

Trading Gamification, Asset Prices, and Liquidity

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Abstract. We run a laboratory experiment to study the impact of trading gamification on price discovery and market liquidity. Participants on gamified markets receive achievement badges for activity and notifications of short-term price trends. Gamified markets trade 31% more than the control group, with a sharp increase in limit-order submissions and intraday churn. Gamification incentivizes market-making strategies: quoted spreads drop by 26% and depth rises by 24%. The induced market making is naïve, as prices respond less to information in order flow. Gamification therefore worsens price discovery, with a 28% increase in mispricing and a two-fold increase in bubble episode frequency. (*JEL* G11, G12, G14)

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1 Introduction

For whatever reasons, markets now exhibit far more casino-like behavior than they did when I was young. The casino now resides in many homes and daily tempts the occupants.

— Warren Buffett ([Annual Report for Berkshire Hathaway Inc.](#), 2023)

Individual investors are increasingly important in modern financial markets, due to the proliferation of online trading platforms and the rise of social media. In April 2025, retail traders accounted for 36% of the U.S. equity and options order flow — compared to less than 10% prior to the 2020 pandemic. In fact, volume driven by individual investors now exceeds mutual funds and traditional hedge funds combined.¹ This shift extends beyond equities: Retail investors account for roughly 60% of same-day (0DTE) option volume ([Bryzgalova, Pavlova, and Sikorskaya, 2023](#)), which itself represents more than half of total S&P options trading. Retail traders are also pivotal in cryptocurrency markets ([Kogan, Makarov, Niessner, and Schoar, 2024](#)) and prediction contracts ([Akey, Gregoire, Harvie, and Martineau, 2026](#)).

As a group, retail traders do not merely act as price takers in modern markets. Individual investors have fuelled recurring meme-stock frenzies leading to 2000% jumps in GameStop and AMC share prices, the boom-bust cycles of cryptocurrencies, and the 2025 AI rally that produced the first \$4 trillion firm, Nvidia. At the end of 2025, [Cornelli, Lombardi, and Schrimpf \(2025\)](#) warned that retail exuberance, amplified by social media and fear of missing out, created conditions conducive to price bubbles in both equities and gold. In the same vein, [Asness \(2024\)](#) notes that markets have grown less efficient over the past three decades, and links this phenomenon to “*technology, gamified 24/7 trading on your phone, and social media in particular*” as the biggest culprits.

In this paper, we study how the gamification of trading affects price formation and market

¹See J.P. Morgan: [Who is buying U.S. equities](#) (June 4, 2025); Financial Times: [Are retail traders the captains now?](#) (December 9, 2025)

liquidity. Our central questions are whether gamified trading (i) leads to larger mispricing of securities, (ii) impacts trading volume and liquidity, and (iii) whether it widens the dispersion of outcomes across participants with different levels of financial literacy and trading experience.

To answer these questions, we design and implement a controlled laboratory experiment following the canonical framework of [Smith, Suchanek, and Williams \(1988\)](#). We build a limit order market in oTree ([Chen, Schonger, and Wickens, 2016](#)), in which participants trade a single dividend-paying asset over multiple periods in a setting known to generate asset price bubbles. Each market consists of 15 trading “days” of one minute each; at the end of each day, the asset pays a dividend drawn from a common knowledge distribution. Therefore, the fundamental value of the asset is also common knowledge, and declines monotonically over the horizon.

We randomly assign participants to one of two interfaces: either to a non-gamified benchmark market, or to a gamified market where — following [Chapkovski, Khapko, and Zoican \(2024\)](#) — traders can earn achievement badges for trading activity, individual trades are accompanied by reward animations, and we display price-trend notifications. Each participant is assigned to a single treatment, and the markets and asset are otherwise identical. Since participants learn from experience in the [Smith, Suchanek, and Williams \(1988\)](#) framework, we repeat each market twice with the same group of participants.

We ran six in-person laboratory sessions at the University of Calgary between May and September 2026. The analysis sample contains 11 gamified and 9 non-gamified independent groups with six participants each, for a total of 120 participants and 40 markets. Participants were paid CA\$15 for participation, and received an average additional bonus of CA\$15 for their trading performance.

We find that trading gamification leads to a 28% increase in mispricing, measured by the difference between the observed prices and fundamental value. While gamification also leads to a fourfold increase in the incidence of bubbles (measured as mispricing greater than two standard deviations of the average mispricing), it does not unconditionally lead to higher prices. In the early periods of the market horizon, traders tend to undervalue the asset relative to fundamentals;

the tendency to undervalue is also stronger in gamified markets. We do not find evidence that gamification leads to sharp jumps in prices (either surges or crashes), indicating a smoother mispricing pattern.

We turn to individual trader strategies to pin down the economic mechanisms. Consistent with an increase in the hedonic value of trading, volume is 31% larger in gamified markets. This increase is driven by a larger share of traders who act as market makers and post two-sided limit orders: Limit order submissions increase by 37% due to gamification, while the share of market maker volume rises from 37.8% to 48.1%. The absolute order flow imbalance is 14% smaller in gamified markets, indicating a more balanced distribution of buy and sell orders. Intraday churn is 19.7% larger in the treated group, as traders turn over their positions more frequently within the same period.

As a result of more intense market making activity, liquidity improves in gamified markets. Quoted spreads drop by 26.5% and depth rises by 24%. Price impact is 5.1 percentage points smaller in the treated group, although the effect is not statistically significant. Market maker competition is sharper: participants undercut spreads 31% more often in gamified markets, and temporary price impact reverts in 12.95 seconds in gamified markets as opposed to 19.41 seconds in control markets.

We argue that gamification leads to an increase in the absorption capacity of behavioral trades, in the sense of [Abreu and Brunnermeier \(2003\)](#), driven by a larger hedonic utility. Rather than gamification impacting irrational exuberance or beliefs, it pushes participants to trade more frequently by naïvely providing liquidity at noisy prices. In traditional market structure models ([Glosten and Milgrom, 1985](#); [Kyle, 1985](#)), market makers rationally set bid and ask quotes conditional on the direction of order flow. Gamification-driven market makers tend to replenish the book at the same price level without internalizing information in the order flow, which leads to better liquidity all while preventing price adjustment. This yields “sticky” prices which, paradoxically, are easier to forecast: we find that forecast accuracy increases by 5.6 percentage points in gamified markets, mostly driven by later rounds.

We finally show suggestive evidence that gamification may widen the dispersion of outcomes

across participants with different levels of financial literacy and trading experience, as measured by the [Gini \(1936\)](#) coefficient, indicating that gamification has the potential to exacerbate the wealth gap in financial markets. While positive, however, the effect of gamification on inequality is not statistically significant at our sample size.

2 Literature review

Our paper contributes to a growing literature on the gamification of financial decision-making. In a series of online experiments, [Chapkovski, Khapko, and Zoican \(2024, 2025\)](#) show that gamified trading environments increase individual risk-taking, elevate trading volume, and lead to noisier and less disciplined strategies when participants trade against an exogenously generated price path. We instead focus on the *market-wide* consequences of gamification, particularly its effects on price formation and asset bubbles.

Empirical evidence on gamification in financial markets remains scarce, primarily due to data availability and identification challenges. Exploiting the staggered introduction of gamification features in U.S. brokerage platforms, [Yelagin \(2024\)](#) shows that gamification reduces retail traders' returns while benefiting market makers by making retail order flow less toxic. [Arnold, Pelster, and Subrahmanyam \(2022\)](#) find that push notifications alerting investors about large price swings nudge them into taking more leverage. Using proprietary data from a Czech gambling company, [Hanousek, Hanousek, Mikulka, and Sokolov \(2025\)](#) finds that exposure to gamification substantially prolongs gambling activity. Identification in these settings may be confounded by the endogenous adoption of gamification by platforms and traders. Our controlled laboratory experiment avoids this concern by exogenously assigning gamification.

More broadly, we connect to a growing literature on trader behaviour in digital markets. Prior work shows that retail algorithmic trading does not mitigate bubbles ([Asparouhova, Bossaerts, Cai, Rotaru, Yadav, and Yang, 2024](#)), that social communication tools induce pump-and-dump dynamics ([Kluger and Saglam, 2025](#)), and that retail traders struggle to process high-frequency order flow

data (Chapkovski, Goswami, Khapko, and Zoican, 2026). Using transaction-level data, Kalda, Loos, Previtero, and Hackethal (2021) find that investors take more risk on smartphones than on traditional platforms, while Barber, Huang, Odean, and Schwarz (2022) show that app design features such as Robinhood’s *Top Movers* tab distort attention and reduce returns. We contribute by studying gamification as a salient design feature of trading apps and its market-wide effects.

Our paper also relates to a large literature on asset price bubbles. Early experimental work documents that bubbles arise even in environments with common knowledge of fundamentals (Smith, Suchanek, and Williams, 1988). In field data, bubbles are linked to heterogeneous beliefs, extrapolation, overconfidence, and limits to arbitrage (Shiller, 2016; Barberis, Greenwood, Jin, and Shleifer, 2015; Scheinkman and Xiong, 2003; Shleifer and Vishny, 1997). Using laboratory markets, Moinas and Pouget (2013) show that disagreement and short-sale constraints interact to fuel speculative bubbles, highlighting the role of belief dispersion in price dynamics. More recent work emphasizes the role of narratives and social interaction in amplifying speculative episodes (Shiller, 2019; Chincio, 2023). We add to this literature by studying how the trading user interface — by shaping attention and engagement — can influence the formation, magnitude, and collapse of asset price bubbles.

Finally, our paper connects to research in computer science, marketing, and psychology examining gamification and its influence on consumer behaviour. Deterding, Dixon, Khaled, and Nacke (2011) define gamification as “the use of game design elements in non-game contexts.” In this literature, gamification is often interpreted through the lens of hedonic consumption, whereby multisensory and affective elements of the user experience generate value beyond a product’s utilitarian function (Hirschman and Holbrook, 1982; Heijden, 2004).

3 Experimental design

3.1 Trading game

Our experiment closely follows [Smith, Suchanek, and Williams \(1988\)](#), henceforth SSW). Subjects are randomly assigned to markets of six participants who trade a single asset in a limit order market over 15 trading days.² At the end of each day, the asset pays a stochastic dividend that is equally likely to be 0, 4, 8, or 20 experimental dollars (E\$), yielding an expected dividend of E\$8 per day. The asset’s fundamental value therefore starts at E\$120 and declines deterministically by E\$8 each day, reaching zero at the end of the market on day 15.

Each trading day lasts one minute, following [Farjam and Kirchkamp \(2018\)](#) and [Kopányi-Peuker and Weber \(2020\)](#), so that each market lasts 15 minutes in total. [Farjam and Kirchkamp \(2018\)](#) argue that bubble magnitudes are nearly identical when using one-minute or four-minute trading intervals. We opt for shorter days to allow each group to repeat the market twice within a session. Each participant completes two markets of 15 days, as well as a three-day training round to gain experience with the environment.

Half of the participants are endowed with 20 assets and E\$2,600 in cash, while the other half receive 10 assets and E\$3,800 in cash. At fundamental value, both endowments are worth E\$5,000. We adopt a relatively high cash-to-asset ratio, which is known to amplify bubble formation (see, e.g., [Caginalp, Porter, and Smith, 1998](#)), thereby increasing statistical power to detect treatment differences in bubble magnitude. Participants are not allowed to take negative asset positions (i.e., short selling) or borrow additional cash.

At the end of days $t \in \{3, 6, 9, 12\}$, after dividends are paid, we elicit participants’ forecasts of the stock price on the subsequent day. Specifically, participants report a point forecast of the end-of-day price for the next day, along with their confidence in this assessment. Price forecasts are elicited using a continuous input field, while confidence is measured on a five-point Likert scale.

²The market is a continuous limit-order book with price-time priority. A WebSocket client displays the book and routes orders to a custom matching engine, which rejects short sales, unfunded buys, and self-crosses.

Participants receive a bonus of E\$20 if their forecast is within 5% of the realized price.

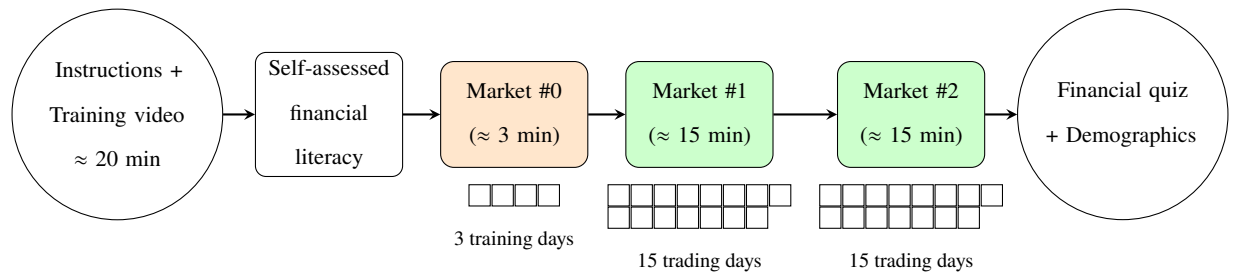
Finally, participants complete 12 financial literacy questions, reported in Appendix A. The questions are adapted from Fernandes, Lynch, and Netemeyer (2014) and include the three-item measure developed by Lusardi and Mitchell (2011), as well as two trading-specific questions based on the MiFID questionnaire used in Inghelbrecht and Tedde (2024). To measure overconfidence and distinguish between subjective and objective financial literacy, participants also report their self-assessed financial knowledge on a scale from 0 (not at all knowledgeable) to 10 (very knowledgeable). This question follows Cupák, Fessler, Hsu, and Paradowski (2020) and is asked before the experiment begins to avoid contamination from trading outcomes or quiz difficulty. To measure cognitive constraints, we record the number of times participants attempt the comprehension quiz.

Participants receive a C\$15 show-up fee plus performance-based earnings. Performance pay equals terminal cash from one randomly selected market, including the final dividend, plus forecast bonuses across both markets and E\$10 for each correct financial-literacy answer. Experimental earnings were converted at E\$1 = C\$0.003, the rate announced in the instructions.

Figure 1 illustrates the experiment timing.³ Appendices B, C, and D contain the consent form, experimental instructions, and comprehension questions, respectively. Participants must correctly answer all five comprehension questions before trading begins.

Figure 1. Experiment timing

This figure displays the experimental flow from the perspective of a participant.



³The training video is available at https://youtu.be/_ujlBTZVXio.

3.2 Treatments

We implement two conditions between participants. The *Gamified* condition combines hedonic elements (i.e., achievement badges and reward animations) and price trend notifications as in Chapkovski, Khapko, and Zoican (2024). The *Non-gamified* condition contains none of these features. The experiment runs in a 40-seat computer lab at the University of Calgary, and each session comprises multiple independent six-participant markets assigned to one of the conditions in Table 1.

Table 1. Experimental conditions

Condition	Interface
Non-gamified	No gamification elements
Gamified	Achievement badges, reward animations, and price-trend notifications

3.2.1 Hedonic gamification. The U.S. Securities and Exchange Commission (SEC) characterizes trading gamification elements as including “*social networking tools; games, streaks, contests with prizes; points, badges, and leaderboards; notifications; celebrations for trading; visual cues; curated ideas at order placement; subscriptions and membership tiers; and chatbots.*”⁴ In this paper, we follow Chapkovski, Khapko, and Zoican (2024) and implement two gamification elements: achievement badges, representing hedonic gamification (defined in the spirit of Deterding et al., 2011), as well as price trend notifications, representing informational gamification.

Achievement badges are awarded based on the number of trades executed by a participant within a market. Unlocking a badge triggers a visual animation consisting of falling confetti, a congratulatory message, and an animated GIF, as summarized in Table 2.

⁴See <https://www.sec.gov/rules/other/2021/34-92766.pdf>, pp. 7–8.

Table 2. Achievement badges

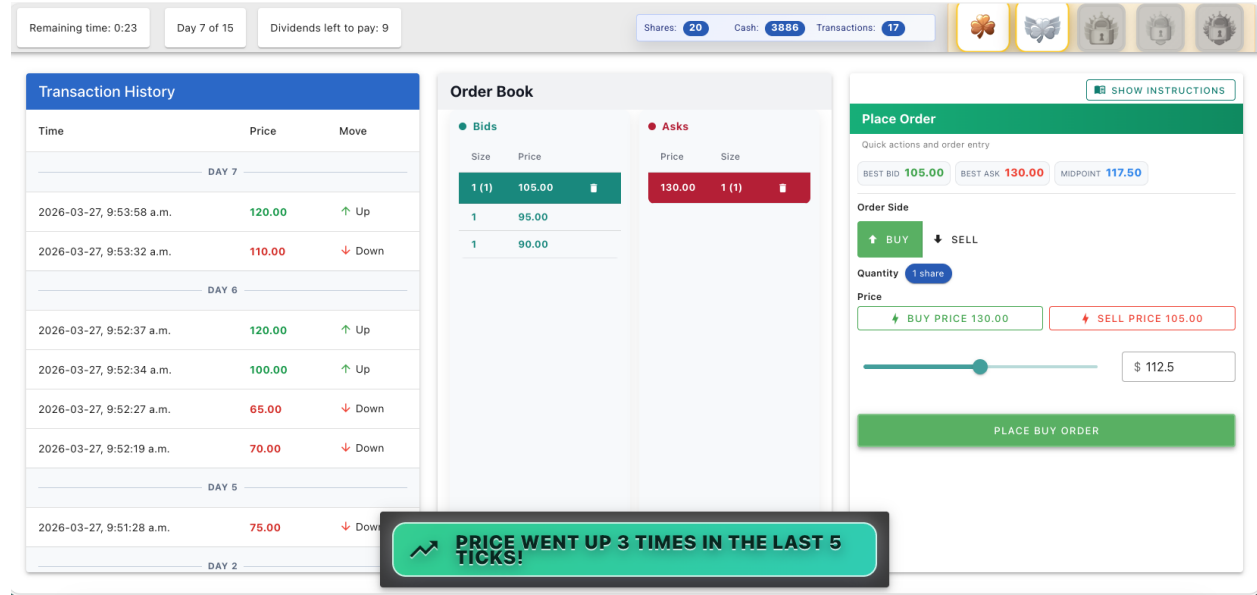
Badge	# trades	Message	GIF link
Bronze	10	Level up! Doing well!	https://bit.ly/3xtGrWk
Silver	15	You belong on the trading floor!	https://bit.ly/3l8kuqD
Gold	35	You are the money maker!	https://bit.ly/3n0wbog
Platinum	50	You are definitely going places!	https://bit.ly/3cNi6Be
Diamond	60	The Wolf of Wall Street	https://bit.ly/3tMKDzE

Badge thresholds are calibrated using evidence from [Farjam and Kirchkamp \(2018\)](#), who report an average of 33.45 trades per participant in a 15-minute market. We therefore set the silver badge to be attainable for the average trader, while higher badge levels require above-average trading intensity.

3.2.2 Price notifications. A second gamification feature emphasizes price trends. Specifically, we introduce price-change alerts whenever the stock price increases or decreases for five consecutive trades. To facilitate clean identification, only one notification is displayed per price run. This ensures that trader responses can be attributed unambiguously to a five-trade run and avoids mechanically assigning greater empirical weight to longer runs.

Figure 2 illustrates user experience on the *Gamified* trading platform.

Figure 2. Trading platform user interface



4 Experimental Results

We compare *Gamified* and *Non-gamified* markets in terms of price discovery, bubble dynamics, trading volume, liquidity, and wealth inequality. Our main conjecture, building on [Chapkovski, Khapko, and Zoican \(2024\)](#), is that gamification stimulates noisy trading volume, leading to worse price discovery.

4.1 Cohort formation

We ran six laboratory sessions at the University of Calgary between May 12 and September 14, 2026. Upon arrival, participants were randomly assigned to six-person markets and one interface for the entire experiment. They read common instructions, watched the same training video, and had to answer the five comprehension questions in [Appendix D](#) correctly.

[Table 3](#) reports participant counts by session. Before data-quality restrictions, the two conditions contain 12 gamified and 10 non-gamified complete groups, or 72 and 60 participants.

Table 3. Session Composition

The table reports the number of participants in each laboratory session. Two groups, one non-gamified group on May 20 and one gamified group on September 4, are excluded from the analysis sample as described below.

Session	Non-gamified	Gamified	Total
May 12, 2026	6	6	12
May 20, 2026	6	12	18
August 26, 2026	12	12	24
September 4, 2026	12	12	24
September 10, 2026	12	18	30
September 14, 2026	12	12	24
Participants	60	72	132
Independent groups	10	12	22

We exclude two groups from the analysis sample due to data quality issues. One non-gamified group from the May 20 session featured a pair of outlier traders who generated about three times the volume of any other group and held the transaction price near E\$130 while fundamental value declined. Another gamified group from the September 4 session opened below E\$10 and remained there in both repetitions, demonstrating a lack of understanding of the asset. The final sample contains 11 gamified and 9 non-gamified groups, 120 participants, 40 market repetitions, and 600 market-day observations.

Table 4 describes the retained cohort. Participants in the two conditions are similar on age, gender, education, prior trading experience, financial literacy, self-assessed knowledge, and comprehension. None of the treatment differences is significant at the 5% level.

Table 4. Cohort Demographics

This table reports participant characteristics in the retained Non-gamified and Gamified cohorts. The financial-literacy score is the percentage of quiz questions answered correctly. Self-assessed financial knowledge ranges from 0 to 10. Finance course and prior trading experience are indicator variables. Standard deviations appear in parentheses under treatment means.

Characteristic	Non-gamified	Gamified	Difference	<i>p</i> -value
Age (years)	22.93 (4.47)	21.65 (4.23)	-1.28 (0.80)	0.111
Female (%)	38.89 (49.21)	34.85 (48.01)	-4.04 (8.93)	0.651
Finance course (%)	57.41 (49.91)	43.94 (50.01)	-13.47 (9.17)	0.142
Prior trading experience (%)	44.44 (50.16)	45.45 (50.17)	1.01 (9.20)	0.913
Financial-literacy score (%)	78.55 (13.98)	73.11 (19.60)	-5.44 (3.07)	0.077
Self-assessed financial knowledge	5.00 (2.25)	4.56 (2.39)	-0.44 (0.42)	0.301
Comprehension-quiz attempts	1.72 (1.00)	1.95 (1.81)	0.23 (0.26)	0.373
Participants	54	66	120	
Independent groups	9	11	20	

The largest differences are a 13.5-percentage-point lower incidence of prior finance coursework and a 5.4-percentage-point lower financial-literacy score in the gamified condition; their *p*-values are 0.14 and 0.08, respectively.

Data filters. There are six trading days when no transaction occurs. We do not impute a price for these days, leaving us with 594 market-day observations. Order-book measures (e.g., quoted spread) require a two-sided book. Each transaction is matched to the last book snapshot sourced strictly before the trade. We also drop the three practice days from every analysis.

4.2 Price discovery

4.2.1 Mispricing Gamification can impair price discovery through two channels. Badges and reward animations give trading hedonic value and induce trades that put little weight on fundamentals (Chapkovski, Khapko, and Zoican, 2024). Price notifications make recent movements salient and can pull attention from the known dividend stream toward the transaction path (Haruvy and Noussair, 2006). Both channels make the prevailing price more persistent.

We define three measures of mispricing. Let $\mathcal{T}_{md}$ be the set of transactions in market repetition m on day d , let P_{nmd} be the price of transaction n , and let $v_d = 8(16 - d)$ be the asset’s fundamental value on day d . First, following Asparouhova et al. (2024), we define absolute mispricing as

$$A_{md} = \frac{1}{|\mathcal{T}_{md}|} \sum_{n \in \mathcal{T}_{md}} |P_{nmd} - v_d|. \quad (1)$$

Second, we define the absolute mispricing ratio as $AMR_{md} = A_{md}/v_d$ (Palan, 2013).

Third, following Stöckl, Huber, and Kirchler (2010), we compute the relative absolute deviation $RAD_{md} = A_{md}/\bar{v}$, where $\bar{v} = 64$ is the average fundamental over the 15 days. The rationale for using this measure is that the denominator in RAD is fixed, so it remains comparable across days. In contrast, the absolute mispricing ratio increases faster as v_d falls even when dollar mispricing is unchanged. Each measure averages absolute deviations transaction by transaction.

Figure 3 plots time series of the three measures as well as the average price path in each treatment. All three mispricing measures are higher in the gamified condition. Panel (D) illustrates that gamification does not simply push prices upward, but instead generates “stickier” mispricing in that prices respond too slowly to the dividend stream. On Day 1, when fundamental value is E\$120, the average transaction price is E\$90.53 in gamified markets and E\$100.75 in non-gamified markets. Therefore, gamification initially produces greater *underpricing*, and the sign reverses as the fundamental declines.

Figure 3. Gamification Impairs Price Discovery

This figure plots treatment means by trading day. Panel A reports the transaction-level mean absolute distance from fundamental value, A_{md} . Panel B reports AMR, A_{md}/v_d . Panel C reports RAD, $A_{md}/64$. Panel D plots the average transaction price and the fundamental value, $v_d = 8(16 - d)$. Shaded regions are 95% confidence intervals computed from the available market-day observations.

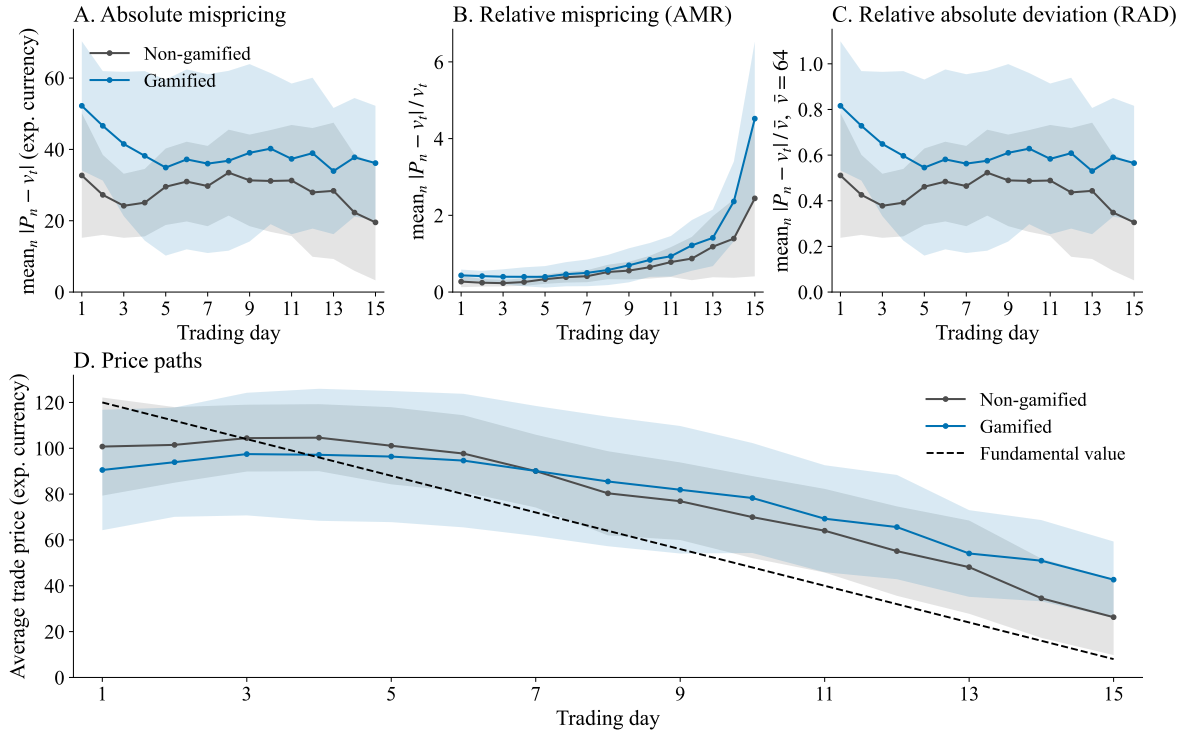


Table 5 formalizes the result in a regression framework with market-wide controls, trading-day and repetition fixed effects, and robust standard errors. It shows that gamification raises absolute mispricing by E\$8.13 from a non-gamified mean of E\$28.30, AMR by 0.226 from 0.708, and RAD by 0.127 from 0.442. The magnitude of the increases ranges from 28.7% for absolute mispricing and RAD to 32% for the absolute mispricing ratio.

Table 5. Gamification and Mispricing

This table estimates the effect of the *Gamified* condition on absolute mispricing, AMR, and RAD. Each dependent variable is defined in Section 4.2. All columns include trading-day and repetition indicators. Even-numbered columns additionally control for market-average overconfidence, comprehension-quiz attempts, and age. Robust standard errors are reported in parentheses.

Dependent Variables:	Abs. mispricing		AMR		RAD	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Gamified	10.762*** (3.335)	8.113** (3.453)	0.337*** (0.128)	0.226* (0.124)	0.168*** (0.052)	0.127** (0.054)
Overconfidence		-76.734*** (20.698)		-2.319*** (0.699)		-1.199*** (0.323)
Comprehension quiz		12.343*** (1.869)		0.337*** (0.070)		0.193*** (0.029)
Age		0.294 (0.255)		0.030* (0.016)		0.005 (0.004)
Constant	28.299*** (1.849)	28.299*** (1.833)	0.708*** (0.089)	0.708*** (0.089)	0.442*** (0.029)	0.442*** (0.029)
Observations	594	594	594	594	594	594
R ²	0.02	0.07	0.23	0.27	0.02	0.07
Repetition dummy	Yes	Yes	Yes	Yes	Yes	Yes
Trading-day dummies	Yes	Yes	Yes	Yes	Yes	Yes

4.2.2 Emergence of bubbles We turn next to asset price bubbles. To capture bubble formation, we follow [Noussair, Robin, and Ruffieux \(2001\)](#) and define normalized mispricing as $M_{md} = (\bar{P}_{md} - v_d)/v_d$, where $\bar{P}_{md}$ is the average transaction price on market m and day d .

A day is classified as a bubble when M_{md} exceeds its mean by more than two standard deviations among market-day observations in the same repetition number (i.e., either the first or second repetition). A bubble episode is defined as a run of consecutive bubble days within a market repetition. As in [Asparouhova et al. \(2024\)](#), we define price surges and crashes as periods in which the day-to-day return lies more than two standard deviations above or below the return distribution for the same repetition number.

Figure 4. Gamification Increases Bubble Frequency

This figure reports treatment means per market repetition. Bubble days have normalized mispricing more than two standard deviations above the mispricing mean. Bubble episodes are defined as consecutive runs of bubble days. Price surges and crashes have close-to-close returns more than two within-repetition standard deviations above or below the mean return. Error bars are 95% confidence intervals.

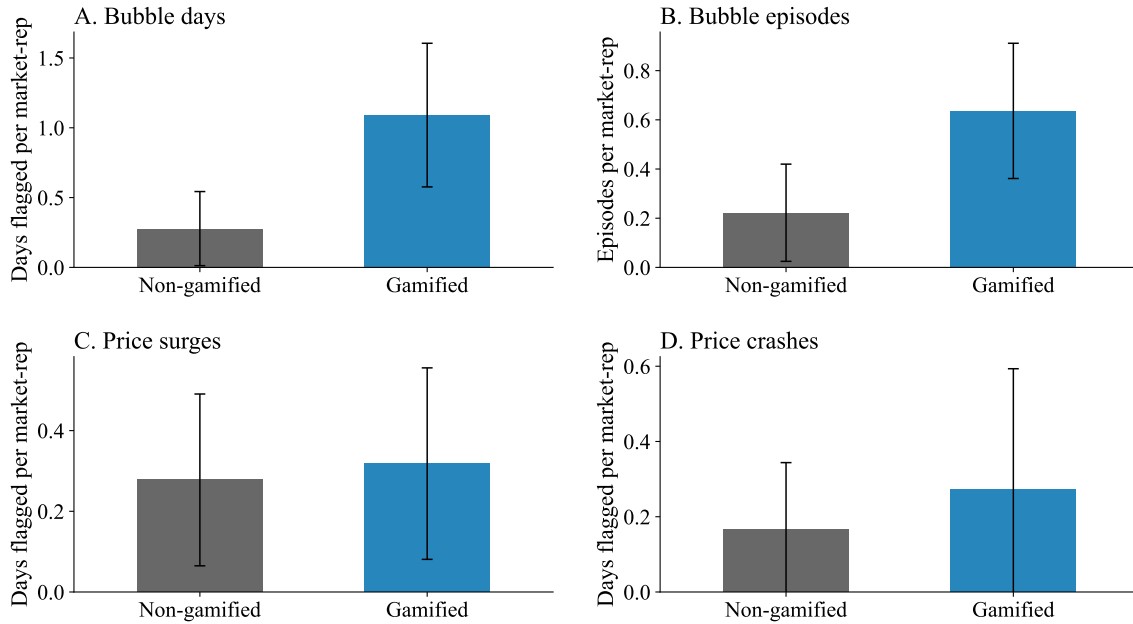


Figure 4 and Table 6 show that bubbles are more prominent in gamified markets. Bubble days are almost four times more frequent in gamified markets than in non-gamified markets (an increase of 0.81 relative to a non-gamified mean of 0.28), whereas bubble episodes are more than twice as frequent.

Table 6. Gamification and Bubble Incidence

This table estimates treatment differences in counts per market repetition. Bubble days, bubble episodes, price surges, and price crashes are defined above. All columns include a repetition indicator. Even-numbered columns additionally control for market-average overconfidence, comprehension-quiz attempts, and age. Robust standard errors are reported in parentheses.

Dependent Variables:	Bubble days		Bubble episodes		Surges		Crashes	
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gamified	0.813** (0.299)	0.805** (0.335)	0.414** (0.175)	0.386** (0.184)	0.040 (0.164)	0.001 (0.158)	0.106 (0.183)	0.110 (0.192)
Overconfidence		-3.174* (1.793)		-2.422** (1.031)		0.431 (1.093)		1.277 (1.399)
Comprehension quiz		0.066 (0.199)		0.186 (0.120)		0.163 (0.155)		-0.038 (0.095)
Age		0.015 (0.014)		0.006 (0.008)		-0.002 (0.007)		-0.005 (0.007)
Constant	0.278** (0.136)	0.278* (0.150)	0.222** (0.102)	0.222** (0.103)	0.278** (0.109)	0.278** (0.121)	0.167* (0.095)	0.167* (0.088)
Observations	40	40	40	40	40	40	40	40
R ²	0.15	0.24	0.12	0.26	0.01	0.09	0.09	0.13
Repetition dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

However, the treatment differences in price surges and crashes are statistically indistinguishable from zero. While gamification makes deviations more common and persistent, it does not appear to generate stronger jumps in prices, consistent with the “sticky” mispricing observed in Figure 3.

4.3 Mechanism: Trading Behaviour and Market Liquidity

4.3.1 Trading activity and order flow We turn next to investigating the mechanisms through which gamification influences price discovery. If gamification increases the hedonic value of trading, we would expect to see larger trading volumes in the treatment group. At the same time, if gamification does not meaningfully impact beliefs about the fundamental value of the asset, we expect to see little change in directional order flow, and more churn (i.e., people buying and selling repeatedly within the same day).

We measure volume as the number of transactions in a market-day. Further, we define the signed order flow imbalance in market m and day d as the difference between buyer- and seller-initiated volume (V_{md}^{buy} and V_{md}^{sell} , respectively), normalized by the aggregate volume:

$$OFI_{md} = \frac{V_{md}^{buy} - V_{md}^{sell}}{V_{md}^{buy} + V_{md}^{sell}}, \quad (2)$$

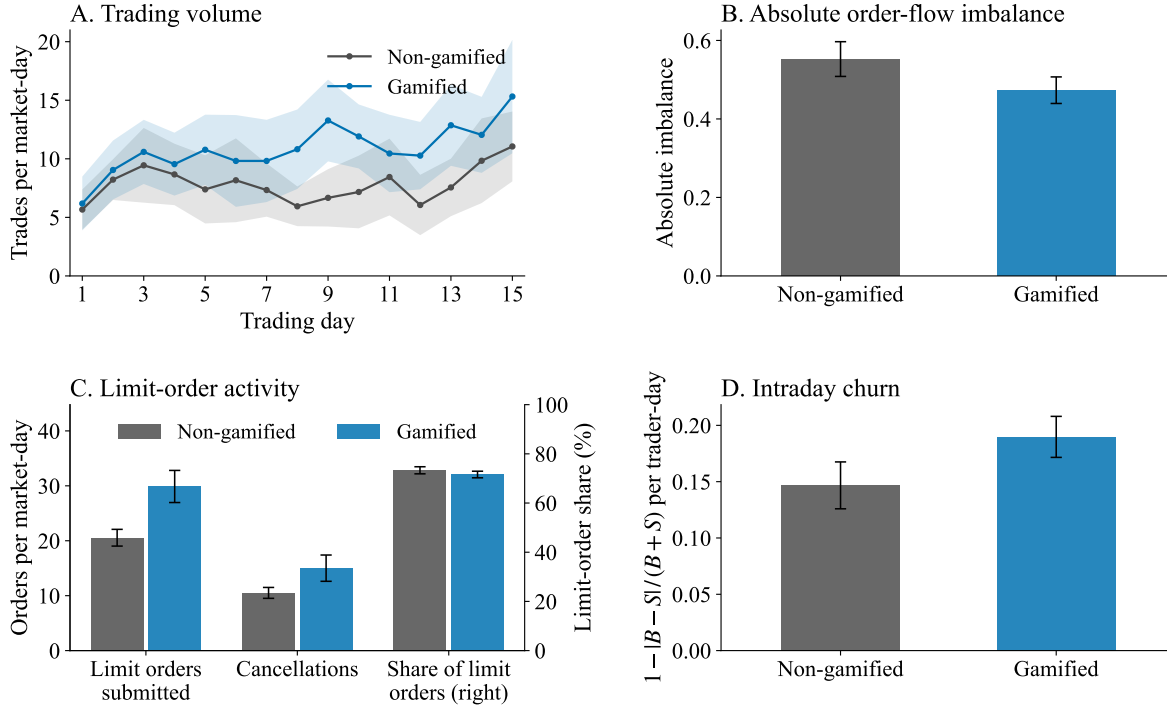
and absolute order-flow imbalance is $|OFI_{md}|$. A value of zero indicates balanced aggressive buying and selling; a value of one indicates entirely one-sided flow.

We count limit orders each day as new non-marketable submissions. Finally, we compute a measure of trading churn. For trader i , let B_{imd} and S_{imd} be executed buys and sells on day d in market m . Intraday churn is $1 - |B_{imd} - S_{imd}| / (B_{imd} + S_{imd})$, averaged across active traders in the market-day. Churn is zero for one-way trading and one for exactly balanced round trips.

Figure 5 and Table 7 illustrate the results. Trading gamification sharply increases trading volume. Gamified markets execute 2.44 additional trades per day, a 31% increase over the non-gamified mean of 7.84. Participants submit 7.63 more limit orders per day in gamified markets, that is 37% more than in the control group.

Figure 5. Gamification Increases Trading and Balances Order Flow

Panel A plots mean transactions per market-day. Panel B reports absolute order-flow imbalance. Panel C reports limit-order submissions, cancellations, and the share of submitted orders that are limits. Panel D reports intraday churn. Lines and bars are treatment means; shaded regions and error bars are 95% confidence intervals.



At the same time, the additional volume in gamified markets is less directional. The absolute order-flow imbalance drops by 14% in gamified markets (i.e., a 0.08 decrease from a non-gamified mean of 0.55), whereas intraday churn rises by 19.7% (0.03 increase from 0.15). The additional flow is therefore high-frequency and two-sided, consistent with an increase in noisy, uninformed trading as in [Chapkovski, Khapko, and Zoican \(2024\)](#).

Table 7. Gamification, Trading Volume, and Order Flow

This table estimates treatment differences in market-day trading activity. Trades is the number of executed transactions. |OFI| is absolute aggressive order-flow imbalance. Limit orders count new non-marketable submissions. Intraday churn is one minus trader directionality, averaged over active traders. All specifications include trading-day and repetition indicators. Even-numbered columns additionally control for market-average overconfidence, comprehension-quiz attempts, and age. Robust standard errors are reported in parentheses.

Dependent Variables:	Trades		OFI		Limit orders submitted		Intraday churn	
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gamified	3.008*** (0.561)	2.408*** (0.525)	-0.079*** (0.029)	-0.079*** (0.029)	9.330*** (1.684)	7.632*** (1.394)	0.043*** (0.014)	0.029** (0.014)
Overconfidence		3.926 (3.735)		0.258 (0.183)		-31.284*** (8.168)		0.062 (0.091)
Comprehension quiz		2.495*** (0.452)		-0.022 (0.020)		12.127*** (1.890)		0.037*** (0.010)
Age		-0.012 (0.033)		0.002 (0.002)		-0.454*** (0.077)		0.002** (0.001)
Constant	7.841*** (0.363)	7.841*** (0.364)	0.553*** (0.023)	0.553*** (0.023)	20.552*** (0.769)	20.552*** (0.755)	0.147*** (0.011)	0.147*** (0.011)
Observations	600	600	594	594	600	600	594	594
R ²	0.09	0.17	0.03	0.03	0.06	0.24	0.03	0.07
Repetition dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Trading-day dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Traders in gamified markets are also more likely to clear badge thresholds. Table 8 reports the share of trader-markets that reach each threshold. Almost all traders clear the Bronze and Silver trading badges. However, gamified traders are more likely to clear the Gold (35 trades) and Diamond (60 trades) badges. The share of traders who clear the Diamond badge (or its counterfactual) is

36.4% versus 15.7% in the control group.

Table 8. Share of Trader-Markets Reaching Each Badge Threshold

We tabulate the share of trader-markets that reach each badge threshold. The average number of trades per trader-market are 54.2 in the gamified condition and 39.2 in the control group.

Badge	Trades	Gamified	Non-gamified	Difference (p.p.)
Bronze	≥ 10	97.7%	95.4%	+2.4
Silver	≥ 15	90.9%	86.1%	+4.8
Gold	≥ 35	59.8%	42.6%	+17.3
Platinum	≥ 50	42.4%	23.1%	+19.3
Diamond	≥ 60	36.4%	15.7%	+20.6

4.3.2 Liquidity provision We show that gamification creates the incentives for traders to act as uninformed market makers and naively supply two-sided liquidity at the prevailing prices. This simultaneously improves displayed liquidity and reinforces the mispricing of the asset by preventing quotes from moving towards the fundamental value.

We compute several standard measures of liquidity. Let B_τ and A_τ denote the best bid and ask at event time τ , and let $M_\tau = (A_\tau + B_\tau)/2$ be the midpoint. The relative quoted spread is computed as $(A_\tau - B_\tau)/M_\tau$, time-weighted over intervals with both quotes. Depth at the best quotes is the time-weighted sum of shares at the best bid and ask over the same intervals.

For a trade at price P_n , let the direction of the trade be $q_n = 1$ for a buyer-initiated trade and $q_n = -1$ for a seller-initiated trade. The effective spread is then computed as $2q_n(P_n - M_n^-)/M_n^-$, where M_n^- is the last two-sided midpoint strictly before execution. Similarly, price impact is computed as $2q_n(M_n^{+10} - M_n^-)/M_n^-$, where M_n^{+10} is the midpoint 10 seconds after the trade.

We further compute two measures of liquidity provider competition. We count the number of spread-improving limit orders, defined as new orders which either raise the best bid or lower the

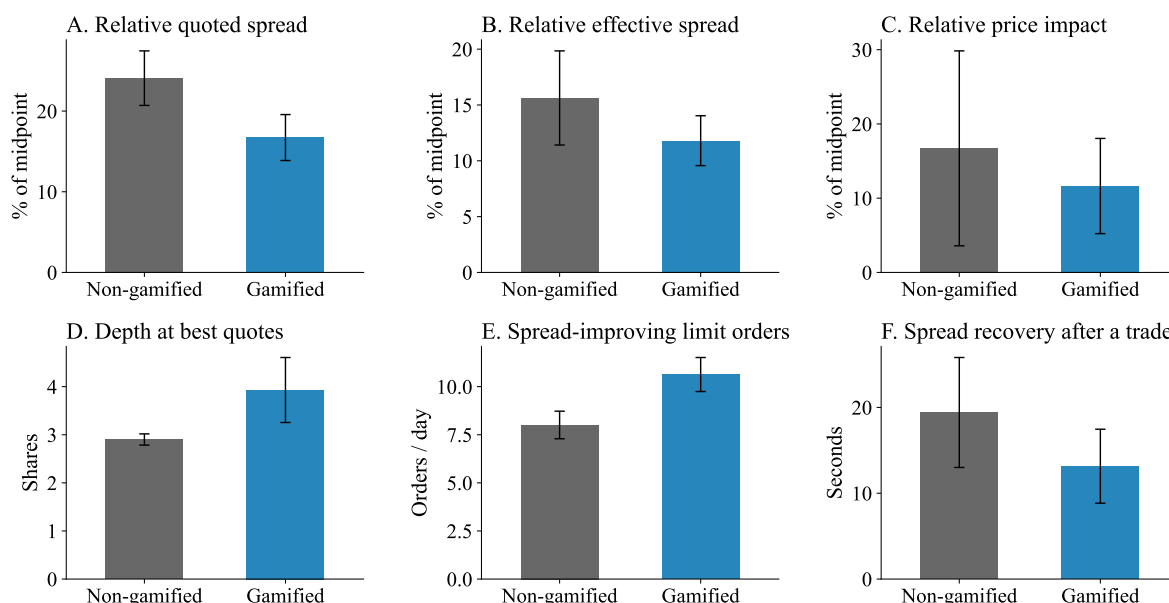
best ask. We also compute the spread recovery time as the median number of seconds after a trade until the temporary price impact is absorbed and the quoted spread returns to its pre-trade level.

Figure 6 illustrates that trading gamification improves liquidity on all these dimensions. Table 9 shows that the quoted spread falls by 6.4 percentage points from a non-gamified mean of 24.1%, a 26.5% reduction. Effective spreads fall by 3.8 percentage points and price impact by 5.1 percentage points, although the estimates are not statistically significant. Depth at the best quotes rises by 0.695 shares in gamified markets, or 24%.

We find evidence of gamification spurring stronger competition in liquidity provision. In gamified markets, participants submit 2.62 additional spread-improving orders per day (31% more than in non-gamified markets), while the median spread-recovery time falls by a third, by 6.46 seconds from 19.41 seconds.

Figure 6. Gamification Improves Displayed Liquidity

Panels A–C report the relative quoted spread, relative effective spread, and relative price impact as percentages of the prevailing midpoint. Panel D reports time-weighted depth at the best bid and ask. Panel E reports the number of limit orders that improve the best quote. Panel F reports the median time after a transaction for the spread to recover to its pre-trade level. Bars are treatment means and error bars are 95% confidence intervals.



The consistent patterns suggest that gamification leads to participants acting as naive, or uninformed, market makers. To realize the hedonic value of trading, they repeatedly quote on both sides, compete to improve the best prices, and replace consumed liquidity around the prevailing midpoint.

A fundamental trader can therefore execute cheaply in gamified markets, but each individual corrective trade has less price impact and is quickly absorbed without a permanent quote revision. Even though liquidity improves, the price remains anchored away from fundamental value. The mechanism echoes the model of [Abreu and Brunnermeier \(2003\)](#) in that the hedonic value of gamification leads to a larger absorption capacity of behavioral traders, which harms price discovery all while ameliorating liquidity.

Table 9. Gamification and Liquidity

This table estimates treatment differences in market-day liquidity. Quoted and effective spreads and price impact are expressed as fractions of the prevailing midpoint. Depth is the time-weighted sum of shares at the best bid and ask. Spread-improving orders tighten the prevailing best quote. Spread recovery is the median number of seconds until the quoted spread returns to its pre-trade level. All specifications include trading-day and repetition indicators. Even-numbered columns additionally control for market-average overconfidence, comprehension-quiz attempts, and age. Observation counts differ because trade-based measures require a transaction and valid pre- and post-trade midquotes, while recovery requires a qualifying post-trade book path. Robust standard errors are reported in parentheses.

Dependent Variables:	Quoted spread		Effective spread		Price impact		Depth at best		Spread-improving orders		Spread recovery (s)	
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Gamified	-0.075*** (0.022)	-0.064*** (0.022)	-0.038 (0.024)	-0.032 (0.025)	-0.051 (0.076)	-0.024 (0.074)	1.018*** (0.345)	0.695*** (0.257)	2.623*** (0.582)	2.502*** (0.551)	-6.462 (3.927)	-7.514* (3.907)
Overconfidence		0.051 (0.129)		-0.060 (0.230)		-0.102 (0.400)		-2.412 (1.530)		-14.032*** (3.166)		15.593 (32.009)
Comprehension quiz		-0.023 (0.016)		-0.005 (0.015)		-0.083* (0.044)		1.804*** (0.511)		2.312*** (0.517)		4.406 (3.605)
Age		-0.003*** (0.001)		-0.002* (0.001)		-0.003* (0.002)		-0.044*** (0.014)		-0.154*** (0.034)		-0.152 (0.163)
Constant	0.241*** (0.016)	0.241*** (0.016)	0.156*** (0.021)	0.156*** (0.021)	0.167** (0.067)	0.167** (0.067)	2.901*** (0.067)	2.901*** (0.073)	8.007*** (0.369)	8.007*** (0.363)	19.410*** (3.184)	19.410*** (3.190)
Observations	594	594	582	582	582	582	594	594	600	600	567	567
R ²	0.10	0.11	0.05	0.06	0.02	0.03	0.04	0.13	0.06	0.12	0.05	0.06
Repetition dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Trading-day dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

One implication of stickier prices is that the next day's close should be easier to forecast. At the end of days $d \in \{3, 6, 9, 12\}$, after dividends are paid, each participant reports a point forecast F_{imd} of the following day's end-of-day price. We classify a forecast as a hit when it falls inside that 5% band,

$$\frac{|F_{imd} - P_{m,d+1}|}{P_{m,d+1}} \leq 0.05, \quad (3)$$

which is when the participants earn the forecast bonus.

Figure 7. Gamification and Forecast Accuracy

A forecast is a hit if it lies within 5% of the next day's closing price, $|F_{imd} - P_{m,d+1}|/P_{m,d+1} \leq 0.05$. Forecasts are elicited on days 3, 6, 9, and 12. Panel A pools all elicitations. Panel B reports the hit rate by forecast day. Bars are treatment means and error bars are 95% confidence intervals.

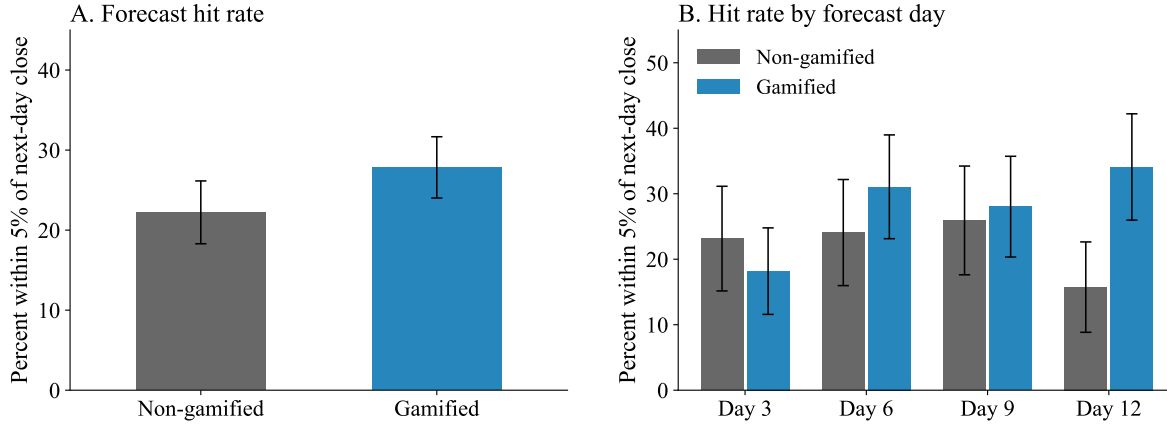


Figure 7 reports the forecast accuracy by treatment. On average, 27.8% of forecasts in gamified markets earn the bonus, versus 22.2% in non-gamified markets ($p = 0.067$). The gap is stronger later in the market, particularly on day 12, where the hit rate is 34.1% under gamification and 15.7% in the control group.

4.3.3 Trader strategies Next, we study the impact of gamification on individual trading strategies to pin down the effect on market making behaviour.

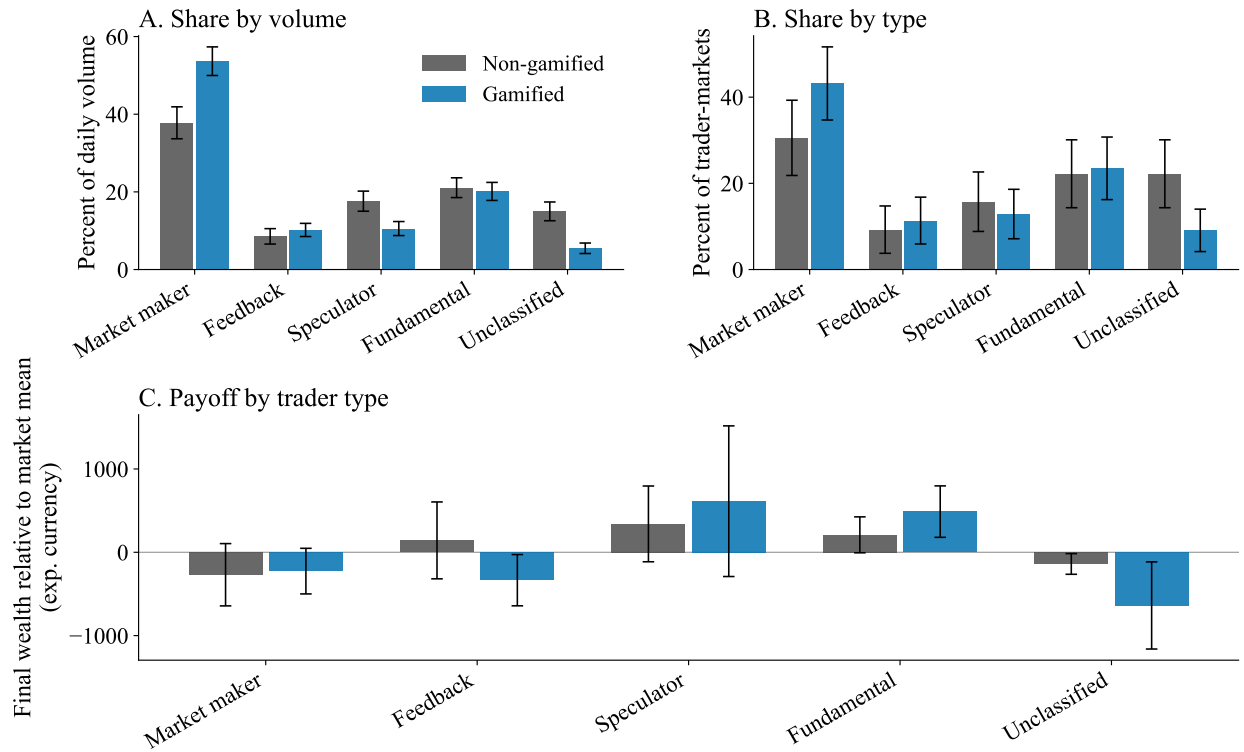
We first isolate two-sided liquidity provision. A trader is therefore classified as a *market maker* (in the spirit of Kirilenko, Kyle, Samadi, and Tuzun, 2017) if the trader executes on both sides on at least 25% of active days and completes at least 30 trades during a particular 15-day market.

Among the remaining traders, we classify types as in Haruvy and Noussair (2006) by comparing position changes to closing-price movements. First, a trader is classified as *feedback* if the change in holdings on day d has the same sign as the closing-price change from $d - 2$ to $d - 1$ (that is, the trader is chasing trends). Second, a trader is a *speculator* if the holding change on day d has the

same sign as the subsequent closing-price change from d to $d + 1$.

Figure 8. Gamification Shifts Traders Toward Market Making

Panel A reports the share of daily trading volume executed by each type. Panel B reports the percentage of trader-market repetitions assigned to each mutually exclusive type. Market makers trade on both sides on at least 25% of active days and execute at least 30 gross trades. Remaining traders are assigned to their dominant directional score if that score reaches five days; otherwise, they are unclassified. Panel C reports day-15 wealth relative to the six-trader market mean. Error bars are 95% confidence intervals.



Finally, a trader is *fundamental* if the holding change has the opposite sign of $P_{md} - v_d$, so the participant trades toward fundamentals. Each trader accumulates a score for each type, incremented by one for each day consistent with that type. We assign the highest-scoring type if that score reaches five (one third of the 15 days). Traders whose scores remain below five are unclassified. The [Haruvy and Noussair \(2006\)](#) taxonomy is directional: it does not capture a trader who buys and sells repeatedly while carrying little net flow, which is why we introduce a market-maker type

before the directional types.

Figure 8 and Table 10 show that gamification leads to the proliferation of market makers, at the expense of speculators and unclassified traders. Market-makers execute 37.8% of daily volume in non-gamified markets and 48.1% in gamified markets, a 10.3 percentage-point increase. Speculator and unclassified volume fall by 5.8 and 8.7 percentage points, respectively.

Table 10. Gamification and Trading Volume by Trader Type

This table estimates the treatment difference in each type's share of daily trading volume. Each observation is a market-day. Market makers satisfy the two-sidedness and activity thresholds described above and are assigned first. Remaining volume is allocated to feedback, speculator, fundamental, or unclassified traders under the directional scoring rule. All models include repetition and trading-day indicators. Even-numbered columns additionally control for market-average overconfidence, comprehension-quiz attempts, and age. The constant is the non-gamified volume share of the corresponding type. Robust standard errors are reported in parentheses.

Dependent Variables:	Market makers		Feedback		Speculators		Fundamental		Unclassified	
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Gamified	0.158*** (0.028)	0.103*** (0.028)	0.016 (0.013)	0.022 (0.015)	-0.070*** (0.016)	-0.058*** (0.016)	-0.009 (0.018)	0.021 (0.017)	-0.095*** (0.014)	-0.087*** (0.015)
Overconfidence		0.322* (0.169)		-0.061 (0.079)		0.253** (0.115)		-0.695*** (0.102)		0.181** (0.077)
Comprehension quiz		0.144*** (0.018)		-0.014** (0.007)		-0.041*** (0.010)		-0.052*** (0.011)		-0.038*** (0.010)
Age		0.010*** (0.002)		-0.001 (0.001)		-0.003*** (0.001)		-0.005*** (0.001)		-0.001 (0.001)
Constant	0.378*** (0.021)	0.378*** (0.022)	0.085*** (0.010)	0.085*** (0.010)	0.176*** (0.013)	0.176*** (0.012)	0.211*** (0.013)	0.211*** (0.013)	0.150*** (0.012)	0.150*** (0.012)
Observations	594	594	594	594	594	594	594	594	594	594
R ²	0.06	0.18	0.03	0.03	0.05	0.08	0.01	0.15	0.08	0.11
Repetition dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Trading-day dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B of Figure 8 reports the same pattern in the trader count, albeit weaker: the share of traders classified as market makers rises from 30.6% to 43.2%. In Panel C, we report the end-of-market wealth by trader type, relative to the average wealth. The effects are noisy, and not statistically significant. Several salient patterns are suggestive, however. Fundamental traders and speculators earn more in gamified markets than in non-gamified markets, while market-makers make losses in either case.

4.4 Wealth inequality

Finally, we investigate the impact of gamification on the distribution of profits. Financially literate traders may be better able to resist interface-induced trading (Lusardi and Mitchell, 2011), while less sophisticated traders appear more susceptible to hedonic design (Chapkovski, Khapko, and Zoican, 2025). If the former trade against the latter, we conjecture that gamification can widen the cross-sectional distribution of wealth.

For each trader-day, wealth (W_{imd}) equals initial cash plus cumulative sale proceeds, minus cumulative purchase costs, plus dividends realized on end-of-day holdings. Relative wealth is a trader's wealth minus the average wealth of the six traders in the same market-day, labeled $\bar{W}_{md}$.

To measure inequality, we compute the Gini (1936) coefficient of wealth each market-day,

$$G_{md} = \frac{\sum_{i=1}^6 \sum_{j=1}^6 |W_{imd} - W_{jmd}|}{2(6)^2 \bar{W}_{md}}, \quad (4)$$

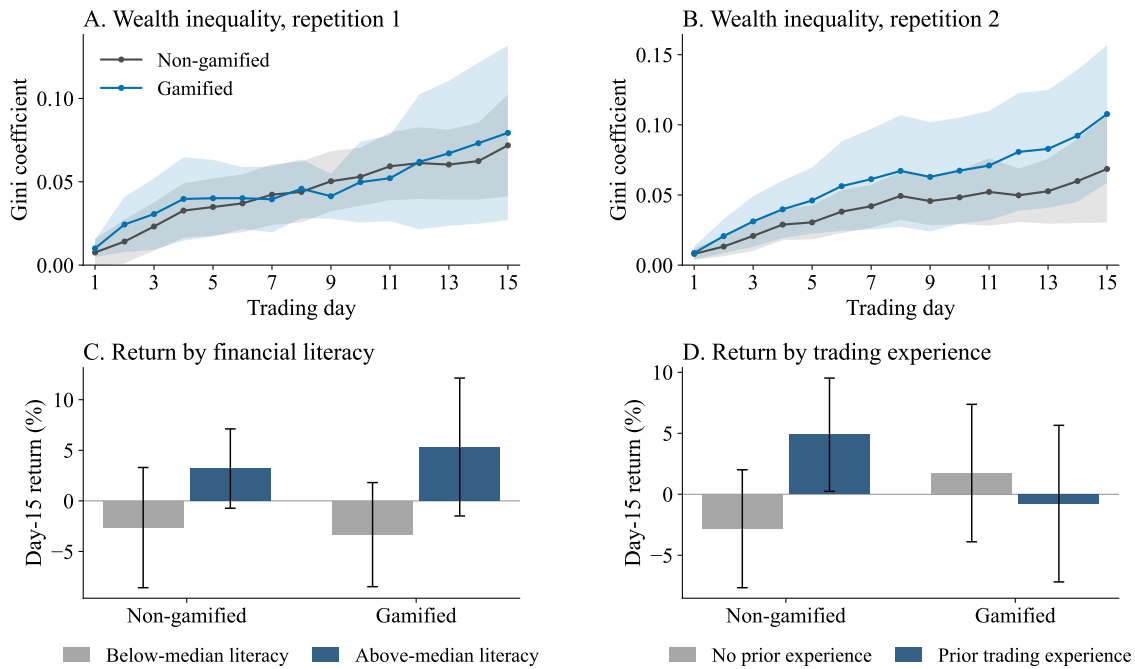
and then take the mean G_m over the 15 days in a market repetition. Further, we compute each trader's day-15 return on initial mark-to-fundamental wealth, $(W_{im,15} - W_{im,0})/W_{im,0}$, where $W_{im,0} = \text{E\$}5,000$ for every participant. We split traders by their financial literacy score, above and below the median of the pooled sample, and by prior trading experience. We also distinguish between inequality levels in both the first and second market repetitions.

Figure 9 suggests that the inequality gap widens with gamification, mainly in the second market repetition. However, Table 11 indicates that the differences in inequality are not statistically

significant. Pooled across repetitions, the mean Gini coefficient is 0.053 in gamified markets and 0.042 in non-gamified markets, a difference of 0.011, or 26% ($p = 0.35$). In repetition 1, the corresponding means are 0.046 and 0.044, a difference of 0.003 ($p = 0.86$). In repetition 2, they are 0.060 and 0.041, a difference of 0.019.

Figure 9. Gamification and Wealth Inequality

Panels A and B plot the mean Gini coefficient over wealth by trading day in the first and second market repetitions. Panel C reports the day-15 return on initial mark-to-fundamental wealth for participants below and above the pooled-sample median financial-literacy score. Panel D reports the same return for participants without and with prior trading experience. Lines and bars are treatment means; shaded regions and error bars are 95% confidence intervals.



The literacy split points in the same direction. Within market, traders with above-median financial literacy earn 8.3 percentage points more than below-median-literacy traders. The differential is 4.2 percentage points larger under gamification, but the impact of gamification is not statistically significant ($p = 0.54$). In non-gamified rounds, prior trading experience is associated with a 9.6 percentage-point higher return. Gamification wipes out the experience premium, as the return drop

by 13.0 percentage points ($p = 0.06$). We conclude that the evidence on gamification and wealth inequality is suggestive, but not conclusive.

Table 11. Gamification and Wealth Inequality

Columns (1) and (2) use one observation per market repetition, the 15-day average of the daily Gini coefficient. Columns (3)–(6) use one observation per trader-market. The outcome is the day-15 return on initial mark-to-fundamental wealth, $(W_{im,15} - W_{im,0})/W_{im,0}$, with $W_{im,0} = \text{E\$}5,000$ for every trader. Robust standard errors are reported in parentheses.

Model:	Gini		Return (literacy)		Return (experience)	
	(1)	(2)	(3)	(4)	(5)	(6)
Gamified	0.011 (0.011)	0.003 (0.015)	-0.007 (0.040)		0.046 (0.038)	
Above-median literacy			0.058 (0.036)	0.083** (0.036)		
Gamified $\times$ Above-median literacy			0.028 (0.057)	0.042 (0.068)		
Trading experience					0.077** (0.034)	0.096** (0.042)
Gamified $\times$ Trading experience					-0.102* (0.055)	-0.130* (0.069)
Repetition 2		-0.003 (0.011)				
Gamified $\times$ Repetition 2		0.016 (0.023)				
Constant	0.042*** (0.005)	0.044*** (0.008)	-0.026 (0.030)		-0.028 (0.025)	
Market FE				Yes		Yes
Observations	40	40	240	240	240	240
R ²	0.02	0.04	0.03	0.17	0.02	0.15

5 Conclusions

We show that a gamified trading interface impairs price discovery while improving displayed liquidity on laboratory limit-order markets. Badges, reward animations, and price-trend notifications generate hedonic value for the act of trading, leading to a 31% increase in volume. This increase is driven by a larger share of traders who act as naïve market makers and post two-sided limit orders: Limit order submissions increase by 37% in gamified markets, while the share of market maker volume rises from 37.8% to 48.1%. Prices respond less to order flow in gamified markets, as participants absorb fundamental orders without adjusting prices (Abreu and Brunnermeier, 2003, i.e., a liquidity provision version of behavioural absorption capacity in). As a result, spreads tighten and depth increases, but prices deviate further from fundamentals. Gamification leads to a 28% increase in mispricing, a fourfold increase in the incidence of bubbles.

Our results speak to the market-wide impact of gamification and complement existing work on how gamified interfaces change individual decisions. Digital engagement features have attracted regulatory attention as individual investors increasingly help set prices, particularly in small-cap stocks, options, and novel assets. The U.S. Securities and Exchange Commission (SEC) expressed concern about broker-dealer digital engagement practices and launched the *Investomania* campaign to raise investors awareness (U.S. Securities and Exchange Commission, 2021, 2022). Following retail engagement in “meme stocks”, the Massachusetts Securities Division alleged that Robinhood used gamification to induce continuous trading by inexperienced customers (Massachusetts Securities Division, 2020). Our experiment results add to these concerns and caution against reading an improvement in liquidity due to retail investor participation as evidence of better market quality. Spreads and depth can improve while price discovery worsens.

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A 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
 - (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. When placing an order, you may see several prices: the last traded price, the ask price, the bid price, and the closing price. What is the bid price?
 - (a) The highest price a buyer is currently willing to pay.
 - (b) The price you personally choose when submitting a buy order.
 - (c) The lowest price a seller is currently willing to accept.
 - (d) The most recent price at which the security traded.

- (e) Don't know / Not sure
 - (f) 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) Stay the same
 - (c) Decrease
 - (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. When viewing a security's quote, you may see both a bid price and an ask price. What is the bid-ask spread?
- (a) The average of the bid price and the ask price.
 - (b) The difference between the lowest ask price and the highest bid price.
 - (c) The fee the broker charges each time you trade.
 - (d) The change in the stock price from market open to market close.
 - (e) Don't know / Not sure
 - (f) 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 is liable for the company's debts
- (c) She has lent money to firm B
- (d) None of the above
- (e) 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) Prefer not to say

B Consent Form

Dear Participant,

You are invited to take part in an economic experiment studying trading behaviour in financial markets. This project is funded by the Social Sciences and Humanities Research Council of Canada. You will be asked to trade stocks on a virtual financial market with other participants.

Your participation in this study is entirely voluntary and presents no known risks or burdens. You will receive a fixed payment for participating, as well as additional compensation based on your trading performance and your answers to a financial literacy quiz. You can withdraw from the study at any time without penalty. However, if you withdraw before the end of the experiment, you will receive only a partial payment reflecting the time spent.

All data generated during this study will remain confidential. You will be asked to provide some basic demographic information, but none of this information will be used to personally identify you and no personal information will appear in any published study. Your decision to participate will remain completely confidential and only the researchers will have access to individual data. We do not collect any data that can personally identify you.

Data will be stored electronically on a secure server accessible only by the research team using a secure password. Data will be retained in de-identifiable format for 7 years and discarded afterwards, in accordance with standard practices of the American Psychological Association. As required by the guidelines of the American Economic Association, during the publication process the data may be shared with other investigators for re-analysis. However, only details sufficient to permit replication will be shared, ensuring security and confidentiality.

This study has been reviewed by the Research Ethics Board at the University of Calgary. The research study you are participating in may be reviewed for quality assurance to ensure that required laws and guidelines are followed. If chosen, representative(s) of the Human Research Ethics Program (HREP) may access study-related data and/or consent materials as part of the review. All information accessed by the HREP will be upheld to the same level of confidentiality stated by the research team.

If you are interested, you can receive a summary of the research study by emailing the primary researchers.

If you wish to obtain further information regarding your rights as a participant, you may contact the Conjoint Faculties Research Ethics Board (CFREB) at the University of Calgary at cfreb@ucalgary.ca or (403) 220-8640.

By proceeding, I agree to participate in research. I understand that I can withdraw my consent to participate at any time and that by giving consent I am not giving up any of my legal rights.

I have read and understood the information above.

C Trading Game Instructions

Welcome to this trading experiment! Please read these instructions carefully. Your payment will be based on your performance in the trading game and your answers to a financial literacy quiz.

Overview

- You will trade a single stock in a market with five other participants. The experiment consists of two consecutive markets with the same group of traders.
- At the beginning of each market you will receive an endowment of either 20 shares and E\$2,600 in cash, or 10 shares and E\$3,800 in cash.
- Each market consists of 15 trading days, each lasting 1 minute (15 minutes total per market). At the end of days 3, 6, 9, and 12, you will be asked to forecast the price at the end of the following day.
- Finally, at the end of both markets you will be asked to complete a financial literacy quiz.

The Stock

- The stock pays a dividend at the end of every day. The dividend is equally likely to be E\$0, E\$4, E\$8, or E\$20, yielding an expected dividend of E\$8 per day. Dividends are drawn independently each day.
- Because the stock pays dividends only during the 15 days of the market, its fundamental value declines over time. The fundamental value equals E\$8 multiplied by the number of remaining days (including the current day). It starts at E\$120 on day 1 and declines by E\$8 each day, regardless of the actual dividend realized. By day 15, the fundamental value is E\$8. After the final dividend is paid, the stock is worthless.

Trading Rules You will trade using a limit order book. You may submit buy or sell orders at prices you specify, or you may trade immediately against existing orders in the book.

- You may only buy shares if you have sufficient cash to pay for them.
- You may only sell shares you own. Short selling is not permitted.
- You cannot borrow additional cash.

Price Forecasting At the end of days 3, 6, 9, and 12, after dividends are paid, you will forecast the end-of-day stock price for the next day. You will also report your confidence in this forecast. If your forecast is within 5% of the realized price, you earn a bonus of E\$20.

Payment

- Your final payoff equals your cash holdings at the end of a randomly selected market, including any day-15 dividends, plus any forecast bonuses earned across both markets.
- Your earnings will be converted from experimental dollars (E\$) to Canadian dollars at a fixed rate of 1 E\$ = 0.003 CAD.
- You will earn 10 E\$ for each correct answer in the financial literacy quiz.

Important Notes

- Your trading screen will show the current order book, recent transaction prices, your cash balance, and your share holdings.
- Each day lasts exactly 1 minute. A timer will indicate the time remaining.
- After completing the first market, you will trade a second market with the same group of participants. The second market is independent: you will receive a fresh endowment, and the stock's fundamental value resets to E\$120.

Training Before the main markets begin, you will watch a short video explaining the trading interface, complete a comprehension quiz, and complete a short three-minute practice market. You must answer all quiz questions correctly before proceeding.

D Comprehension Quiz

1. At the end of each period, the asset pays a dividend. Which of the following statements is correct?
 - (a) The dividend is always E\$8.
 - (b) The dividend is equally likely to be E\$0, E\$4, E\$8, or E\$20.
 - (c) The dividend depends on the asset's trading price.
 - (d) The dividend is determined by your trading activity.
2. Whenever a forecast is collected, when do you earn a bonus?
 - (a) If your forecast is within 1% of the realized price.
 - (b) If your forecast exactly equals the realized price.
 - (c) You earn E\$20 for every forecast submitted.
 - (d) If your forecast is within 5% of the realized price.
3. How is the fundamental value related to dividends?
 - (a) The fundamental value decreases each period by the expected dividend.
 - (b) The fundamental value decreases each period by the previously realized dividend.
 - (c) The fundamental value does not depend on dividends.
 - (d) The fundamental value always equals E\$120.
4. Which of the following best describes how your final payoff is determined?
 - (a) Your cash holdings at the end of a random market.
 - (b) Your cash holdings plus number of shares you hold at the end of a market, evaluated at the last trading price.
 - (c) Your cash holdings at the end of a random market, plus any forecast and quiz bonuses earned.
 - (d) Your cash holdings at the start of period 15, plus any forecast bonuses earned.
5. Which of the following actions are not allowed in this market?
 - (a) Selling shares you do not own (short selling).
 - (b) Borrowing cash to purchase additional shares.
 - (c) Buying shares if you have sufficient cash.
 - (d) Neither (a) or (b) are allowed.