales, we map Bayesian probabilities π_t to a similar five-point scale. From equation (5), the Bayesian probability is bounded in $\pi_t \in [0.35, 0.65]$.[17] We split the bounded interval in five partitions of equal measure, and assign each partition a value from one to five as below:

Bayesian estimate π_t	$[0.35, 0.41)$	$[0.41, 0.47)$	$[0.47, 0.53)$	$[0.53, 0.59)$	$[0.59, 0.65]$
Likert scale codification $\mathcal{L}(\pi_t)$	1	2	3	4	5

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

$$\Delta = |\mathcal{L}(\pi_t) - \text{investor belief}|\,. \tag{21}$$

For example, if a participant indicates that the stock is very unlikely to be in a good state (i.e., answers 1 on the 1-5 scale), but the Bayesian probability is $\pi_t = 0.56$ (i.e., a 4 on the "true" scale), the distance is computed as $\Delta = |1 - 4| = 3$. Hypothesis 5 implies that $\beta_1 < 0$ in the following regression model:

$$\Delta_{j,r} = \beta_0 + \beta_1 d_{\text{game},j,r} + \text{Controls} + \text{error}, \tag{22}$$

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. For robustness, we also estimate (22) where we weigh the distance by the confidence level of the belief.

Hypothesis 6. (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.*

Hypothesis 4 and 5 test whether investors learn better on aggregate on the gamified platform, using one observation for each participant-round. Hypothesis 6 pins down the alert notifications as the causal channel driving enhanced learning. To test this conjecture, we focus on trading activity within each gamified round where the unit of observation is a trial 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. For the subset of participants that own

[17] 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 $z_t = -1$.

the stock at the time of notification, we estimate Probit and linear probability models for

$$d_{\text{sell},t} = \beta_0 + \sum_{k=1}^{3} \beta_k \text{GreenAlert}_{t-k} + \sum_{k=1}^{3} \gamma_k \text{RedAlert}_{t-k} + \delta_0 \pi_t + \delta_1 (p_t - c_t) + \text{Controls} + \text{error}, \quad (23)$$

where $d_{\text{sell},t}$ takes the value one if the participant sold the stock at trial t and zero otherwise. Hypothesis 6 implies that $\sum_{k=1}^{3} \beta_k < 0$ (you are less likely to sell the asset after a positive alert) and $\sum_{k=1}^{3} \gamma_k > 0$ (you are more likely to sell the asset after a negative alert). If participants react immediately to the notification and trade the very next round following the alert, then also we expect $\beta_1 < 0$ and $\gamma_1 > 0$. To focus on the impact of notifications themselves, we control for the Bayesian probability of a good state π_t and also for the capital gains $p_t - c_t$ (price minus cost) which also drive the selling decision.

Similarly, we estimate a model pertaining to buying decisions following a notification:

$$d_{\text{buy},t} = \beta_0 + \sum_{k=1}^{3} \beta_k \text{GreenAlert}_{t-k} + \sum_{k=1}^{3} \gamma_k \text{RedAlert}_{t-k} + \delta_0 \pi_t + \text{Controls} + \text{error}, \quad (24)$$

where $d_{\text{buy},t}$ takes the value one if the participant purchased the stock at trial t. We test whether $\sum_{k=1}^{3} \beta_k > 0$ (participants buy assets after positive notifications) and $\sum_{k=1}^{3} \gamma_k < 0$ (participants are less likely to buy assets after receiving negative alerts).

4.3 Trading gamification and the disposition effect

Does the gamification of trading platforms impact well-known investor biases such as the disposition effect? We follow Odean (1998) and for each price update we label investors' position as 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:

$$\begin{aligned} PGR_{j,r} &= \frac{\text{Realized gains}}{\text{Realized gains} + \text{Paper gains}} \quad \text{(proportion of gains realized)}, \\ PLR_{j,r} &= \frac{\text{Realized losses}}{\text{Realized losses} + \text{Paper losses}} \quad \text{(proportion of gains realized)}. \end{aligned} \quad (25)$$

Hypothesis 7. (Realized losses) *The proportion of losses realized (PLR), defined as in Odean (1998), is higher on the gamified platform than on the non-gamified platform. Further, PLR is highest for the gamified platform with both hedonic and informational elements.*

Pooling observations from Sessions I, II, and III, we estimate a linear regression model using the proportion of losses realized as the dependent variable:

$$PLR_{j,r} = \beta_0 + \beta_1 d_{\text{game},j,r} + \beta_2 d_{\text{Session II},j} + \beta_3 d_{\text{Session III},j} + \beta_4 d_{\text{game},j,r} \times d_{\text{Session II},j} + \beta_5 d_{\text{game},j,r} \times d_{\text{Session III},j} + \text{Controls} + \text{error}. \quad (26)$$

There are at least two reasons why investors are more likely to realize losses on the gamified platform. First, a rising tide lifts all boats: a higher hedonic value of trading encourages investors to transact more, including selling the "loser" stocks in their portfolio. The channel implies $\beta_1 > 0$ – that is, PLR is larger – on the gamified platforms with hedonic elements. Second, Hypothesis 6 postulates that investors are more willing to sell a stock following a price drop notification, precisely when the position is more likely to be labeled as a paper loss. Therefore, we hypothesize that the PLR is also higher for platforms with informational gamification elements when compared to a non-gamified trading environment, that is $\beta_1 + \beta_4 > 0$. Finally, there is an added positive PLR effect due to the presence of both notifications and the hedonic elements – consistent with $\beta_5 > 0$ and $\beta_5 > \beta_4$.

Hypothesis 8. (Realized gains) *The proportion of gains realized (PGR), defined as in Odean (1998), is higher (lower) on the gamified platform with hedonic (informational) elements only than on the non-gamified platform.*

The aggregate impact of gamification on the proportion of realized gains is less clear ex ante. Using observations from Sessions I, II, and III we estimate the following pooled regression:

$$PGR_{j,r} = \beta_0 + \beta_1 d_{\text{game},j,r} + \beta_2 d_{\text{Session II},j} + \beta_3 d_{\text{Session III},j} + \beta_4 d_{\text{game},j,r} \times d_{\text{Session II},j} + \beta_5 d_{\text{game},j,r} \times d_{\text{Session III},j} + \text{Controls} + \text{error}. \quad (27)$$

On the one hand, Hypothesis 6 conjectures that investors should be more willing to hold winners in their portfolio as they receive positive notifications. However, the augmented hedonic value of trade on the gamified platform implies that participants are more willing to realize gains, pushing in the opposite direction. The implication would be that $\beta_1 > 0$ and $\beta_1 + \beta_4 < 0$ when estimating model (27).

4.4 Revealed preferences

We also aim to understand which subset of participants prefers the gamified trading platforms by asking them a few direct questions outlined in Appendix D.

In Hypothesis 9, we conjecture that participants with low levels of financial literacy are more likely to answer that they prefer the gamified platform: either because they assign more weight to its hedonic value, or because the price alerts have a higher marginal value to them or a combination of both reasons. If participants across the board prefer the gamified platform, then gamification can prove a useful tool to improve stock market participation.

Hypothesis 9. (Revealed preference) *Participants with a lower level of financial literacy are more likely to choose the gamified platform when presented with the option.*

For each of Sessions I, II, and III, we estimate Probit and linear probability models of the platform preference:

$$d_{\text{choice},j} = \beta_0 + \beta_1 \text{FinLiteracy}_j + \text{Controls} + \text{error}, \tag{28}$$

where $d_{\text{choice},j}$ is the dummy encoding participant answers to Questions 1 or Question 2 in Appendix D. We use two financial literacy measures: (i) objective financial literacy defined as the proportion of correct answers in the financial quiz, and (ii) perceived financial literacy defined as the self-assessed knowledge about financial matters. We additionally control for the realized profit in gamified versus non-gamified rounds, since participants might simply prefer the platform design for which they were the most successful.

Hypothesis 9 maps to β_1; however, estimating (30) allows us to explore the demographic characteristics of traders who prefer to trade on gamified platforms and which might not be captured in the theoretical framework. Further, by including in (30) the subjects' ranking of the gamification elements they were exposed to (Question 4 in Appendix D), we can directly investigate which platform design element (i.e., achievement badges or rating notifications) had a stronger impact on participants' preferences, across various levels of financial literacy. For example, for Session III, the model would include both informational and hedonic features:

$$\begin{aligned} d_{\text{choice},j} = {} & \beta_0 + \beta_2 \text{RatingBadge}_1 + \beta_2 \text{RatingNotification}_j + \\ & + \text{FinLiteracy}_j (\beta_3 + \beta_4 \text{RatingBadge}_j + \beta_5 \text{RatingNotification}_j) + \text{Controls} + \text{error}. \end{aligned} \tag{29}$$

We further hypothesize that some traders may incur losses while using gamified trading apps, acknowledge the losses, but still find the experience enjoyable and consider it a fair trade-off. This kind of behavior may be considered rational and not pose a concern for policymakers. However, 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. Given the importance of this distinction for policy considerations, we aim to distinguish between a "rational" gamification preference and an addictive one. For this we re-evaluate model (30) by utilizing the response to Question 3 in Appendix D as the dependent variable:

$$d_{\text{option},j} = \beta_0 + \beta_1 \text{FinLiteracy}_j + \text{Controls} + \text{error}, \tag{30}$$

where the $d_{\text{option},j}$ dummy takes the value of one if participant j indicates a preference for being given the option to choose between two designs, and zero if they express a preference for not being offered a choice and being exposed only to the non-gamified design. We anticipate that participants are likely to exhibit a preference for having the option to choose if the "rational" channel prevails.

4.5 Interaction effects and robustness

Trading biases. 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 the one hand, the hedonic features of gamification can enhance learning by engaging investors better and thereby lowering attention costs. On the other hand, 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 either leading to a higher or to 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 Session II and Session III. Namely, we test for a difference in the coefficients between two sessions by including an interaction term in the following regression model:

$$y_{j,r} = \beta_0 + \beta_1 d_{\text{game},j,r} + \beta_2 d_{\text{session III},j} + \beta_3 d_{\text{game},j,r} \times d_{\text{session III},j} + \text{Controls} + \text{error}, \tag{31}$$

where $d_{\text{session III},j}$ is the dummy variable taking the value one for participants in Session III and zero else, and $y_{j,r} \in \left\{ \text{ExcessiveTrading}_{j,r}, \bar{\theta}_{j,r}^{\text{buy/sell}}, \text{var}\left(\theta^{\text{buy/sell}}\right)_{j,r}, \Delta_{j,r} \right\}$.

Informational effects. By analyzing data from Session IV, we can delve deeper into the influence of price notifications on investor behavior. Our aim here is to investigate if the notifications merely prompt more trading or if they offer a beneficial boost to informed decision-making. Given the presence of momentum, following the alerts from the gamified platform can be beneficial. However, when prices follow a random walk in Session IV, these notifications become meaningless. Our objective is to understand whether the price notifications encourage blind following or if they promote rational attention. To investigate this, we re-estimate the model used to test Hypothesis 6 and test for the positive difference, if any, between the effect of notifications in Session II and Session IV by including the interaction terms. For observations from Sessions II and IV and for the subset of participants that own the stock at the time of notification, we estimate the following model concerning the decision to sell:

$$\begin{aligned} d_{\text{sell},t} = {} & \alpha_0 + \beta_0 d_{\text{Session II}} + \sum_{k=1}^{3} \alpha_k \text{GreenAlert}_{t-k} + \sum_{k=1}^{3} \beta_k \text{GreenAlert}_{t-k} \times d_{\text{Session II}} \\ & + \sum_{k=1}^{3} \zeta_k \text{RedAlert}_{t-k} + \sum_{k=1}^{3} \gamma_k \text{RedAlert}_{t-k} \times d_{\text{Session II}} + \delta_0 \pi_t + \delta_1 \left(p_t - c_t\right) + \text{Controls} + \text{error}. \end{aligned} \tag{32}$$

Similarly, for the subset of participants that do not own the stock at the time of notification, we estimate the following model concerning the decision to buy:

$$d_{\text{buy},t} = \alpha_0 + \beta_0 d_{\text{Session II}} + \sum_{k=1}^{3} \alpha_k \text{GreenAlert}_{t-k} + \sum_{k=1}^{3} \beta_k \text{GreenAlert}_{t-k} \times d_{\text{Session II}} \tag{33}$$
$$+ \sum_{k=1}^{3} \zeta_k \text{RedAlert}_{t-k} + \sum_{k=1}^{3} \gamma_k \text{RedAlert}_{t-k} \times d_{\text{Session II}} + \delta_0 \pi_t + \text{Controls} + \text{error}.$$

4.6 Policy relevance

By examining the hypotheses outlined above, our study aims to contribute to the spirited policy debate on the impact of trading gamification. As of June 2022, the U.S. Securities and Exchange Commission (SEC) plans to design new rules to "crack down" on behavioral prompts and trading gamification used by online stock brokerages.[18] Do digital engagement practices, in line with the SEC concerns[19], encourage investors to buy and sell more stocks and make sub-optimal trading decisions? Hypotheses 1 and 2 aim to establish whether this is true or not – in a randomized environment that largely eliminates selection biases and confounding macro-economic factors (e.g., quantitative easing due to the pandemic).

In June 2022, the SEC launched the "Investomania" campaign to improve financial literacy, in recognition that "sometimes investing may look and feel like a game."[20] Hypothesis 3 aims to see whether the impact of gamification is indeed reduced by financial literacy, i.e., whether the SEC campaign is likely to be successful. In testing Hypothesis 3 we investigate other potential avenues to mitigate negative effects of gamification: trading experience (i.e., the SEC could potentially mandate brokerages to ask inexperienced traders to start out with a demo account for a short period) or tweaking other platform elements such as the salience of returns – linked to the disposition effect (Frydman and Rangel, 2014).

Hypotheses 4 through 8 aim to provide a more nuanced view of digital engagement practices and disentangle the effect of gamification strategies that convey information about stock prices from those that simply increase the enjoyment of trading itself. Do information-driven gamification elements help investors by increasing the accuracy of their trades and reducing the disposition effect? If that is the case, regulators such as the SEC would need to specifically target only a subset of harmful gamification practices and encourage the beneficial ones.

Hypothesis 9 tackles investor self-selection. A common narrative is that novice traders are attracted to online trading platforms – is this due to gamification strategies? If so, are traders choosing gamified platforms for hedonic reasons (it is more fun to trade there) or because gamification

[18] See https://www.reginfo.gov/public/do/eAgendaViewRule?pubId=202204&RIN=3235-AN14 and Bloomberg, SEC to Propose New Rules for Online Brokers' Game-Like Features, June 22, 2022.

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

[20] See https://www.sec.gov/news/press-release/2022-95.

helps them to better process stock price information – which is potentially a beneficial effect? Disentangling the two channels is important to better understand what drives investor choices.

5 Results

5.1 Cohort formation

Participants will be recruited from Prolific, an online subject pool specifically catering to academic research (Palan and Schitter, 2018). The experimental sessions will take place online shortly after the experimental design is approved by the reviewing team and the university ethics board. On average, participants should need approximately 30 minutes to complete the entire experiment.

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 United States and United Kingdom residents – both anglophone countries with well-developed securities markets. Prolific uses census data from both countries to build a stratified sample over age groups, gender, and ethnicity.

Since most of our hypotheses focus on testing the impact of either hedonic or informational gamification strategies, we recruit two times more participants in Sessions I and II than in Sessions III and IV. We breakdown our sample across treatments as follows:

Table 5: **Participant sample size across experimental sessions**

Session #	U.S. Participants	U.K. Participants	Total session
1	160	160	320
2	160	160	320
3	100	100	200
4	100	100	200
Total	520	520	1,040

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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 any 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 any stock changes between two consecutive price updates

   (b) If your position in both stocks changes 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 6 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.

Table 6: **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.