Gamification of Stock Trading: Losers and Winners*

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Abstract. Gamification of stock trading is a novel practice in which brokers embed game-like features into mobile trading apps to increase client engagement. This study examines how the market responds to 142 gamification features introduced by 17 major U.S. brokerage firms. I find that gamification creates a conflicting tradeoff: it increases retail trading activity while degrading retail performance, thereby harming retail investors. Crucially, this shift reduces the toxicity of retail order flow—benefiting brokers, market makers, other traders, and ultimately improving overall market quality.

Key words: Gamification, retail traders, equity trading, market quality.

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1. Introduction

The information revolution has radically reshaped the financial landscape, enabling more immediate, personalized, and visually rich interactions in the trading environment. One consequence of this shift is the rise of *gamification*—the incorporation of game design elements into trading platforms to increase user engagement. This practice has conquered numerous industries and has been widely used in education, healthcare, and business.[1] Meanwhile, the all-time high participation rate of retail investors (McCabe (2021)), the recent case of market manipulation with meme stocks (Pedersen (2022)), and continual debates in the Securities and Exchange Commission (SEC (2021)) call for a market microstructure study of stock trading gamification.

The U.S. retail brokerage industry is innovating rapidly to attract more individual investors. Many brokerages offer zero-commission trades and fractional shares, making the market more accessible to investors. Moreover, the introduction of mobile trading apps allows retail traders to access the market anytime and anywhere, further motivating them to trade more frequently. Increasingly, these platforms employ gamification to engage users and increase trading volume. Features like rewards systems and interactive visuals appeal to retail traders' behavioral tendencies, encouraging frequent trading and blurring the lines between investing and entertainment (see Figure 1; Zweig (2024)).

To capture the effect of stock trading gamification, I analyze 17 U.S. brokers' mobile trading platforms over a 4 year time period. Brokers regularly update their apps to keep pace with evolving technology and shifting industry standards. Developers outline the purpose of these updates in accompanying notes. Using this information, I identify updates associated with the gamification of a trading process. In total, 142 updates introduced new game-like features into the apps.

The results reveal a multifaceted dynamic. Gamification substantially increases retail trading volume and compensation from wholesalers, benefiting brokerage firms. Yet, there is little

[1] See Caponetto, Earp, and Ott (2014); Wünderlich, Gustafsson, Hamari, Parvinen, and Haff (2020); Johnson, Deterding, Kuhn, Staneva, Stoyanov, and Hides (2016).

evidence that it attracts new users to trading platforms. Instead, gamification primarily deepens engagement among existing clients, encouraging more active trading. This heightened activity, however, comes at a cost to retail investors: gamification undermines their trading strategies, resulting in lower intraday returns and increased return volatility. Although wholesalers respond by offering larger and more frequent price improvements, these concessions fail to offset the trading losses retail investors incur due to the diminished quality of their trades.

An inferior retail trading strategy benefits the counterparties of retail traders, namely liquidity providers, as gamification reduces the toxicity of retail order flow. First, a decrease in retail return following gamification implies a reduction in adverse selection costs. Second, gamification nudges retail investors toward noisier trading strategies, leading to a reduction in retail volume imbalance, which in turn simplifies inventory management for liquidity providers.

Eventually, the competitive environment prompts market makers to extend acquired benefits to the broader market, captured by transaction costs decrease post-gamified updates. In particular, the data reveals that quoted, effective, realized spreads, and price impact decline after such updates. Additionally, market quality improves, as shown by increased traded volume and decreased market-wide price and return volatility.

The results above have substantial economic significance. To illustrate, a typical gamified update increases retail traded volume by 0.25% and reduces retail return by 0.15%. The overall market benefits from these changes as the effective spread declines by 0.08%. Cumulatively, all gamification updates implemented during the sample period contribute to a 35.93% increase in retail trading volume, a 21.95% decline in retail returns, and a 11.46% decrease in the effective spread.

Finally, the appendices enrich the main analysis by providing additional insights into mechanisms of gamification. Appendices A.2, A.3, and A.4 explore how gamification differentially affects various groups of retail traders, brokerage firms, and stocks. Appendix A.5 leverages Rule 605 and Rule 606 filings to validate the effects of gamification on execution quality and retail

order flow. In particular, Rule 606 data provide additional insights through an analysis of retail option trading around gamification events. Appendix A.6 investigates the strategic considerations behind brokers' decisions to gamify their platforms. Lastly, Appendix A.7 disentangles the transitory and permanent components of gamification's impact on retail trading behavior.

Related literature. This study is related to the literature that examines retail trading. Earlier works show that retail traders are unsophisticated and tend to be swayed by behavioral biases (Barber and Odean (2000); Barber and Odean (2008)), while later studies indicate that retail traders may predict future returns and use a contrarian strategy to provide liquidity (Kaniel, Saar, and Titman (2008); Kelley and Tetlock (2013)). The most recent findings about retail traders vary. Barber, Huang, Odean, and Schwarz (2022) shows that retail traders demonstrate the same type of biases found in earlier studies, whereas Welch (2022) suggests an overall good trading performance by retail traders.

Whether retail traders are systematically informed remains an open question. While some studies document positive returns among retail investors (Boehmer, Jones, Zhang, and Zhang (2021)), others portray their trades as predominantly noise-driven (Peress and Schmidt (2020)). One reason for this mixed evidence may lie in the heterogeneity of retail traders. Eaton, Green, Roseman, and Wu (2022) show that order flow characteristics vary across brokerage firms. My analysis goes a step further. Whereas Eaton, Green, Roseman, and Wu (2022) examine heterogeneity *across* retail traders, I focus on heterogeneity *within* the retail trader by tracking behavioral shifts over time. I demonstrate that brokers can actively influence the toxicity of their clients' order flow by introducing app features that nudge trading behavior—ultimately reshaping how retail investors trade in ways that benefit other market participants. These findings underscore that retail trading behavior is not fixed but can be shaped by platform design.

Gamification is one of the key mechanisms capable of reshaping retail trading behavior. The existing literature provides mixed evidence on its impact. On one hand, gamification can amplify behavioral biases—fueling excessive and distracted trading (Barber and Odean (2000); Peress

and Schmidt (2020)). On the other hand, in an era of democratized market access, gamified platforms may serve an educational function by engaging retail investors and promoting financial literacy through hands-on experience (Baptista and Oliveira (2017)). This study finds that the negative channel dominates. Gamification increases retail participation but does so by encouraging more frequent and noisier trading. While traders appear more engaged, there is no evidence that this engagement translates into better financial decision-making. On the contrary, gamification reduces retail returns and raises return volatility. Although there is some indication that traders adapt to new gamified features over time, this learning is limited and fails to restore the level of trading quality observed prior to gamification (see Appendix A.7).

This paper further contributes to the literature on retail brokerage firms and wholesalers. In today's market structure, brokerage firms act as intermediaries between retail traders and wholesalers. The prevailing arrangement, known as payment for order flow, allows brokers to aggregate retail order flow and sell it to wholesalers at a premium (Easley, Kiefer, O'hara, and Paperman (1996); Battalio (1997); Bessembinder and Kaufman (1997); Comerton-Forde, Malinova, and Park (2018); Dyhrberg, Shkilko, and Werner (2025)). Most of these trades are then executed off-exchange (Menkveld, Yueshen, and Zhu (2017); Buti, Rindi, and Werner (2017); Battalio and Jennings (2023b)). Because the size of the premium depends on the volume of retail trades routed through their platforms (Bryzgalova, Pavlova, and Sikorskaya (2023)), brokerage firms have strong incentives to stimulate trading activity (Egan (2019); Heimer and Simsek (2019)). To that end, they increasingly deploy new technologies designed to attract and engage retail investors, including zero-commission trading (Jain, Mishra, O'Donoghue, and Zhao (2024)), fractional share offerings (Bartlett, McCrary, and O'Hara (2024); Da, Fang, and Lin (2024)), mobile trading platforms (Cen (2024)), and the gamification of the trading process. As these technologies take hold, their influence extends beyond mere retail participation. In particular, gamification not only boosts trading activity but also alters the composition of order flow in ways that affect the cost of liquidity provision—namely, through changes in adverse selection and inventory risk.

Retail traders often move in the same direction following market-wide events, creating inventory risks for wholesalers who serve as their counterparties (Barber, Odean, and Zhu (2008); Barber, Lin, and Odean (2021); Ho and Stoll (1981); Grossman and Miller (1988); Hendershott and Menkveld (2014)). In contrast, when retail order flow is more balanced—for example due to greater disagreement among investors—market makers benefit from lower inventory and adverse selection costs (Garfinkel (2009); Cookson and Niessner (2020); Cookson, Fos, and Niessner (2022)). However, how gamification might alter retail trading strategies—and thus affect market makers' costs—remains unclear. Gamification has been shown to induce noisier, less-informed trading by retail investors, which ultimately benefits market makers by reducing order toxicity (Chapkovski, Khapko, and Zoican (2025)). In contrast, the recent meme-stock frenzy (e.g., GameStop) illustrates how retail traders' excitement and impulsivity, which can be triggered by gamification, can spur herd-like, coordinated behavior that imposes substantial costs on wholesalers (Costola, Iacopini, and Santagiustina (2021); SEC (2023)). My findings indicate that gamification shifts retail behavior in favorable direction for a market maker. Following gamified updates, retail traders trade larger volumes in a noisier and less-informed manner, leading to a substantial drop in order imbalance and a reduction in retail returns. This behavioral shift reduces order flow toxicity and allows liquidity providers to execute trades more efficiently. In line with Baldauf, Mollner, and Yueshen (2024), this shift enhances overall market liquidity by easing execution for wholesalers like Citadel Securities and Virtu Financial, who increasingly perform both wholesaling and market-making functions (Jain, Mishra, O'Donoghue, and Zhao (2024); Dyhrberg, Shkilko, and Werner (2025)).

This altered dynamic between wholesalers and retail traders can have spillover effects on overall market quality. Eaton, Green, Roseman, and Wu (2022) show that outages on Robinhood—an online broker popular among novice investors—improve market quality by reducing the influx of toxic retail orders that wholesalers must process. By analogy, if gamification encourages more random (i.e., less informed) trading, it could similarly make retail order flow less toxic

and thereby enhance market quality. However, prior studies indicate that surges in speculative retail trading can worsen market quality, for example, by increasing volatility (Barber, Huang, Odean, and Schwarz (2022); Lipson, Tomio, and Zhang (2023)). Given that gamification can act as a catalyst for speculative trading, its net effect on market quality is a priori ambiguous. This study documents a net positive effect of gamification on market quality: transaction costs and stock-price volatility decrease, while overall traded volume increases.

Finally, the present study enriches the broader literature on gamification by examining how game-like design principles—long applied in domains such as education and healthcare—are increasingly shaping financial behavior. Gamification can be defined as "the use of game design elements in non-game contexts" (Deterding, Dixon, Khaled, and Nacke (2011)). It has been widely used in education (Caponetto, Earp, and Ott (2014)), business (Wünderlich, Gustafsson, Hamari, Parvinen, and Haff (2020)), and healthcare (Johnson, Deterding, Kuhn, Staneva, Stoyanov, and Hides (2016)) as a method to enhance performance in a given task. Whereas in finance, the first documented cases of the use of gamification are in the banking sector (Rodrigues, Oliveira, and Costa (2016); Baptista and Oliveira (2017)). In the context of stock trading, gamification can be viewed as an umbrella term that unites various brokerage practices that nudge retail investors to trade more by stimulating their engagement. These practices include but are not limited to, push notifications (Arnold, Pelster, and Subrahmanyam (2022); Moss (2022)), leaderboards (Heimer (2016); Kirchler, Lindner, and Weitzel (2018)), non-economic rewards, progress framing and feedback (Chapkovski, Khapko, and Zoican (2024); Chapkovski, Khapko, and Zoican (2025)).[2]

Both academics and regulators are actively investigating how gamification affects capital markets. Research shows that in experimental settings, gamification increases traders' engagement, prompts excessive risk-taking, and induces noisier trading behavior (Chapkovski, Khapko, and Zoican (2024); Chapkovski, Khapko, and Zoican (2025)). Similarly, studies conducted by

[2]The comprehensive list of gamification practices is not rigid and depends on specific regulator. You can refer to examples of such lists for different regulators: US - SEC (2023); Canada - OSC (2022); UK - FCA (2022); France - AMF (2022).

Canadian, French, and UK regulators report comparable effects of gamification on retail traders (OSC (2022); AMF (2022); FCA (2022)). To my knowledge, this paper is the first empirical study to examine gamification in the context of equity markets. I extend the focus beyond retail traders to investigate how gamification influences other capital market participants. The evidence reveals an asymmetry in outcomes: retail traders bear the costs of gamification, while brokerage firms, market makers, and the broader market reap the rewards. This divergence raises critical questions about fairness, incentives, and the evolving role of technology in shaping market behavior.

2. Data and metrics

My data come from five primary sources: (i) MobileAction (https://www.mobileaction.co/), (ii) AppTweak (https://www.apptweak.com/en), (iii) the Trade and Quote (TAQ) database, (iv) Rules 605 & 606 reports, and (v) Center for Research in Security Prices (CRSP). Additionally, for the robustness test, I use data on a Canadian stock sample that comes from a financial data aggregator TMX money (https://money.tmx.com/).

2.1 Brokerage apps updates and number of downloads

MobileAction is a company that helps to promote mobile apps in the App Store. For that purpose, it keeps the data for all past updates of all apps in the App Store. MobileAction has been tracking app update data since 2018. I obtain apps activity data of 17 major brokerage firms in the U.S. from 2018 to 2021. I use two pieces of information: (i) the date of an update and (ii) a description of an update. On average, each app updates every 13 days or 112 times during the sample time. The vast majority of these updates (93%) are routine bug fixes, while the rest (7%) include new functionality or services that are integrated into an app and discussed by developers in the "Description" section of an update. I implemented a keyword-based screening to identify app updates most likely associated with gamification. Specifically, I classified an update as po-

tentially gamified if its description included any of the following terms: *design*, *engage(ment)*, *color(s)*, *font(s)*, *notification(s)*, *referral(s)*, *reward(s)*, and *leaderboard(s)*. For example, the description of one update from Fidelity reads: "Updated design for improved trading experience." Although the description of an update might not directly mention an introduction of game-like features into an app design, some users have noticed a more "gamified" and "bubblegum-like" interface.[3] Following this rationale, I selected all app updates that potentially gamify an app based on the update description. In total, I have identified 142 such updates.

I observe substantial cross-sectional variation in the types and frequency of gamification updates. The majority of gamified updates focus on enhancing the app's design, accounting for 85% of all gamified updates. The remaining updates are divided between notification updates and other types, with corresponding shares of 9% and 6%, respectively. When it comes to brokers, the periodicity of gamified update releases also varies. To illustrate, Vanguard gamified their platform only once during the four years covered in my sample, while Webull or TD Ameritrade gamified their platform 19 times each.[4] Table 1 lists the full sample of the brokerage firms as well as the number of gamified updates, and bug-fix updates.

[Table 1]

One issue with this identification strategy is a potential overestimation of the number of gamified updates since changing an app design does not always lead to more game-like features. Indeed, if some updates changed the app design in a way that did not alter the behavior of the app's clients, the findings will be attenuated toward zero. The following sections demonstrate that this is not a concern and that the power of the tests is sufficient to draw conclusions from them.

AppTweak is another company that helps mobile apps promote themselves in the App Store. Unlike MobileAction, AppTweak uses a more quantitative and data science approach to help its

[3] Link to a Reddit post: https://www.reddit.com/r/fidelityinvestments/comments/n0fvgz/meet_the_new_fidelity_mobile_beta_trading/

[4] For further discussion on the differences in brokers' gamification strategies, see Appendix A.3

clients. For that purpose, AppTweak has developed a proprietary algorithm that estimates the number of downloads of each app in an App Store on a daily basis since 2014. From them, I obtain the number of downloads for 17 brokerages apps from 2018 to 2021. On average, each app had 2,361 daily downloads from new users. This number varies substantially across brokers: for example, 16,159 daily downloads for Robinhood and only 24 for LightSpeed. Table 1 lists the average daily downloads for all brokers in the sample.[5]

2.2 Retail trading metrics

To calculate the retail trading metrics, I use the TAQ dataset and an algorithm proposed by Boehmer, Jones, Zhang, and Zhang (2021) (BJZZ) with the adjustment of Barber, Huang, Jorion, Odean, and Schwarz (2024). This identification algorithm relies on the fact that retail traders obtain price improvements in sub-penny amounts. For example, a trade at $100.001 is a retail sell, and a trade at $99.999 is a retail buy. In that way, trades with sub-penny prices of 1 to 4 are identified as retail sells, and those with sub-penny prices from 6 to 9 as retail buys. Sub-penny amounts from 4 to 6 are excluded since they often come from institutional dark market trades that are matched at the mid-quote. Barber, Huang, Jorion, Odean, and Schwarz (2024) contribute to an algorithm by switching the signing strategy from the sub-penny amount to the prevalent quoted spread midpoint during a trade, significantly decreasing the signing error of retail trades.

The average retail volume in my sample is 0.2 million shares a day, which constituting 11% of the overall volume (see Table 2). To put this number into context, it is important to mention a couple of caveats about the BJZZ identification algorithm. While today's stock market witnesses the all-time high participation rate of retail traders, which approximately equals to 20% of the overall trading activity (McCabe (2021)), the initial study by Boehmer, Jones, Zhang, and Zhang (2021) shows that their algorithm identifies only 50% of that retail volume. A recent study by

[5] Appendix A.3 provides a detailed discussion of how the effects of gamification vary with the size and maturity of retail brokerage firms.

Barber, Huang, Jorion, Odean, and Schwarz (2024) finds that this number is lower for more recent years, around 35%. Finally, Battalio, Jennings, Saglam, and Wu (2023) estimates that the BJZZ algorithm captures less than 28% of retail orders. Even such a low identification rate will be adequate for the analysis if (i) the power of the tests will be sufficient to infer statistical significance and (ii) BJZZ captures a sample of retail trades representative of the overall population. To address the first point, I will demonstrate in the following sections that my regression setups have sufficient power to yield statistically significant results. The second point, however, requests further elaboration.

Battalio, Jennings, Saglam, and Wu (2023) examines the BJZZ identification algorithm and finds two major issues: (i) BJZZ misclassifies institutional orders as retail, and (ii) retail trades identified by BJZZ differ from those that are not captured by the algorithm. While these issues raise concerns, two factors mitigate the first in the context of my study. First, it is difficult to establish a causal link by which gamification in retail brokerage firms might lead to a disproportionately greater increase in institutional trading volume compared to retail trading volume. Second, since retail order imbalance positively correlates with institutional trading volume (Barardehi, Bernhardt, Da, and Warachka (2021); Battalio, Jennings, Saglam, and Wu (2023)) and gamification decreases retail order imbalance (see Section 3.1.4), it is reasonable to assume that after gamification, the BJZZ algorithm misclassifies fewer institutional orders, which should attenuate my findings toward zero. Therefore, if anything, my results serve as a lower bound for the effect of gamification on retail traders.

The second issue is that retail orders classified by the BJZZ algorithm as retail differ from those not identified. Battalio, Jennings, Saglam, and Wu (2023) demonstrates that BJZZ identifies retail orders relatively accurately if they are marketable orders that take a short time to execute. For my study, it is reasonable to assume that retail traders submitting this type of order are the target audience affected by gamification, as previous research indicates that gamification targets impulsive individuals (Gong, Levine, Lin, and Xie (2024)). Therefore, the BJZZ algo-

rithm is expected to perform well in this context. In summary, although the BJZZ algorithm may poorly identify the *level* values of retail trading, its capacity to capture *changes* in retail trading is sufficient for drawing meaningful conclusions.

Finally, to address any remaining concerns about the main identification strategy, I validate the robustness of my results using retail trading data from Rule 605 reports. These filings, submitted directly by market makers, provide stock-month level data on retail trading volume and execution quality, thereby eliminating the need for any trade classification algorithm. Using this alternative dataset, I find results that closely mirror those presented in the main analysis (see Appendix A.5).

I use four retail trading metrics calculated from the TAQ database: (i) retail volume, (ii) retail imbalance, (iii) retail intraday return, and (iv) retail intraday return volatility. Retail volume is a sum of all traded shares volume identified as those that have originated from a retailer for stock i and day t. Retail imbalance is the absolute difference between the total buy and sell retail shares volume scaled by the total retail shares volume:

$$retail_imbalance_{it} = |\frac{buy_vol_{it} - sell_vol_{it}}{retail_volume_{it}}|, \tag{1}$$

where buy_vol_{it} and $sell_vol_{it}$ are the total sell and buy retail shares volume for stock i on day t. Retail intraday return is the traders' profit plus the value of the end-of-day holdings scaled by the total dollar volume traded by retailers:

$$retail_return_{it} = [(\$_sell_vol_{it} - \$_buy_vol_{it}) + (buy_vol_{it} - sell_vol_{it}) \times close_price_{it}] / (0.5 \times \$_vol_{it}), \tag{2}$$

where $\$_sell_vol_{it}$ and $\$_buy_vol_{it}$ are the total sell and buy retail dollar volume, $close_price_{it}$ is the closing price, and $\$_vol_{it} = \$_sell_vol_{it} + \$_buy_vol_{it}$. To avoid double counting, I divide $\$_vol_{it}$ by two. Finally, retail intraday return volatility is calculated as squared retail intraday

return, i.e., $return_volatility_{it} = retail_return_{it}^2$.

2.3 Liquidity metrics

I obtain liquidity metrics from the TAQ database. I compute quoted and effective spreads as well as the two components of the latter: price impact and realized spread. The *quoted spread*, or the National Best Bid and Offer (NBBO), measures the displayed liquidity and is computed as the difference between the national best offer (NBO) and the national best bid (NBB). That is $quoted_spread_{it} = \frac{best_ask_{it} - best_bid_{it}}{midpoint_{it}}$, where $best_ask_{it}$ is the lowest ask price, $best_bid_{it}$ is the highest bid price, and $midpoint_{it}$ is the average of the NBO and NBB, i.e., $midpoint_{it} = \frac{best_ask_{it} + best_bid_{it}}{2}$. Further, to measure trading costs incurred by the liquidity demanders, I compute the *effective spread* as twice the signed difference between the traded price and the NBBO midpoint at the time of the trade: $effective_spread_{it} = 2 \times (price_{it} - midpoint_{it})$, where $price_{it}$ is a trade price. Next, to assess the levels of adverse selection, I compute the *price impact* as twice the signed difference between the NBBO midpoint at the time of the trade and the midpoint at a future time: $price_impact_{it} = 2 \times (midpoint_{it+\gamma} - midpoint_{it})$, where γ is the time elapsed since the trade. Finally, the *realized spread* is computed as the difference between the effective spread and price impact. It is often associated with liquidity provider inventory and order processing costs as well as profits (e.g., Hendershott, Jones, and Menkveld (2011); Brogaard, Hagströmer, Nordén, and Riordan (2015)): $realized_spread_{it} = 2 \times (price_{it} - midpoint_{it+\gamma})$.

To sign trades, I relied on the Lee and Ready (1991) algorithm. Chakrabarty, Pascual, and Shkilko (2015) shows that this algorithm performs well in modern markets. All variables are scaled by the quote midpoints. To compute daily aggregates, I weigh quoted spreads by the time they are outstanding and weigh all trade-related metrics by the corresponding trading volume. To calculate price impacts, I use 15-second horizons.

Price improvement refers to the difference between the execution price of a retail trade and

the prevailing National Best Bid and Offer (NBBO) at the time of execution. The percentage of price-improved trades—defined as the share of retail trades receiving any positive price improvement—serves as a key indicator of execution quality. I obtain both metrics from Rule 605 reports, which are monthly disclosures mandated by the SEC for all market centers executing customer orders in National Market System (NMS) securities.

In addition, I examine Payment for Order Flow (PFOF) using data from Rule 606. While Rule 606 requires brokers to disclose their order routing practices quarterly, some wholesalers—such as Citadel Securities and Virtu Financial—voluntarily publish their own Rule 606 reports, which include average PFOF paid per share. I use these disclosures to construct a wholesaler-level measure of compensation. See Appendix A.5 for further details.

2.4 Other market participants

I define the rest of the market as all trades excluding those classified as retail. Using the TAQ database, I construct three trading metrics for the rest of the market: (i) volume, (ii) intraday return, and (iii) intraday return volatility. $volume_{it}$ is a sum of traded shares volume for stock i on day t. Intraday return is the traders' profit plus the value of the end-of-day holdings scaled by total dollar volume:

$$return_{it} = [(\$_sell_vol_{it} - \$_buy_vol_{it}) + (buy_vol_{it} - sell_vol_{it}) \times close_price_{it}] / (0.5 \times \$_vol_{it}), \tag{3}$$

where $\$_sell_vol_{it}$ and $\$_buy_vol_{it}$ are sell and buy dollar volume, buy_vol_{it} and $sell_vol_{it}$ are the sell and buy shares volume, $close_price_{it}$ is the closing price, and $\$_vol_{it} = \$_sell_vol_{it} + \$_buy_vol_{it}$. To avoid double counting, I divide $\$_vol_{it}$ by two. Finally, intraday return volatility is calculated as squared intraday return, i.e., $return_volatility_{it} = return_{it}^2$.

2.5 Sample

To define the sample, I begin with all common equities traded in the TAQ in January 2018, which is the beginning of the sample period. The sample includes stocks that survived the entire 2018-2021 period and those with non-zero traded volume for each trading day in a time series. The final sample consists of 1404 stocks.

Table 2 presents the summary statistics. On average, sample stocks have a market capitalization of approximately $20 billion, trade about 1.6 million shares daily, and are priced at $81. The quoted and effective bid-ask spreads are 23.93 and 13.99 basis points, respectively. The price impact averages 7.42 basis points, and the realized spread is 6.56 basis points. Consistent with prior literature, retail traders in the sample earn a positive intraday return of 4.46 basis points. Retail order flow exhibits an average imbalance of 20%, with retail investors trading around 182,000 shares per day. Retail trades benefit from notable price improvements: on average, they receive a discount of 6.53 cents per share, and 94% of these trades are executed with some form of price improvement. Lastly, brokerage firms earn an average payment for order flow (PFOF) of 0.01 cents per share.

[Table 2]

2.6 Methodology

I conduct my analysis in three steps. First, I present a figure to illustrate how the variable of interest changes around the time of gamified updates. Second, I estimate linear regressions in various setups. Third, I report the economic significance of my findings. The figure from step one plots the variable of interest over a period of 20 trading days before and after the gamified update.[6]

[6]The results are robust to alternative event-window length. See Section 3.4.

A potential challenge in interpreting the results of this setup is the presence of confounding events. If an unrelated event coincides with gamified updates and independently influences trading outcomes, it could introduce omitted variable bias. One illustrative example is the default smartphone animation that appears when any app is updated. This animation may capture users' attention and prompt them to open the app and initiate trades—behavior unrelated to the update's actual content. To address this concern, I incorporate a control group in both the figures and regression analyses. Specifically, I define the control group as app updates that solely involve bug fixes and do not alter the app's content. These control updates are broker-matched to the gamified updates.[7] This approach mitigates the risk of confounding effects arising from factors such as the default update animation, strategic timing of updates by brokers, or temporary disruptions triggered by updates. Finally, all variables of interest are winsorized at the 1st and 99th percentiles and standardized at the stock level.

Univariate results report the average value of the variable before and after 20 trading days of a gamified update. In such a setup, the variables are not yet standardized. Gamified group regressions include a regression on the intercept and variable $Post_{tb}$, which is a dummy variable equal to one during the first 20 trading days after the gamified update and zero during the 20 trading days before the gamified update.[8]. Further analysis includes a regression setup with volume and volatility as control variables, as they might be correlated with $Post_{tb}$ and could drive changes in the dependent variable. Formally, I specify this type of linear regression as follows:

$$DepVar_{itb} = \alpha_i + \beta_1 Post_{tb} + \beta_2 Volume_{itb} + \beta_3 Volatility_{itb} + \varepsilon_{itb}, \tag{4}$$

where $DepVar_{itb}$ represents the variable of interest for stock i on day t for a broker b; $Post_{tb}$ is a

[7] Alternatively, I use a Canadian sample of matched stocks as my control group during the period when U.S. brokers introduced gamified updates. I observe similar results in this context; see Section 3.4.5 for details.

[8] As a robustness test, I have examined both a shorter and longer window of 15 and 25 trading days and find similar results. For further details, see Section 3.4.1. Additionally, in Appendix A.7, I investigate whether the effect of gamification varies over longer time horizons.

dummy variable equal to one after the gamified update period and zero before the gamified update period; $Volume_{itb}$ is the trading volume; and $Volatility_{itb}$ is the difference between the high and low prices scaled by the high price. For the difference-in-differences (DiD) analysis, I use the differences between gamified updates and bug-fix updates for the same broker in a regression setup similar to the one discussed earlier:

$$\Delta DepVar_{itb} = \alpha_i + \beta_1 Post_{tb} + \beta_2 \Delta Volume_{itb} + \beta_3 \Delta Volatility_{itb} + \varepsilon_{itb}, \tag{5}$$

where $\Delta DepVar_{itb}$ is the difference between the gamified updates and the bug-fix updates computed for stock i on day t for a broker b; $\Delta Volume_{itb}$ and $\Delta Volatility_{itb}$ controls are the differences between the volume and volatility estimates for stock i on day t for a broker b during gamified updates and its average value during bug-fix updates.[9] For regressions (4) and (5), variables are winsorized at 1% and 99% and standardized by symbol. Finally, to calculate economic significance, I take the β_1 coefficient from regression (4), which represents the change in the standard deviations post-gamified update, multiply it by standard deviation from the time-series summary statistics (see Appendix A.1 and Table A.1), and divide it by sample mean. This number will represent a change in the variable of interest during the gamified period. Finally, to calculate an effect per update, I divide this number by the average number of updates in the post-gamified period time windows, which is 4.10 in the sample.

[9]To quantify the impact of gamified updates relative to routine bug-fix updates for a given variable, I proceed in two steps. First, I compute the average value of the variable by stock, event day, and broker, using all available bug-fix updates. Then, for each gamified update, I subtract this benchmark average from the corresponding post-update value. For example, suppose a broker implemented 50 bug-fix updates, and the average retail volume for AAPL on the first day following those updates was 2,500 shares. Now consider two gamified updates introduced by the same broker, which resulted in retail volumes of 10,000 and 20,000 shares, respectively, on the first day after each update. The corresponding changes in retail volume, denoted as $\Delta RetailVolume$, would be 7,500 (10,000 - 2,500) for the first gamified update and 17,500 (20,000 - 2,500) for the second.

3. Empirical results

3.1 Retail trading metrics

3.1.1 Retail volume. Retail volume is the lifeblood of the current brokerage business model—and the primary target of gamification. Brokerage firms generate substantial revenue by selling retail order flow to wholesalers, and boosting activity among current users is a direct way to increase that revenue. Experimental studies confirm that game-like features significantly elevate trading intensity among retail participants (Chapkovski, Khapko, and Zoican (2024); OSC (2022); AMF (2022)). However, if retail investors behave rationally and trade based on fundamentals—as suggested by a growing body of research documenting informed behavior and predictive skill among retail traders (Boehmer, Jones, Zhang, and Zhang (2021); Welch (2022))—then app design should play little to no role in shaping their trading volume. In this section, I test which of these competing views better explains retail behavior in real-world markets. The results reveal a clear answer: gamification works.

Figure 2, Panel A illustrates these effects. I capture an increase in retail traded volume post-gamified update.

[Figure 2]

The univariate setup confirms this finding, along with gamified group regressions, where I document an increase in retail traded volume by $2,744$ shares or by 0.012 standard deviations in regression with control variables (Table 3, specifications 1 and 2). Finally, the DiD setting shows a similar increase of 0.012 standard deviations.

[Table 3]

The average gamified update increases retail volume by 0.25%, with the cumulative effect of all gamified updates during the sample period amounting to a striking 35.93% increase in

retail volume.[10] This substantial growth highlights the dramatic impact of gamification on retail trading over the four years analyzed. Such an increase can come from two possible sources: either gamification brings in more retail traders, or it causes existing users to trade more. The following section examines which of these is the main driver behind the rise in retail volume.

3.1.2 Number of retail traders. One key advantage of the experimental design used by Chapkovski, Khapko, and Zoican (2024) and Chapkovski, Khapko, and Zoican (2025) is that it allows researchers to directly control the number of participants. This control enables a clean mapping between changes in trading volume and changes in trading intensity per participant. In contrast, in an empirical setting, I cannot directly observe the number of retail traders before and after a gamified update. Therefore, to draw conclusions about trading intensity, it is critical to first verify that the number of active retail traders remains stable across the pre- and post-update periods.

To address this, I analyze the number of app downloads by new users surrounding gamified updates. If these updates attract new retail traders, we would expect to see an increase in downloads. However, Figure 2, Panel B, shows no such evidence. The dynamics of app downloads remain unchanged relative to the control group and across the pre- and post-event windows. Furthermore, regressions in the univariate, gamified-only, and difference-in-differences settings (Table 3, specifications 3 and 4) confirm that app downloads do not significantly change following gamified updates.

The findings indicate that the rise in retail trading volume following gamified updates is driven primarily by increased trading intensity among existing users, rather than by the entry of new users. This suggests that gamification strengthens engagement among current clients, encouraging them to trade more actively. As a result, brokerage firms stand to benefit, since their revenues under the current market structure are largely tied to trading volume (Sack and Roantree (2021)). However, the magnitude of this benefit depends on how wholesalers respond.

[10] To support the causal interpretation of my findings, I conduct several robustness checks in Section 3.4, including multiple de-trending approaches, a placebo test, and the use of alternative control groups and sample constructions.

If wholesalers lower the per-share payments they offer brokers for routing order flow, the revenue gains from gamification could diminish or even turn negative. This makes it critical to examine how payment for order flow evolves in response to gamified updates.

3.1.3 Payment for Order Flow. Beneath the sleek interfaces of trading apps lies a complex ecosystem governing retail order execution in U.S. markets. When a retail investor places a trade, the order typically bypasses public exchanges and is routed to a wholesaler such as Citadel Securities or Virtu Financial. These firms compete for access to retail flow by offering brokers small monetary incentives per trade—a practice known as payment for order flow (PFOF) (Dyhrberg, Shkilko, and Werner (2025); Ernst and Spatt (2022)). The compensation reflects the expected profitability of internalizing retail order flow: the more uninformed and balanced the flow, the more valuable it is to wholesalers, who are then willing to pay more for it.

Gamification has the potential to alter the value of retail order flow in either direction. If gamified features drive retail investors to act more strategically or coordinate their trades, wholesalers face greater adverse selection and inventory costs, leading them to reduce the PFOF offered to brokers. But if gamification nudges retail traders toward impulsive or noisier strategies, their flow becomes less toxic—posing fewer risks and becoming more valuable to wholesalers.

Figure 2, Panel C and the univariate results show that PFOF increases following gamified updates. In regressions with control variables, I document an increase in PFOF by one-thousandth of a cent per share, or 0.013 standard deviations (Table 3, specifications 5 and 6). The difference-in-differences (DiD) analysis yields a nearly identical estimate. On average, each gamified update raises PFOF by 0.16% with a cumulative increase of 22.99% across the sample—clear evidence that brokers financially benefit via gamifying their platforms.[11][12]

[11] Note that the regression specification in this analysis differs from the baseline model, which uses panel data of stocks over time. Citadel and Virtu report Rule 606 statistics monthly, separately for S&P 500 and non-S&P 500 stocks. See Appendix A.5 for further details.

[12] I also estimate this specification with retail volume as a control variable, given its potentially stronger explanatory power for the variation in the dependent variable. The results remain qualitatively similar to the baseline model and are available upon request.

These results show that gamification alters retail order flow in ways that make it more attractive to wholesalers. Brokerage firms benefit from this shift: gamification increases both the volume of retail trades and the per-share payments they receive for routing them.[13] To explore why retail flow becomes less toxic, the next two sections delve into its most critical components from a wholesaler's perspective: inventory risk and adverse selection, proxied by retail trading imbalance and returns.

3.1.4 Retail imbalance. Previous research shows that retail traders tend to herd, imposing additional inventory costs on market makers (Barber, Odean, and Zhu (2008); Barber, Lin, and Odean (2021)). Whether gamification amplifies or mitigates this herding behavior—and thus alters the cost of liquidity provision—remains an important empirical question. On one hand, experimental evidence suggests that gamification induces noisier and more impulsive trading (Chapkovski, Khapko, and Zoican (2025)). On the other hand, recent meme-stock episodes (e.g., GameStop) demonstrate how excitement—potentially fueled by gamification—can trigger coordinated, herd-like behavior (Costola, Iacopini, and Santagiustina (2021); SEC (2023)). In this section, I test whether gamification affects retail herding, using changes in trading imbalance as a proxy.

Figure 2, Panel D plots the retail imbalance before and after gamified and bug-fix updates as a control group. The chart indicates that retail imbalance tends to decrease following a gamified update. Univariate results show a decrease in retail imbalance by one percentage point (Table 4, specifications 7 and 8). Furthermore, regressions on gamified updates and the DiD setting reveal a decrease in the retail imbalance of 0.020 standard deviations. These numbers translate to a reduction in the retail imbalance of 0.15% per update, amounting to a cumulative decrease of 20.78% due to all gamified updates in the sample.

Taken together, these findings reveal that gamification softens retail inventory pressure on

[13] While I cannot observe the cost of producing these features, brokers' consistent use of gamification suggests it delivers net benefits.

market-makers. By reducing herding, gamified updates foster a noisier retail order flow—one that is easier for liquidity providers to absorb and manage. While this behavioral shift benefits market makers by lowering inventory risks, it also raises concerns about the second channel of market-making costs: adverse selection. The following section examines whether gamification nudges retail traders not only to trade more noisily, but also to trade worse.

3.1.5 Retail return and volatility. Investors typically evaluate their performance using two key metrics: (i) return on investment and (ii) return volatility. Gamification can influence both—either improving retail trading outcomes or undermining them. It may act as a harmful distraction that impairs judgment and encourages excessive risk-taking (Chapkovski, Khapko, and Zoican (2025); Peress and Schmidt (2020)), or as a motivating force that fosters engagement and financial learning (Baptista and Oliveira (2017)). Depending on which channel dominates, gamification might reduce the toxicity of order flow—or intensify it.

To examine which effect prevails, I study how retail traders' returns and return volatility respond to gamified updates. Figure 3, Panel A and B plots intraday return and intraday return volatility following gamified updates (green solid line) and control group updates (gray dotted line). The plots show that retail traders' performance deteriorates in both respects: their return declines and their return volatility increases post-gamified update.

[Figure 3]

The regression results corroborate this finding (Table 4, specifications 1 through 4). The retail return declines by 0.06 bps in a univariate setting, by 0.011 standard deviations in the regression on gamified updates, and by 0.008 standard deviations in the DiD setup. This is accompanied by a return volatility increase of 0.01 bps in a univariate setting, 0.015 standard deviations in the regression on gamified updates, and 0.015 standard deviations in the DiD setup. Each gamified update decreases the retail return by 0.15% and increases the return volatility by 0.20%. The

cumulative effect from all gamified updates in the sample is 21.95% for the retail return and 27.71% for the return volatility.

[Table 4]

The findings reveal that gamification benefits market makers by making retail order flow less toxic, but it comes at the expense of retail traders. Their performance deteriorates along two key dimensions: their strategies yield lower returns and expose them to greater risk.[14] This decline appears to stem from disrupted judgment. Prior research suggests that crowds can make wise decisions when left undisturbed by external influences (Kelley and Tetlock (2013); Da and Huang (2020); Frey and Van de Rijt (2021)). Gamification likely acts as such a disruptor, diverting limited attention away from rational decision-making and toward noisier, more impulsive trading behavior (Chapkovski, Khapko, and Zoican (2024)).[15]

One way wholesalers might offset the losses retail traders incur due to gamification is by improving the terms of trade. In modern markets, this often takes the form of *price improvement*—a practice in which wholesalers execute retail orders at better prices than those quoted on public exchanges. This benefits retail traders by shaving a fraction off execution costs. If market makers consistently offer greater price improvement—and do so more frequently after gamification—they may partially compensate for the deteriorated performance of retail investors. The next section examines whether market makers adopt this strategy in response to gamified retail flow.

[14] At first glance, it might seem counterintuitive that intraday retail return volatility can increase while retail trading imbalance declines. It is important to note that retail trading imbalance is simply the difference between retail buy and sell volumes. In contrast, intraday retail return volatility is more concerned with the timing of trades rather than their direction. Even if retail imbalance declines, intraday retail return volatility can still rise if retail investors time the market well at one point and fail to do so at another.

[15] While the decline in retail returns clearly harms retail investors, the rise in return volatility requires further discussion. My conclusion that increased volatility is detrimental assumes retail traders are risk-averse. In reality, gamification may increase their appetite for risk, prompting lottery-like trading behavior (Eraker and Ready (2015)). Though my data cannot directly test this, I find suggestive evidence: the effect of gamification is stronger for stocks with lottery-like characteristics, such as small-cap and high-beta stocks (see Appendix A.4).

3.1.6 Price Improvement. Price improvement sits at the center of a strategic tradeoff for wholesalers. On one hand, offering better and more frequent price improvements can help attract additional retail volume—especially valuable after gamification reduces order flow toxicity. It also provides a practical justification for the higher payments wholesalers make to brokerages, helping legitimize the increased payment for order flow discussed in Section 3.1.3 (Battalio and Jennings (2023a)). On the other hand, better execution quality comes at a cost: wholesalers must sacrifice spread revenue on each trade. The data show that the first incentive prevails—wholesalers respond to gamified retail flow by increasing both the size and frequency of price improvement.

Figure 3, Panels C and D, plots standardized price improvement and the percentage of price-improved trades following gamified updates (green solid line) and control group updates (gray dotted line). The plots indicate that retail trading conditions improve along both dimensions: retail orders begin to receive larger and more frequent price improvements after gamified updates.

The regression results support this pattern (Table 4, specifications 5 through 8). The average price improvement increases by 3 cents in the univariate setting, by 0.011 standard deviations in the regression using only gamified updates, and by 0.012 standard deviations in the difference-in-differences (DiD) specification. Similarly, the share of price-improved trades rises by 0.29 percentage points in the univariate setting, 0.142 standard deviations in the gamified-update regression, and 0.124 standard deviations in the DiD setup. In economic terms, each gamified update is associated with a 0.05% increase in average price improvement and a 0.08% increase in the frequency of price-improved trades. Cumulatively, all gamified updates in the sample yield a 7.51% increase in average price improvement and a 11.05% increase in the percentage of price-improved trades.[16][17]

[16] I also estimate this specification with retail volume as a control variable, given its potentially stronger explanatory power for the variation in the dependent variable. The results remain qualitatively similar to the baseline model and are available upon request.

[17] Note that the regression specification in this analysis differs from the baseline model, which uses daily panel data of stocks. In contrast, Rule 605 provides trading characteristics at a monthly frequency. See Appendix A.6 for

Gamification reshapes not only how retail investors trade, but also how wholesalers respond to that flow. As shown above, retail orders receive both larger and more frequent price improvements following gamified updates. Yet while wholesalers enhance execution quality for retail traders, they reward brokers even more generously. The increase in payment for order flow, as discussed in Section 3.1.3, is roughly three times larger in economic magnitude than the rise in price improvement—suggesting that wholesalers prioritize incentivizing brokers to maintain and expand gamification features. Despite receiving better trade prices, retail investors remain net losers in this system—their returns deteriorate even after accounting for the improved execution. Ultimately, gamification alters the economics of trading in ways that benefit brokers and wholesalers more than the clients they serve.

To this point, the evidence suggests that gamification benefits brokerage firms and market makers while harming retail investors. Yet this might not be the whole story. Financial markets are not made up of isolated participants; they operate as tightly interconnected systems. A shift in behavior by one group can reshape the incentives, strategies, and outcomes for others. This prompts an exploration of whether the effects of gamification extend beyond retail trading to influence broader market dynamics.

3.2 Market-wide liquidity

What begins as a design tweak in a trading app can cascade through the entire market ecosystem. Gamification shifts retail behavior—but its implications may not end there. On one hand, as shown by Eaton, Green, Roseman, and Wu (2022), a less toxic retail order flow can lower trading costs and improve operating efficiency for market makers. In a competitive environment, these savings may translate into narrower spreads and improved market quality. Yet the opposite scenario is also plausible: gamification might trigger speculative surges in retail trading, increasing

further details.

volatility and undermining liquidity, as cautioned by Barber, Huang, Odean, and Schwarz (2022). This concern is far from abstract, given the rise in retail return volatility documented in Section 3.1.5. Finally, if the effect of gamification is modest or the market-making landscape is concentrated enough, wholesalers might internalize all gains, leaving no footprint on broader market quality. As the results show, however, gamification doesn't stay contained—it alters the market itself.

3.2.1 Quoted and effective spreads. To test if gamification changes market-wide liquidity, I examine two liquidity proxies: quoted spread and effective spread. The quoted spread measures displayed liquidity, that is, trading costs advertised by liquidity providers. In turn, the effective spread captures liquidity costs that market participants actually incur. Thus, effective spread accounts for the fact that trades are often timed to periods when liquidity is relatively cheap.

[Figure 4]

Both liquidity metrics decline following gamified updates (Figure 4, Panels A and B). The univariate setting shows a decrease in quoted and effective spreads by 0.02 bps and 0.03 bps, respectively (Table 5, specifications 1 through 4). In a regression setting, these values are 0.163 and 0.089 standard deviations, respectively. Finally, the DiD setup shows a significant decline in spreads by 0.130 and 0.064 standard deviations. These numbers translate to a decrease in quoted and effective spreads of 0.10% and 0.08% per update or by 13.92% and 11.46% cumulatively across all gamified updates in the sample.

[Table 5]

The results provide evidence that market makers transmit the associated benefits of gamification to the rest of the market, resulting in a decline in quoted and effective spreads. To better understand the source of these benefits, in the following section, I decompose effective spread into

its components, price impact and realized spread, to see how these are changing post-gamified updates.

3.2.2 Price impact and realized spread. The previous findings show that trading gamification decreases retail return, which should reduce the adverse selection that retail traders impose on market makers. Moreover, retail imbalance also decreases, which should decrease market makers' trading costs associated with order processing. Since price impact is considered a proxy of adverse selection and realized spread is regarded as a proxy of order processing costs, these variables are expected to decrease post-gamified updates.

In line with this argument, the results show that price impact and realized spreads decreased post-gamified period (Figure 4, Panels C and D). Price impact and realized spread declined by 0.02 and 0.01 bps in the univariate setup (Table 5, specifications 5 through 8). The regressions analysis run on gamified updates, and the DiD setup have corresponding decreases of 0.072, 0.040, 0.054, and 0.054 standard deviations, respectively. On average, each gamified update decreases the price impact by 0.09% and the realized spread by 0.06%. Taken together, all gamified updates in the sample decrease the price impact by 13.11% and the realized spread by 8.55%.

The results show that while gamification starts with retail traders, its effects ripple through the entire market. By reducing the toxicity of retail order flow, gamified updates ease execution for liquidity providers. This, in turn, fosters broader improvements in market quality. Specifically, trading costs decline—both adverse selection and order processing costs fall, as captured by narrower price impact and realized spread measures. These changes align with the theory of Baldauf, Mollner, and Yueshen (2024), which argues that market makers intermediate heterogeneous order flows and pass cost savings on to other market participants. The findings also echo Eaton, Green, Roseman, and Wu (2022), who find that less toxic retail flow improves spreads and overall market quality. The next section investigates whether gamification influences additional facets of market quality beyond trading costs.

3.3 Market-wide volume and return

In the earlier sections, I used market-wide volume and stock price volatility as regression controls since these two variables are known trading cost determinants. Now, I ask if these market-wide variables, along with return and return volatility, undergo changes due to gamification. The lower trading costs identified in the previous section due to gamification may result in greater trading volume, as more agents engage in trading activity when doing so is cheaper.

When it comes to market-wide price and return volatility, I rely on theory and prior empirical evidence to expect a decline in volatility following gamification. Specifically, Roşu (2019) suggests that trading strategies that generate adverse selection often result in greater volatility. Shkilko and Sokolov (2020) and Indriawan, Pascual, and Shkilko (2022) empirically confirm this association. Since the data show adverse selection declines post-gamified updates, volatility may also decline.

Figure 5, Panels A and B confirms these expectations. Gamification increases traded volume by non-retail traders. In the univariate setting, gamification leads to a volume increase of 42 thousand shares. Moreover, regressions on gamified updates and the DiD setting report an increase in volume by 0.051 standard deviations. Meantime, gamification does not significantly affect market returns. Although univariate results indicate a slight increase in market returns following gamification updates, this finding disappears in regression analyses.

[Figure 5]

Both price and return volatility decrease after the gamification update, as shown in Figure 5, Panels C and D and the univariate results in Table 6, specifications 5 through 8. Regressions on gamified updates and control variables indicate that price and return volatility decrease by 0.066 and 0.009 standard deviations, respectively. Similarly, in DiD analysis, price and return volatility decrease by 0.066 and 0.010 standard deviations, respectively.[18]

[18]It is important to note that the BJZZ algorithm does not identify 100% of retail trading volume in the TAQ

[Table 6]

On average, each gamification update is associated with a 0.15% increase in traded volume, a 0.08% decrease in price volatility, and a 0.04% decrease in return volatility. The cumulative effect of 142 updates leads to a 21.19% increase in traded volume, a 12.00% decrease in price volatility, and a 5.20% decrease in return volatility. These results suggest that gamification is associated with greater price and return stability and potentially greater gains from trade, as more market participants may enter the market to engage in asset exchange.

Taken together, the evidence paints a multifaceted picture of trading gamification: it harms retail traders, enriches intermediaries, and yet improves market quality. Retail traders trade more but perform worse, experiencing lower returns and higher risk—even as trading conditions improve due to better execution from wholesalers. Brokerage firms benefit from increased trading volume and higher payment for order flow, while market makers profit from less toxic order flow. Crucially, some of these efficiency gains are passed on to the broader market in the form of tighter spreads, lower volatility, and greater trading activity. The next section tests the robustness of these findings, followed by a final discussion that concludes the paper.

3.4 Robustness

3.4.1 Varying event windows. In Section 2.6, I mentioned that the results are robust to varying the length of event windows. In the main text, the event windows include 20 trading days before a gamified update and 20 trading days after. Table 7 shows the results of these robustness checks, with the first line referencing the base regression case with a 20 trading days event windows.

[Table 7]

dataset. As a result, the rest-of-the-market variables in my analysis may be contaminated by unidentified retail trades. To ensure this does not bias my results, I conduct a robustness check by re-estimating the main regressions with retail volume included as an additional control variable. The rationale is that identified retail volume should be positively correlated with the unidentified portion, thereby mitigating—if not fully eliminating—the bias. The results from this specification are qualitatively similar to those in the baseline model and are available upon request.

First, I examine several adjustments to the event windows. In line 2 of Table 7, I shortened the period to 15 trading days before and 15 trading days after the gamified update. Line 3 reports the *Post* coefficient for an extended event window of 25 trading days. All the results remain consistent with the base case. In Appendix A.7, I extend event windows even further to test if the effect of gamification is different in the short and long run.

3.4.2 De-trend. One potential concern for a causal interpretation of the results is the confounding effect of long-term trends. Indeed, the analysis spans over four years of stock trading data. Angel, Harris, and Spatt (2015) reported that in the 21st century, spreads generally trend downward, while trading volume trends upward. Moreover, McCabe (2021) has reported a steady increase in retail trading over recent years. The direction of these changes coincides with my findings, which may bias the results upward. To mitigate these effects, in Table 7, line 4, I regress every variable of interest on the time trend as follows:

$$DepVar_{it} = \alpha + \beta Trend_t + \varepsilon_{it}, \tag{6}$$

and use the estimated residuals $\hat{\varepsilon}_{it}$ as dependent variables in all subsequent tests. Results stay consistent with the base case.

Next, I use an alternative detrending procedure. I follow Hausman and Rapson (2018) and detrend the time-series on a symbol-by-symbol basis using polynomial time trend regressions. Hausman and Rapson (2018) also suggests that it may be useful to account for possible serial dependence in the dependent variable and error terms. Following this suggestion, I detrend my variables using the polynomial and an additional AR(1) term. Besides detrending, I follow the same data cleaning and adjustment procedures. The line 5 in Table 7 shows that the results obtained using this approach remain in line with those in the main text. Regression results for PFOF are not reported due to data limitations.

3.4.3 Placebo test. An additional way to confirm that background trends do not drive the results is to use a placebo test. If such a trend drives the regression results, the findings will hold regardless of the timing of gamified updates. To test it, I capture the performance of the dependent variable precisely one year before the actual gamified update occurred, following an approach similar to Li and Tang (2016). Then, I subtract this value from the baseline regression:

$$\Delta DepVar_{i,t,t-1,b} = \alpha_i + \beta_1 Post_{t,b} + \beta_2 \Delta Volume_{i,t,t-1,b} + \beta_3 \Delta Volatility_{i,t,t-1,b} + \varepsilon_{i,t,t-1,b}, \quad (7)$$

where $\Delta DepVar_{i,t,t-1,b}$ represents the difference between the gamified update and the date one year prior for stock i on the day t for a broker b and one year prior on day $t-1$. The $\Delta Volume_{i,t,t-1,b}$ and $\Delta Volatility_{i,t,t-1,b}$ controls represent the differences between the volume and volatility. The results for $Post_{t,b}$ are reported in Table 7, line 8. None of the findings deviate substantially from the baseline.

3.4.4 Tick-constrained stocks. One limitation of the BJZZ retail trading identification algorithm is its reliance on the amount of sub-penny price improvement. If the bid-ask spread for a stock is wide, the reliability of inferences based on price improvement decreases. Consequently, Barber, Huang, Jorion, Odean, and Schwarz (2024) notes that stocks with bid-ask spreads constrained by one tick should have the highest BJZZ identification rate. Although the results in the main analysis show statistical significance (see Table 3.4, line 1), it is still interesting to examine the effect of the gamification of stock trading on the most liquid stocks in my sample.

From the initial sample of 1,404 stocks, I selected those that traded at a 1-tick bid-ask spread for more than half of the total trading hours on each trading day between 2018 and 2021. This filtering yielded a final sample of 63 of the most liquid stocks in the market. Results for this subsample are reported in line 9 of Table 7. The findings for retail trading metrics remain consistent with the main analysis. However, I find that gamification does not affect market-wide outcomes—other than trading volume—likely because these stocks already exhibit exceptionally

high market quality, leaving limited room for further improvement.

3.4.5 Canadian control group. One concern about using bug-fix updates as a control group is their timing. Since gamified and bug-fix updates occur at different times, comparability may be an issue. To alleviate this concern, I plot bug-fix and gamified updates for all figures in this paper. Visual analysis of these figures is convincing that the parallel trend assumption is not violated.

To further assuage concerns about the timing of bug-fix updates, I use an alternative control group that coincides with the dates of gamified updates. I used a control sample of stocks traded in Canada, which was matched with the main U.S. sample by market capitalization and trading volume. The Canadian data have daily granularity and resemble CRSP data.[19] To compare the two samples, I rely on two low-frequency spread proxies developed for CRSP-like datasets: (i) the end-of-day quoted spread, EOD, and (ii) the effective spread proxy of Abdi and Ranaldo (2017), AR. Abdi and Ranaldo (2017) shows that the EOD quoted spread is the most accurate low-frequency liquidity proxy. Still, since the high-frequency metrics distinguish between quoted and effective spreads, I complement the EOD quoted spreads with the above-mentioned effective spread proxy.

For this analysis, I use the differences in the variables of interest as well as regressors between the sample stocks and their controls in a regression setup similar to that discussed earlier:

$$\Delta DepVar_{itb} = \alpha_i + \beta_1 Post_{tb} + \beta_2 \Delta Volume_{itb} + \beta_3 \Delta Volatility_{itb} + \varepsilon_{itb}, \tag{8}$$

where $\Delta DepVar_{it}$ is the difference between the spread proxies (i.e., EOD and AR) computed for day t, broker b, that falls into the event window for a pair of stocks i that includes a U.S. sample stock and its matched Canadian counterpart, $Post_{tb}$ is a dummy variable equal to one after the gamified update and zero before, $\Delta Volume_{itb}$ and $\Delta Volatility_{itb}$ controls are the differences between the U.S. and Canadian volume and volatility estimates. As before, this regression stan-

[19] Canadian data comes from TMX money, a financial data aggregator (https://money.tmx.com/)

dardizes all non-dummy variables by stock and uses standard errors clustered by stock and day. Table 7 line 10 reports the *Post* coefficient estimates.

While it is unfortunate that Canadian data are unavailable for many key variables in this study, the results for the variables we can observe closely mirror those from previous specifications. This consistency strengthens the case that observed changes in the dependent variables are attributable to gamified updates rather than model misspecification.

4. Conclusion

Since the start of the informational revolution, humanity has gained an unprecedented ability to capture, quantify, and rapidly update countless aspects of its activities. This data can be organized and presented back to people through eye-catching infographics, stylish visualizations, and projected trends. For individuals, such tools can transform even the most ordinary tasks into enjoyable and engaging experiences that resemble a game, from which the word *gamification* gets its root.

Gamification of stock trading is a recent tactic by brokerage firms to add game-like features to their trading apps and boost user engagement. In this study, I analyzed all updates that 17 major U.S. brokerage firms implemented in their mobile trading apps from 2018 to 2021. In total, I identified 142 updates associated with the gamification of the trading process in these apps. The results of the study reveal that gamification creates a distinct set of winners and losers.

Brokerage firms emerge as clear beneficiaries of gamification. Retail trading volume rises substantially, as does the per-share payment for order flow they receive from wholesalers. These effects reveal strong financial incentives for brokers to gamify their platforms, encouraging excessive and sub-optimal trading among existing clients.

Gamification also reshapes the character of retail order flow. Trading becomes noisier and less informed, as evidenced by declines in both retail return and trading imbalance. This shift

makes order flow easier to manage for market makers, improving their operational efficiency by reducing adverse selection and inventory risks. The resulting ease of execution ultimately benefits the broader market, manifesting in lower trading costs and improved market quality—narrower spreads, higher volumes, and reduced volatility.

But these market-wide gains come at a cost. Retail traders—the primary targets of gamified features—are the only group consistently worse off. Their trading becomes more volatile and less profitable, despite modest improvements in execution quality provided by wholesalers.

These findings point to an ethical dilemma. Gamification improves market functioning but does so by exploiting behavioral vulnerabilities among retail investors. Whether such a trade-off is acceptable depends on how much value we place on investor protection—and whose welfare the modern market is ultimately built to serve.

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Table 1: Sample of Brokerage Firms

This table lists U.S. brokerage firms in the sample, their mobile app names available for download on the AppStore, the number of updates associated with the introduction of new game-like features on their app, the number of bug-fix updates, and the average number of daily app downloads. The data cover the period from 2018 to 2021.

Broker Name	Mobile App Name	# Gamified Updates	# Bug Fix Updates	# App Downloads
Fidelity	Fidelity Investments	9	46	3,412
Vanguard	Vanguard	1	43	1,267
TD Ameritrade	TD Ameritrade Mobile	19	44	2,706
Interactive Brokers	IBKR Mobile - Invest Worldwide	15	42	165
E*TRADE	E*Trade: Invest. Trade. Save.	10	53	2,379
Merrill Edge	Merrill Edge	5	44	440
Webull	Webull: Investing & Trading	19	145	4,474
Robinhood	Robinhood: Investing for All	2	242	16,159
TradeStation	TradeStation - Trade & Invest	11	73	164
Ally Invest	Ally Mobile: Bank & Invest	7	56	1,293
Charles Schwab	Schwab Mobile	8	23	1,373
Betterment	Betterment: Investing & Savings	6	138	416
SoFi	SoFi - Invest, Trade, Borrow	7	123	2,092
Tastyworks	tastyworks	9	47	104
M1 Finance	M1 Finance – Free Investing	3	195	833
Public	Public.com - Stocks & Crypto	9	101	2,840
Lightspeed	Lightspeed Mobile	2	4	24

Table 2: Descriptive Statistics

This table reports sample summary statistics. Panel A includes market capitalization, daily trading volume, and share price. Panel B reports retail trading metrics, including retail traded volume, retail trading imbalance, price improvement amount, percentage of price-improved trades, per-share payment for order flow, retail intraday return, and retail intraday return volatility calculated as squared retail intraday return. Panel C reports liquidity metrics including quoted, effective, and realized spreads, as well as price impact. Panel D reports market-wide metrics that exclude retail trades from the calculation. These include daily trading volume, intraday return, price volatility, and intraday return volatility, with the former computed as the difference between the day's high and low prices scaled by the high price. The data cover the sample period of 2018-2021. I first compute the averages for each stock during the sample period and then calculate the reported statistics across stocks.

	Mean	St. dev.	25^{th}	Median	75^{th}
Panel A: Sample characteristics					
Market capitalization, $B	19.54	73.93	1.33	3.71	12.55
Volume, sh. '000	1,649	3,845	299	653	1,521
Price, $	80.89	157.11	20.00	48.05	93.86
Panel B: Retail trading					
Retail volume, '000	182	657	15.82	38.06	117
Retail imbalance	0.20	0.06	0.15	0.19	0.24
Price improvement, ¢	6.53	23.39	0.17	3.92	5.98
Price improved trades, %	94.32	3.88	92.35	94.75	100.00
Payment for order flow, $\frac{1}{100}$¢	1.05	1.28	0.43	1.56	2.72
Intraday return, bps.	4.46	5.82	1.17	2.94	5.37
Intraday return volatility, bps	0.15	0.20	0.04	0.08	0.16
Panel C: TAQ liquidity metrics, bps.					
Quoted spread	23.93	23.19	9.84	18.16	29.22
Effective spread	13.99	17.50	5.20	8.52	14.96
Price impact	7.42	6.12	3.30	5.46	9.11
Realized spread	6.56	1.21	1.80	3.18	5.70
Panel D: The rest of the market					
Volume, sh. '000	1,467	3,251	279	606	1,521
Intraday return, bps.	2.29	4.12	0.75	1.19	2.08
Price volatility, bps.	0.04	0.02	0.03	0.03	0.04
Intraday return volatility, bps	0.06	0.22	0.01	0.02	0.04

Table 3: Retail Metrics - Volume, App Downloads, PFOF, and Imbalance

This table presents three sets of results: Panel A reports univariate comparisons; Panel B shows regression estimates following gamification updates; and Panel C provides difference-in-differences regression estimates comparing gamification updates to bug-fix updates. The analyses assess the impact of gamified updates on retail traded volume, the number of daily app downloads, per-share payment for order flow, and retail volume imbalance. Panel A compares the metrics in the pre-gamified update window to those in the post-gamified update window. Panel B reports the coefficient estimates from the following model:

$$DepVar_{itb} = \alpha_i + \beta_1 Post_{tb} + \beta_2 Volume_{itb} + \beta_3 Volatility_{itb} + \varepsilon_{itb}, \tag{4}$$

where $DepVar_{itb}$ represents some variable of interest for stock i on day t for a broker b; $Post_{tb}$ is a dummy variable equal to one after the gamified update period and zero before the gamified update period; $Volume_{itb}$ is the trading volume; and $Volatility_{itb}$ is the difference between the high and low prices scaled by the high price. Panel C reports the coefficient estimates from the following model:

$$\Delta DepVar_{itb} = \alpha_i + \beta_1 Post_{tb} + \beta_2 \Delta Volume_{itb} + \beta_3 \Delta Volatility_{itb} + \varepsilon_{itb}, \tag{5}$$

where $\Delta DepVar_{itb}$ is the difference between the gamified updates and the bug fix updates computed for stock i on day t for a broker b; $\Delta Volume_{itb}$ and $\Delta Volatility_{itb}$ controls are the differences between the volume and volatility estimates for stock i on day t for a broker b during gamified updates and its average value during bug-fix updates. For regressions (4) and (5), the variables are winsorized at 1% and 99% and standardized by symbol, as such models control for stock fixed effects. Standard errors in parentheses are double-clustered across firms and over time. I do not report the coefficient estimates for the control variables in gamified group regressions to conserve space. Asterisks ***, **, and * denote the 0.01, 0.05, and 0.10 levels of statistical significance.

	Retail Volume				App Downloads				Payment For Order Flow				Retail Imbalance			
	[1]		[2]		[3]		[4]		[5]		[6]		[7]		[8]	
Panel A: Univariate Results																
Pre	177.8				1,914				1.01				0.20			
Post	180.5	***			1,916				1.11	***			0.19	***		
Panel B: Gamification Updates																
Post	0.025	***	0.012	***	0.000		0.001		0.017	***	0.013	***	-0.020	***	-0.020	***
Panel C: Gamification vs. Bug-Fix Updates (DiD)																
Post	0.025	***	0.012	***	0.002		0.003		0.016	***	0.013	***	-0.020	***	-0.020	***
	(0.00)		(0.00)		(0.01)		(0.01)		(0.00)		(0.00)		(0.01)		(0.01)	
ΔVolume			0.650	***			0.032	***			0.004	**			-0.050	***
			(0.00)				(0.00)				(0.00)				(0.00)	
ΔVolatility			0.129	***			0.043	***			-0.042	***			-0.035	***
			(0.00)				(0.00)				(0.00)				(0.00)	
Intercept	0.001		0.002		-0.001		0.001		0.005	**	0.003		0.000		0.000	
	(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.01)	

Table 4: Retail Metrics - Return, Volatility, and Price Improvement

This table presents three sets of results: Panel A reports univariate comparisons; Panel B shows regression estimates following gamification updates; and Panel C provides difference-in-differences regression estimates comparing gamification updates to bug-fix updates. The analyses assess the impact of gamified updates on retail intraday return, retail intraday return volatility, retail trades price improvement, and percentage of price-improved trades. Panel A compares the metrics in the pre-gamified update window to those in the post-gamified update window. Panel B reports the coefficient estimates from the following model:

$$DepVar_{itb} = \alpha_i + \beta_1 Post_{tb} + \beta_2 Volume_{itb} + \beta_3 Volatility_{itb} + \varepsilon_{itb}, \tag{4}$$

where $DepVar_{itb}$ represents some variable of interest for stock i on day t for a broker b; $Post_{tb}$ is a dummy variable equal to one after the gamified update period and zero before the gamified update period; $Volume_{itb}$ is the trading volume; and $Volatility_{itb}$ is the difference between the high and low prices scaled by the high price. Panel C reports the coefficient estimates from the following model:

$$\Delta DepVar_{itb} = \alpha_i + \beta_1 Post_{tb} + \beta_2 \Delta Volume_{itb} + \beta_3 \Delta Volatility_{itb} + \varepsilon_{itb}, \tag{5}$$

where $\Delta DepVar_{itb}$ is the difference between the gamified updates and the bug fix updates computed for stock i on day t for a broker b; $\Delta Volume_{itb}$ and $\Delta Volatility_{itb}$ controls are the differences between the volume and volatility estimates for stock i on day t for a broker b during gamified updates and its average value during bug-fix updates. For regressions (4) and (5), the variables are winsorized at 1% and 99% and standardized by symbol, as such models control for stock fixed effects. Standard errors in parentheses are double-clustered across firms and over time. I do not report the coefficient estimates for the control variables in gamified group regressions to conserve space. Asterisks ***, **, and * denote the 0.01, 0.05, and 0.10 levels of statistical significance.

	Retail Return				Return Volatility				Price Improvement				Price-Improved Trades			
	[1]		[2]		[3]		[4]		[5]		[6]		[7]		[8]	
Panel A: Univariate Results																
Pre	4.63				0.14				6.51				94.15			
Post	4.57	***			0.15	***			6.54	***			94.44	***		
Panel B: Gamification Updates																
Post	-0.011	***	-0.011	***	0.030	***	0.015	***	0.013	***	0.011	**	0.147	***	0.142	***
Panel C: Gamification vs. Bug-Fix Updates (DiD)																
Post	-0.008	***	-0.008	***	0.030	***	0.015	***	0.012	***	0.012	**	0.137	***	0.124	***
	(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)	
ΔVolume			-0.001				0.017	***			0.005	*			0.003	
			(0.00)				(0.00)				(0.00)				(0.00)	
ΔVolatility			0.000				0.292	***			-0.019	***			-0.011	**
			(0.00)				(0.00)				(0.00)				(0.00)	
Intercept	-0.001		-0.001		-0.001		0.000		0.000		0.000		0.000		-0.001	
	(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)	

Table 5: Liquidity Costs

This table presents three sets of results: Panel A reports univariate comparisons; Panel B shows regression estimates following gamification updates; and Panel C provides difference-in-differences regression estimates comparing gamification updates to bug-fix updates. The analyses assess the impact of gamified updates on quoted spread, effective spread, price impact and realized spread. Panel A compares the metrics in the pre-gamified update window to those in the post-gamified update window. Panel B reports the coefficient estimates from the following model:

$$DepVar_{itb} = \alpha_i + \beta_1 Post_{tb} + \beta_2 Volume_{itb} + \beta_3 Volatility_{itb} + \varepsilon_{itb}, \tag{4}$$

where $DepVar_{itb}$ represents some variable of interest for stock i on day t for a broker b; $Post_{tb}$ is a dummy variable equal to one after the gamified update period and zero before the gamified update period; $Volume_{itb}$ is the trading volume; and $Volatility_{itb}$ is the difference between the high and low prices scaled by the high price. Panel C reports the coefficient estimates from the following model:

$$\Delta DepVar_{itb} = \alpha_i + \beta_1 Post_{tb} + \beta_2 \Delta Volume_{itb} + \beta_3 \Delta Volatility_{itb} + \varepsilon_{itb}, \tag{5}$$

where $\Delta DepVar_{itb}$ is the difference between the gamified updates and the bug fix updates computed for stock i on day t for a broker b; $\Delta Volume_{itb}$ and $\Delta Volatility_{itb}$ controls are the differences between the volume and volatility estimates for stock i on day t for a broker b during gamified updates and its average value during bug-fix updates. For regressions (4) and (5), the variables are winsorized at 1% and 99% and standardized by symbol, as such models control for stock fixed effects. Standard errors in parentheses are double-clustered across firms and over time. I do not report the coefficient estimates for the control variables in gamified group regressions to conserve space. Asterisks ***, **, and * denote the 0.01, 0.05, and 0.10 levels of statistical significance.

	Quoted Spread				Effective Spread				Price Impact				Realized Spread			
	[1]		[2]		[3]		[4]		[5]		[6]		[7]		[8]	
Panel A: Univariate Results																
Pre	22.64				14.04				7.59				6.42			
Post	22.62	***			14.01	***			7.57	***			6.41	***		
Panel B: Gamification Updates																
Post	-0.179	***	-0.163	***	-0.104	***	-0.089	***	-0.088	***	-0.072	***	-0.057	***	-0.054	***
Panel C: Gamification vs. Bug-Fix Updates (DiD)																
Post	-0.144	***	-0.130	***	-0.074	***	-0.064	***	-0.050	***	-0.040	***	-0.056	***	-0.054	***
	(0.02)		(0.02)		(0.02)		(0.02)		(0.01)		(0.01)		(0.01)		(0.01)	
ΔVolume			-0.102	***			-0.024	***			-0.014	***			-0.017	***
			(0.01)				(0.01)				(0.00)				(0.00)	
ΔVolatility			0.190	***			0.173	***			0.184	***			0.031	***
			(0.01)				(0.01)				(0.01)				(0.00)	
Intercept	0.001		0.019	***	-0.006		-0.008		-0.012	**	-0.016	**	0.005		0.004	
	(0.01)		(0.01)		(0.01)		(0.01)		(0.01)		(0.01)		(0.00)		(0.01)	

Table 6: Market-Wide Metrics

This table presents three sets of results: Panel A reports univariate comparisons; Panel B shows regression estimates following gamification updates; and Panel C provides difference-in-differences regression estimates comparing gamification updates to bug-fix updates. The analyses assess the impact of gamified updates on market volume, return, price volatility and return volatility where retail trades are excluded. Panel A compares the metrics in the pre-gamified update window to those in the post-gamified update window. Panel B reports the coefficient estimates from the following model:

$$DepVar_{itb} = \alpha_i + \beta_1 Post_{tb} + \beta_2 Volume_{itb} + \beta_3 Volatility_{itb} + \varepsilon_{itb}, \tag{4}$$

where $DepVar_{itb}$ represents some variable of interest for stock i on day t for a broker b; $Post_{tb}$ is a dummy variable equal to one after the gamified update period and zero before the gamified update period; $Volume_{itb}$ is the trading volume; and $Volatility_{itb}$ is the difference between the high and low prices scaled by the high price. Panel C reports the coefficient estimates from the following model:

$$\Delta DepVar_{itb} = \alpha_i + \beta_1 Post_{tb} + \beta_2 \Delta Volume_{itb} + \beta_3 \Delta Volatility_{itb} + \varepsilon_{itb}, \tag{5}$$

where $\Delta DepVar_{itb}$ is the difference between the gamified updates and the bug fix updates computed for stock i on day t for a broker b; $\Delta Volume_{itb}$ and $\Delta Volatility_{itb}$ controls are the differences between the volume and volatility estimates for stock i on day t for a broker b during gamified updates and its average value during bug-fix updates. For regressions (4) and (5), the variables are winsorized at 1% and 99% and standardized by symbol, as such models control for stock fixed effects. Standard errors in parentheses are double-clustered across firms and over time. I do not report the coefficient estimates for the control variables in gamified group regressions to conserve space. Asterisks ***, **, and * denote the 0.01, 0.05, and 0.10 levels of statistical significance.

	Volume				Return		Price Volatility				Return Volatility			
	[1]		[2]		[3]	[4]	[5]		[6]		[7]		[8]	
Panel A: Univariate Results														
Pre	1,452				2.354		0.041				0.005			
Post	1,494	**			2.372	*	0.036	***			0.004	***		
Panel B: Gamification Updates														
Post	0.025	***	0.051	***	-0.001	-0.000	-0.050	***	-0.066	***	-0.013	***	-0.009	***
Panel C: Gamification vs. Bug-Fix Updates (DiD)														
Post	0.025	***	0.051	***	-0.003	-0.003	-0.050	***	-0.066	***	-0.013	***	-0.010	***
	(0.00)		(0.00)		(0.00)	(0.00)	(0.00)		(0.00)		(0.00)		(0.00)	
ΔVolume						0.000			0.527	***			0.071	***
						(0.00)			(0.00)				(0.00)	
ΔVolatility			0.527	***		0.000							0.255	***
			(0.00)			(0.00)							(0.00)	
Intercept	0.005	*	0.004	**	0.002	0.002	-0.001		-0.001		0.000		-0.001	
	(0.00)		(0.00)		(0.00)	(0.00)	(0.00)		(0.00)		(0.00)		(0.00)	

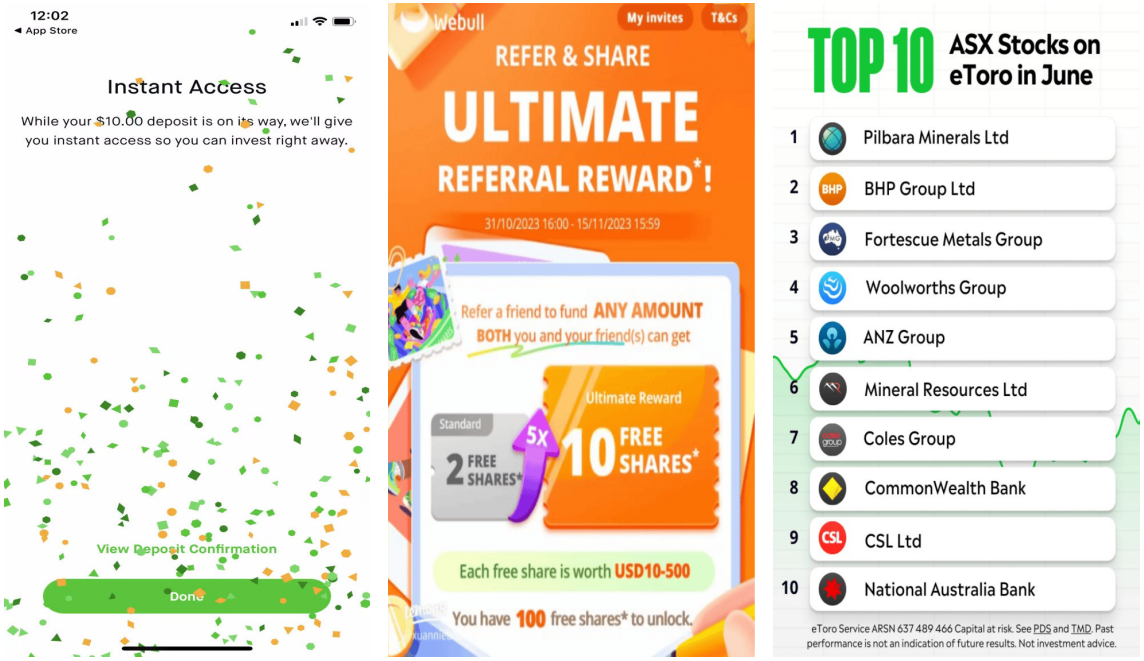
Table 7: Robustness

This table reports the results of robustness tests that estimate the coefficients of the regression equation (5) using a set of various adjustments:

$$\Delta DepVar_{itb} = \alpha_i + \beta_1 Post_{tb} + \beta_2 \Delta Volume_{itb} + \beta_3 \Delta Volatility_{itb} + \varepsilon_{itb}, \quad (5)$$

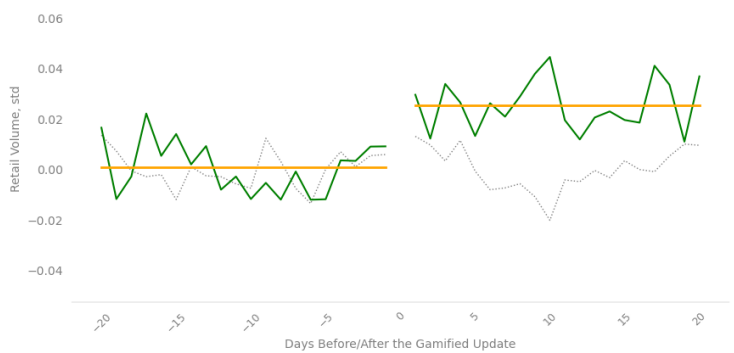
where $DepVar_{itb}$ represents the retail traded volume (Vol), per-share payment for order flow (PFOF), retail trading imbalance (RetImb), retail intraday return (Ret), retail intraday return volatility (RetVolat), retail trade price improvement (PrImp), percentage of price-improved trades (PrImpT), quoted spread (QS), effective spread (ES), price impact (PI), realized spread (RS), traded overall volume minus retail volume (Vol), stock price volatility (PrVolat), and market intraday return volatility (RetVolat) for stock i on day t for a broker b, and all other variables as defined previously. The first line reports the $Post_{tb}$ coefficient for the base case used throughout the paper. The base case covers 1404 stocks, the 2018-2021 sample period, and the event window of 20 trading days before a gamified update and 20 trading days after it. The following two lines examine adjustments to the event window: first, shortening it from 20 to 15 trading days (line 2) and then expanding it to 25 trading days (line 3). Lines 4 and 5 report the $Post_{tb}$ coefficient for time-detrended variables and the polynomial time-detrend of order 2 with an autoregressive parameter AR(1) (see Section 3.4.2). Line 6 omits the year 2020 (COVID year). Line 7 reports regression coefficients only for the year 2020 (COVID year). The line 8 reports the difference between the $Post_{tb}$ coefficients of gamified updates and placebo event dates precisely one year before the actual gamified update occurred (see Section 3.4.3). The line 9 reports results only for the sample of tick-constrained stocks. Finally, line 10 reports the differenced $Post_{tb}$ coefficient between U.S. stocks and matched Canadian stocks before and after gamified updates (see Section 3.4.5). Some results are missing due to data limitations. All variables are standardized, and as such, the models control for stock fixed effects. Standard errors in parentheses are double-clustered across firms and over time. Given the size of the table, I omit the asterisks. Instead, the coefficient estimates reported in regular font are statistically significant at the 0.01 level, and the coefficient reported in italicized font is statistically significant at the 0.05 level. For statistically insignificant coefficients, I report the result as 0.000. A number of daily app downloads and intraday market returns are excluded from the table because they do not exhibit statistically significant changes in any models. Results for these variables are available upon request.

	Retail Metrics							Liquidity Costs				Market Metrics		
	Vol	PFOF	RetImb	Ret	RetVolat	PrImp	PrImpT	QS	ES	PI	RS	Vol	PrVolat	RetVolat
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]
1. Base case	0.012	0.013	-0.020	-0.008	0.015	*0.012*	0.124	-0.130	-0.064	-0.040	-0.054	0.051	-0.066	-0.010
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
2. 15 days	0.013	0.015	-0.019	-0.007	0.015	*0.012*	0.126	-0.117	-0.059	-0.040	-0.051	0.059	-0.051	*-0.008*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)
3. 25 days	0.014	0.017	-0.022	-0.008	0.019	0.013	0.131	-0.091	-0.057	-0.038	-0.058	0.057	-0.058	-0.009
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)
4. De-trend	0.009	0.011	-0.020	-0.006	0.015	*0.009*	0.122	-0.123	-0.052	-0.031	-0.040	0.056	-0.065	-0.010
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)
5. Poly+AR(1)	0.008		-0.020	*-0.005*	0.015	*0.008*	0.112	-0.106	-0.048	-0.030	-0.037	0.056	-0.067	-0.010
	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)
6. No COVID	0.010	0.014	-0.015	-0.008	*0.011*	*0.011*	0.143	-0.154	-0.066	-0.045	-0.065	0.042	-0.045	*-0.008*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
7. COVID	0.018	0.008	-0.025	-0.007	0.022	0.018	0.085	-0.080	-0.053	-0.031	-0.044	0.074	-0.078	-0.016
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
8. Placebo	0.013	0.013	-0.018	-0.009	0.014	*0.012*	0.124	-0.108	-0.062	-0.042	-0.054	0.055	-0.067	-0.012
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
9. 1 tick	0.014		-0.020	*-0.004*	*0.009*	0.015	0.089	0.000	0.000	0.000	0.000	*0.015*	0.000	0.000
	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)
10. Canada								-0.142	-0.075			0.050	-0.062	
								(0.03)	(0.02)			(0.01)	(0.01)	

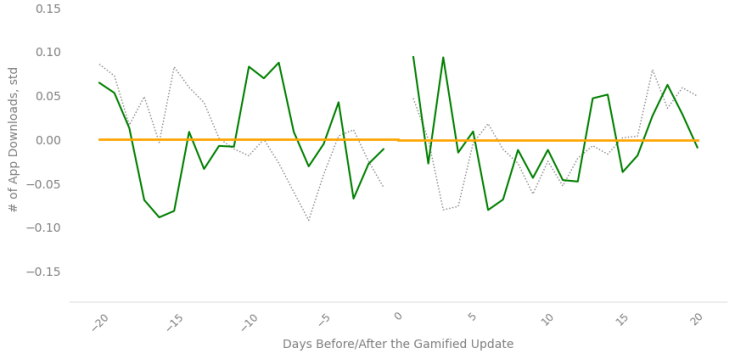


(a) Robinhood **(b) Webull** **(c) eToro**

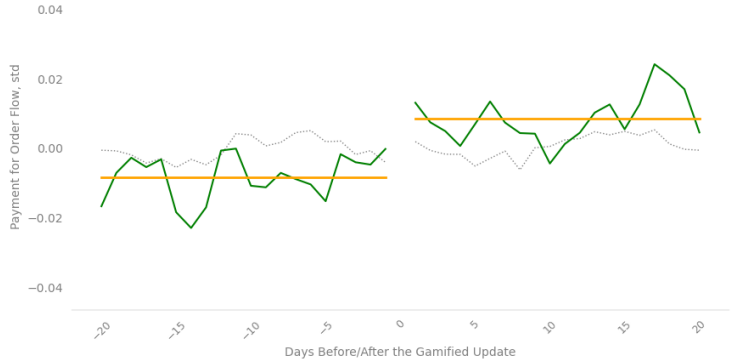
Figure 1. Gamification Examples
This figure provides particular examples of gamification strategies of various brokers. Panel A illustrates an interactive visual of confetti after Robinhood users deposit funds and trade. Panel B depicts a reward system for Webull users if they refer a friend to an app. Finally, Panel C shows recent top movers' stock on the eToro platform, nudging investors for trading.



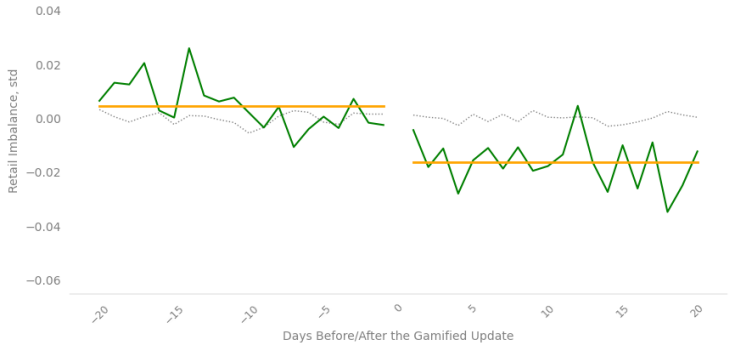
Panel A



Panel B



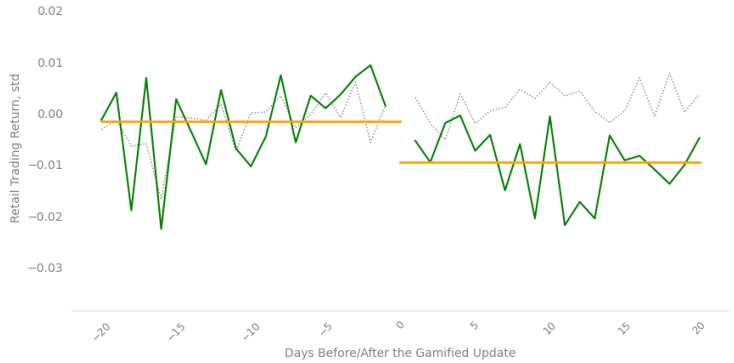
Panel C



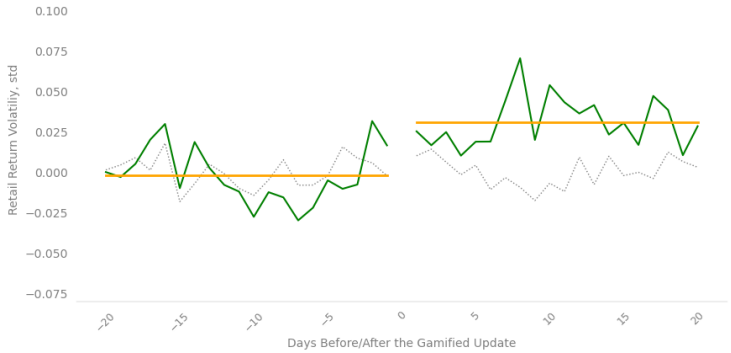
Panel D

Figure 2. Retail Trading Metrics Around App Updates

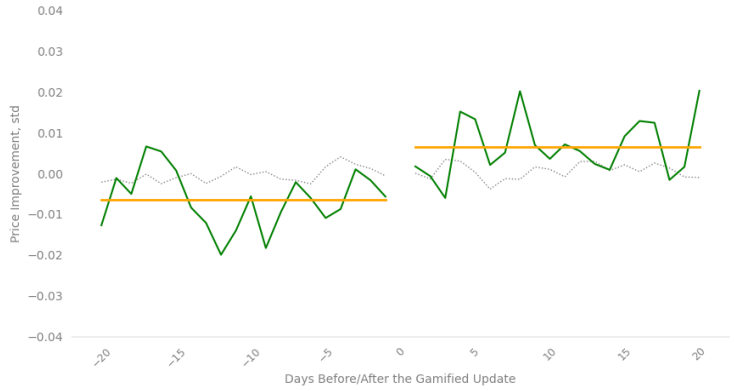
This figure displays four standardized retail trading metrics in the 20-day window surrounding gamified brokerage app updates: Panel A shows retail trading volume, Panel B shows the number of app downloads, Panel C shows payment for order flow, and Panel D shows retail volume imbalance. The green solid line shows the dynamic around gamified updates, while the gray dotted line represents a control group of bug-fix updates.



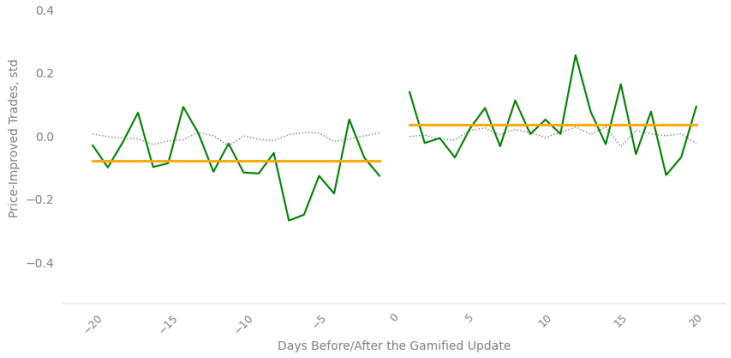
Panel A



Panel B



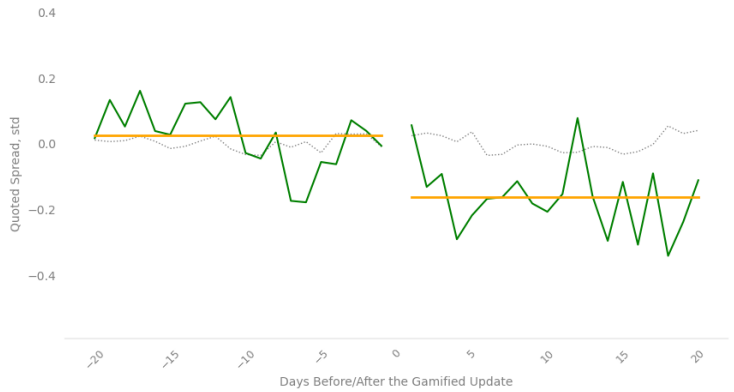
Panel C



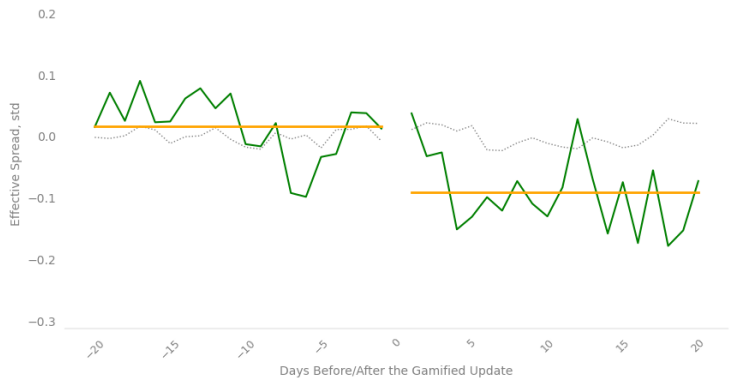
Panel D

Figure 3. Retail Trading Metrics Around App Updates

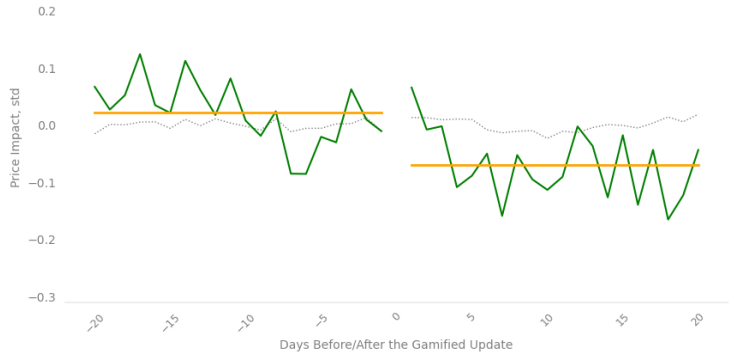
This figure displays four standardized retail trading metrics in the 20-day window surrounding gamified brokerage app updates: Panel A shows retail intraday return, Panel B shows retail return volatility, Panel C shows price improvement, and Panel D shows percentage of price-improved trades. The green solid line shows the dynamic around gamified updates, while the gray dotted line represents a control group of bug-fix updates.



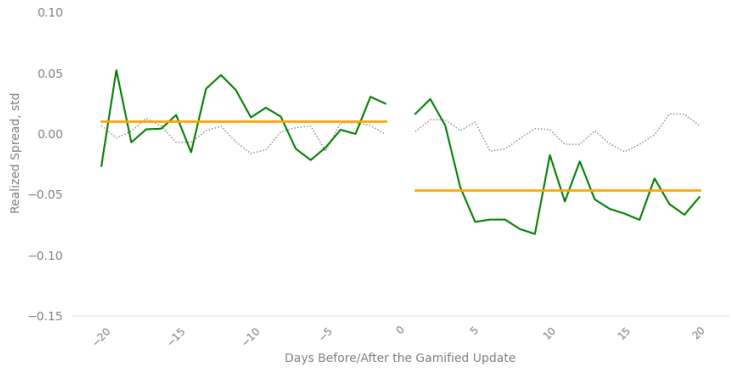
Panel A



Panel B



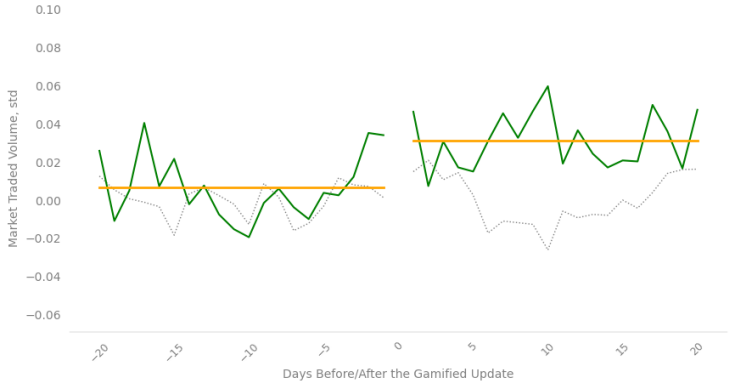
Panel C



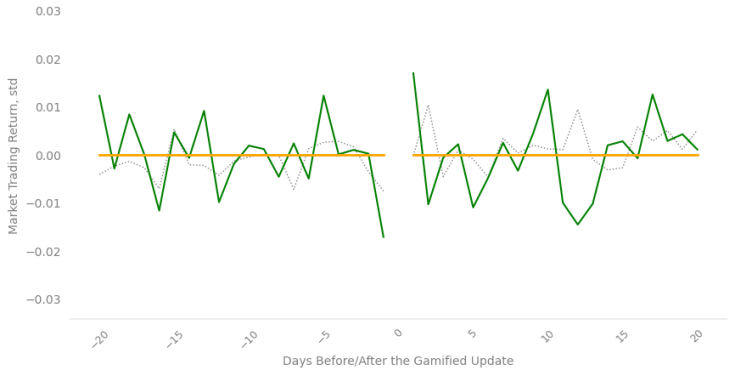
Panel D

Figure 4. Liquidity Metrics Around App Updates

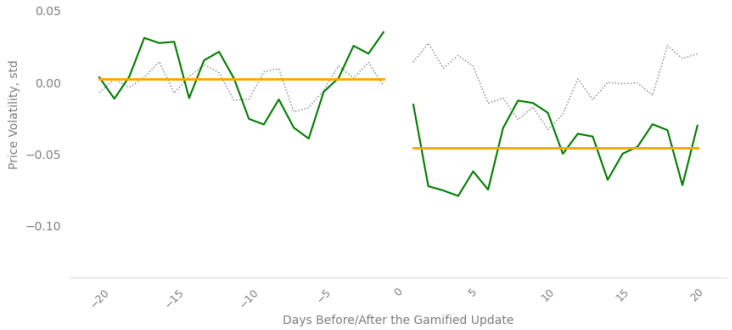
This figure displays four standardized market-wide liquidity metrics in the 20-day window surrounding gamified brokerage app updates: Panel A shows quoted spread, Panel B shows effective spread, Panel C shows price impact, and Panel D shows realized spread. The green solid line shows the dynamic around gamified updates, while the gray dotted line represents a control group of bug-fix updates.



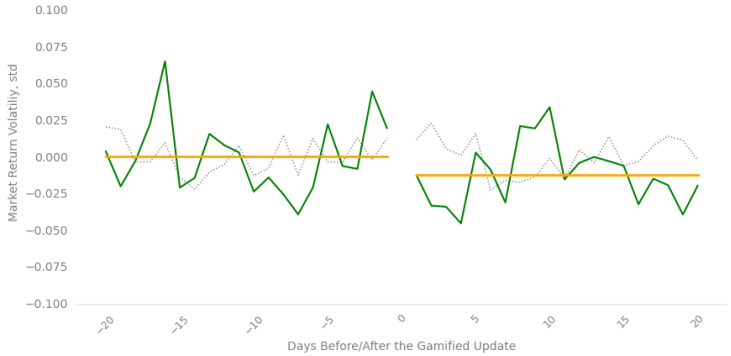
Panel A



Panel B



Panel C



Panel D

Figure 5. Market Quality Around App Updates

This figure displays four standardized market quality metrics in the 20-day window surrounding gamified brokerage app updates: Panel A shows market volume, Panel B shows market return, Panel C shows price volatility, and Panel D shows return volatility. The green solid line shows the dynamic around gamified updates, while the gray dotted line represents a control group of bug-fix updates.

Appendix to "Gamification of Stock Trading: Losers and Winners"

A.1 Sample statistics estimated across time

In Table 2 of the main text, I report the summary statistics estimated across stocks. For instance, the standard deviation of 657 reported for retail volume measures the dispersion of stock-level means. While informative about the sample, this statistic is less useful when interpreting coefficient estimates from fixed effect panel regressions that I use throughout the paper. Therefore, when discussing economic significance, I rely on the time-series summary statistics and, more specifically, the standard deviations estimated across sample days rather than across sample stocks. For comparison to the above-mentioned figure, the standard deviation for retail volume is 157.32 when computed via this method. We report these standard deviations and the other summary statistics in Table A.1.

A.2 The cross-section of retail traders

In the main text, I show that the gamification of stock trading increases total retail volume while negatively impacting retail trading strategies. In this section, I explore whether this effect is consistent across different groups of retail traders. The experiment by Chapkovski, Khapko, and Zoican (2024) shows that gamification has the most potent effect on unsophisticated investors and does not significantly alter the trading behavior of more experienced and financially literate traders.

To test the effect of stock trading gamification across various retail trader groups, I rely on prior literature that shows a link between retail traders' sophistication and the size of the orders they submit to the market (Boehmer, Jones, Zhang, and Zhang (2021)). Specifically, the larger the trade size, the more likely the order originates from a more sophisticated retail trader. Following this logic, I split all retail orders for each stock in my sample into terciles based on dollar volume.

I then estimate the following regression model:

$$\begin{aligned} DepVar_{itb} &= \alpha_i + \beta_1 Post_{tb} + \beta_2 Post_{tb} \times Medium_{itb} + \beta_3 Post_{tb} \times Small_{itb} \\ &\quad + \beta_4 Volume_{itb} + \beta_5 Volatility_{itb} + \varepsilon_{itb}, \end{aligned} \tag{A.9}$$

where $Medium_{itb}$ and $Small_{itb}$ are dummy variables for medium and small-sized retail orders, and all other variables are as previously defined. In this setup, the $Post_{tb}$ dummy captures the effect of large-sized retail orders, while the two interaction terms capture the incremental effects for the other two size categories, representing the effects *in addition to* those of large retail orders.

[Table A.2]

The results in Table A.2 show that the effects of gamification are more pronounced in medium and small-sized trades since they are more likely to come from less sophisticated traders, confirming the experimental findings of Chapkovski, Khapko, and Zoican (2024) and Chapkovski, Khapko, and Zoican (2025). This indicates that the main group affected by the gamification of stock trading are less experienced investors who trade in smaller amounts.[20]

A.3 The cross-section of brokerage firms

Gamification's effect might differ for different brokers since their clientele often differs (Eaton, Green, Roseman, and Wu (2022)). In this section, I analyze how the gamification of different brokers in terms of size and age affects retail traders and the stock market.

A.3.1 Brokers separated by size. To conduct my analysis, I separate all brokers in my sample into two bins, depending on the average number of downloads these brokers had during the time

[20] I do not report results for payment for order flow (PFOF) and price improvement due to data limitations.

period I analyzed (see Table 1). Next, I run the following regression model:

$$DepVar_{itb} = \alpha_i + \beta_1 Post_{tb} + \beta_2 Post_{tb} \times Large_{tb} + \beta_3 Volume_{itb} + \beta_4 Volatility_{itb} + \varepsilon_{itb}, \quad \text{(A.10)}$$

where $Large_{tb}$ is a dummy variable for brokers with above-average clientele size in terms of the number of app downloads, and all other variables are as previously defined. In this setup, the $Post_{tb}$ dummy captures the effect of small-sized retail orders, while the interaction term captures the incremental effects for the large-size category, representing the effects *in addition to* those of small brokerage firms, and all other variables are as previously defined.

[Table A.3]

Results in Table A.3, Panel A and B show that gamification by small brokerage firms does not substantially affect a market. While there are minor benefits to liquidity costs due to the gamification of small brokerage firms (specifications 5 through 8), the major effect of gamification on retail metrics, liquidity costs, and other market metrics comes from large brokers, as evident from $Post_{tb} \times Large_{tb}$ coefficients.

A.3.2 Brokers separated by age. Eaton, Green, Roseman, and Wu (2022) show that brokerage firms have heterogeneous retail traders that employ different trading strategies. In this section, I ask if gamification affects different retail traders in the same way. To test it, I separate retail brokers into two bins based on the age of the broker, with the assumption that new brokers try to attract new young investors on their platforms while mature brokers work with established and more sophisticated clientele.[21] Formally, I run following regression model:

$$DepVar_{itb} = \alpha_i + \beta_1 Post_{tb} + \beta_2 Post \times Mature_{tb} + \beta_3 Volume_{itb} + \beta_4 Volatility_{itb} + \varepsilon_{itb}, \quad \text{(A.11)}$$

[21] This assumption is confirmed both in the brokerage industry and research. See https://www.aboutschwab.com/mss/story/the-rise-of-generation-investor, https://www.finra.org/media-center/newsreleases/2022/new-finra-foundation-research-examines-changing-investor-landscape, and Eaton, Green, Roseman, and Wu (2022)

where $Mature_{tb}$ is a dummy variable for brokers with above-average age, and all other variables are as previously defined. In this setup, the $Post_{tb}$ dummy captures the effect of young brokers, while the interaction term captures the incremental effects for the mature group, representing the effects *in addition to* those of young brokerage firms.

Results in Table A.3, Panels C and D, reveal several important patterns. First, gamification affects all retail trader groups in similar ways: it increases retail trading volume (specification 1) while worsening trading performance, as indicated by lower returns and higher volatility (specifications 4 and 5). Second, the decline in retail imbalance is more pronounced among younger brokerage firms (specification 3), likely because their predominantly younger and less experienced clientele are more susceptible to behavioral biases such as herding—biases that gamification appears to attenuate (Barber, Lin, and Odean (2021)). This is consistent with the larger increases in PFOF (specification 2) and price improvement (specifications 6 and 7) observed at these brokers following gamification, suggesting that wholesalers are willing to pay more as gamification reduces the particularly high toxicity of retail order flow originating from younger platforms.

Finally, gamification by younger brokers yields greater improvements in market quality than similar efforts by mature firms. This aligns with findings from Eaton, Green, Roseman, and Wu (2022), who show that order flow from younger platforms tends to be more toxic for market makers. Since gamification promotes more noise-like trading behavior,[22] market makers can intermediate such flow more efficiently—especially when it comes from younger brokerages.

Overall, I find substantial heterogeneity in the effect of gamification on different brokerage firms. Generally, the impact of gamification is more pronounced in brokerage firms that serve larger clientele. Additionally, while all retail traders are hurt by gamification, the positive effect of gamification on the market is more pronounced for younger brokerage firms.

[22] See Section 3.1 and Chapkovski, Khapko, and Zoican (2024)

A.4 The cross-section of stocks

Prior research suggests that changes in financial markets may have different effects on the cross-section of stocks (Hendershott, Jones, and Menkveld (2011); Haslag and Ringgenberg (2023)). Given these findings, it is interesting to examine whether the gamification effect differs in the cross-section of stocks. To do so, I split my stock sample by two criteria: (i) market capitalization and (ii) stock beta.

A.4.1 Separation by market capitalization. I split my sample into two bins based on market capitalization. If market capitalization is higher than average, I assign this firm to the *Large* group. Then, I run the following regression:

$$DepVar_{itb} = \alpha_i + \beta_1 Post_{tb} + \beta_2 Post_{it} \times Large_{itb} + \beta_3 Volume_{itb} + \beta_4 Volatility_{itb} + \varepsilon_{it}, \quad \text{(A.12)}$$

where $Large_{itb}$ is a dummy variable for stocks with above-average market capitalization, and all other variables are as previously defined. In this setup, the $Post_{tb}$ dummy captures the effect of small-sized stocks, while the interaction term captures the incremental effects for the large-size category, representing the effects *in addition to* those of small-sized stocks, and all other variables are as previously defined.

[Table A.4]

Results in Table A.4, Panel A and B show that the effect of gamification is somewhat heterogeneous across stocks. After gamification, smaller cap stocks experience a higher retail volume increase and better market-wide liquidity improvement. A key characteristic of smaller-cap stocks that may attract retail traders following gamification updates is their higher risk profile (Fama and French (1993)). To examine this hypothesis, the next section analyzes the sample by grouping stocks based on their beta values.[23]

[23] Due to limitations in the available data, results for payment for order flow could not be estimated.

A.4.2 Separation by beta. I calculate the beta of each stock in my sample over the previous month and assign a firm to the Low_{itb} group if the absolute value of beta is lower than average. Then, I run the following regression:

$$DepVar_{itb} = \alpha_i + \beta_1 Post_{tb} + \beta_2 Post_{tb} \times Low_{itb} + \beta_3 Volume_{itb} + \beta_4 Volatility_{itb} + \varepsilon_{itb}, \quad \text{(A.13)}$$

where Low_{itb} is a dummy variable for stocks with below-average beta, and all other variables are as previously defined. In this setup, the $Post_{tb}$ dummy captures the effect of high-beta stocks, while the interaction term captures the incremental effects for the low-beta category, representing the effects *in addition to* those of high-beta stocks, and all other variables are as previously defined.

Results in Table A.4, Panel C and D show that heterogeneity is even more pronounced across different beta stocks than when I separate my stock sample by size. Interestingly, the main findings are interconnected with the previous case: gamification attracts more retail volume and improves market quality more in riskier assets. Although stock beta and firm size generally go hand-in-hand, it is interesting to think why heterogeneity in the gamification effect is more pronounced in riskier stocks than in smaller stocks. A potential explanation may lie in the preference of retail traders to switch underlying assets to trade. Gamification might spike the risk appetite of retail traders and prompt them to migrate from less-riskier assets to those that offer higher, lottery-like potential rewards (Eraker and Ready (2015); Chapkovski, Khapko, and Zoican (2025)).

A.5 Rules 605 & 606

Rule 605. In the paper's main analysis, I rely on the BJZZ algorithm to identify retail volume from the TAQ dataset. While this method is used widely in the literature, recent work shows that it has some limitations (Battalio, Jennings, Saglam, and Wu (2023); Barber, Huang, Jorion, Odean, and Schwarz (2024)). To alleviate this concern, I complement my results by looking at alternative

data sources that provide information on retail trades at the stock-month-market center level. The main advantage of this approach is the lack of reliance on any identification strategies to capture retail trades.

Data comes from the SEC Order Execution Obligations regulation[24], by which market centers are required to publicly disclose execution quality metrics for customer orders, such as retail volume and its execution characteristics. Under the Rule 605 provision, exchanges and alternative trading systems are required to publish monthly reports detailing the execution quality of orders for National Market System (NMS) securities[25].

For my analysis, I downloaded Rule 605 reports for the two largest retail market centers – Citadel Securities and Virtu Financial.[26] Together, they account for more than 70% of total retail flow (Dyhrberg, Shkilko, and Werner (2025)). Using this data, I test how gamified updates of retail brokerage firms change the quality and quantity of retail order execution for these two market centers. Formally, I run the following regression model:

$$DepVar_{itb} = \alpha_i + \beta_1 PostNum_{t-1} + \beta_2 Volume_{itb} + \beta_3 Volatility_{itb} + \varepsilon_{itb}, \tag{A.14}$$

where $DepVar_{itb}$ represents the variable of interest for stock i on month t for a market center b. Variables of interest include the total retail volume executed by all market centers in my sample, the average effective spread of retail orders, the average realized spread of retail orders, and the average price impact of retail orders. $PostNum_{t-1}$ equals the total number of gamification updates that all brokerage firms in my sample introduced one month before; $Volume_{itb}$ is the overall traded volume, calculated from TAQ; and $Volatility_{itb}$ is the difference between the high and low prices scaled by the high price and averaged across month t.

[Table A.5]

[24] https://www.sec.gov/files/rules/final/34-43590.htm

[25] https://www.finra.org/rules-guidance/guidance/sec-rule-605

[26] Data is publicly available for download on market-centers websites.

Results in Table A.5 show that retail traded volume increases and order execution quality improves. For example, a coefficient of 5.91 for retail volume in a regression setting with control variables indicates that, on average, market centers will execute by 5.91 million shares more if the retail brokerage firm has created a gamified update the previous month. Generally, these results align with my earlier findings, where I show the beneficial effect of gamification on market-makers (see Section 3.2).

Rule 606. Along with Rule 605, Rule 606 is also part of Regulation NMS, which focuses on order routing transparency for broker-dealers. Starting in 2020, Rule 606 expanded its scope to include additional disclosures about options order routing[27]. Although my analysis primarily focuses on stock trading, there are strong reasons to hypothesize that retail option trading might be affected by gamification. Ernst and Spatt (2022) show that retail brokerage firms might motivate their clients to trade options, even though it is sub-optimal for retail traders. Additionally, Bryzgalova, Pavlova, and Sikorskaya (2023) argues that retail option market making is not competitive, which might create additional benefits for market-makers to attract retail traders to this market.

I start my analysis by looking at net payments received by market orders in the options market by retail traders. Since Virtu does not participate in the market-making of retail options trading, my sample is limited only to Citadel option trading from 2020 to 2021. Formally, I run the following regression model:

$$OptionsPayment_t = \alpha + \beta_1 PostNum_{t-1} + \varepsilon_t, \tag{A.15}$$

where $OptionsPayment_t$ represents the net payment amount Citadel gets for executing market orders on the retail options market for month t. $PostNum_{t-1}$ equals the total number of gamification updates that all brokerage firms in my sample introduced one month before.

[27] https://www.finra.org/rules-guidance/notices/24-05

[Table A.6]

Results show that gamification increases retail option trading. On average, Citadel will receive 130 dollars more for all retail option market orders for each brokerage gamified update implemented one month prior. At first glance, the economic significance of this estimate may appear trivial, but the fact that brokerage firms gamified their apps 73 times during this time period makes the cumulative effect of these updates rather substantial—an increase in net payments by 35% of the sample mean.

In summary, Rules 605 & 606 data provide scope and richness that allow us to look at retail trading on a more granular level. Using this data, I find similar results to my findings from the main text, where I use the BJZZ algorithm to identify retail trades from the TAQ dataset.

A.6 Why do brokers gamify?

It is important to understand what drives brokers to gamify their trading platforms. On one hand, gamification may be a routine practice whereby brokers continuously engage in the development of new game-like features. On the other hand, gamification may be a strategic response to various market-wide events, such as recent gamification by rival brokers, earnings announcements, or brokerage innovations that lower the entry threshold of retail traders to a stock market, such as zero commission trading and fractional shares trading. If gamification is a routine practice, app updates are likely introduced without the influence of external triggers, simply when they are deemed ready for widespread use. Conversely, if gamification is largely driven by external changes, such gamification is likely timed to synergize with these events. I examine these possibilities using the following probit model:

$$Pr(Gamification = 1)_{tb} = \alpha + \beta_1 interest_var_{tb} + \beta_2 Volume_t + \beta_3 Volatility_t + \varepsilon_{tb}, \quad \text{(A.16)}$$

where the dependent variable is a binary indicator equal to one if broker b releases gamified update in day t and equal to zero otherwise, $interest_var_{tb}$ is one of the four variables: the number of gamified updates released by the rival brokers in the past month, the number of quarterly earnings announcement by companies in my sample in a current week (based on I/B/E/S data), dummy variable equal to one if the broker allows zero commission trading on its platform, and dummy variable equal to one if the broker allows fractional shares trading on its platform. $Volume_t$ is market-wide traded shares volume, and $Volatility_t$ is market-wide volatility. As previously mentioned, all variables are standardized, and therefore, the changes in variables represent deviations from an expected value of zero.

[Table A.7]

The results in Table A.7 are consistent with both the routine and strategic response explanation. Based on the marginal effects reported in square brackets, a one standard deviation increase in the number of gamification updates by rivals (specification 1) increases the probability of introducing a new gamified update by 0.12%. The comparable figures for zero commission trading and fractional shares trading are 0.40% and 0.52%, respectively, indicating that brokers gamify significantly more after they allow zero commission trading and fractional shares trading. Additionally, results indicate that brokers do not release gamified updates more than usual during earning announcement week. To assess the economic significance, these figures should be compared to the base probability of gamification during the same time period, which is 0.58%.

Results indicate that besides routine gamification, brokerage firms additionally consider various factors to decide the timing of gamification updates. My results show that the most important factors are the functionality of the brokerage app itself. These factors determine how easy it will be for retail traders to use new gamification features. Zero commission and fractional shares trading remove substantial barriers for retail traders and create a fertile environment for its use. This is captured by my probit model, where brokers with the aforementioned functionality cre-

ate gamified updates 2.59 times more than those without. Finally, brokers also consider external market-wide factors, such as gamification updates from rivals.

A.7 Transitory vs. Permanent effect of gamification

In the main text of my paper, I analyze the effect of gamification on relativity short interval horizons, 20 trading days before and after the gamification update. Although I extended my event windows to 25 trading days in my robustness check, it is not enough to understand if the effect of gamification holds in the long run or disappears shortly after retail traders get used to and adapt to released gamified features. To test it, I add two additional time frames to my base case results. I study retail volume from 21 to 40 and from 41 to 60 trading days after gamification. Formally, I run the following regression:

$$DepVar_{itb} = \alpha_i + \beta_1 Post_{tb} + \beta_2 Volume_{itb} + \beta_3 Volatility_{itb} + \varepsilon_{itb}, \tag{4}$$

where $DepVar_{itb}$ represents the variable of interest for stock i on day t for a broker b; $Post_{tb}$ is a dummy variable equal to zero in pre-gamified update period (from 1 to 20 trading days before gamification) and one during the post-gamified update period (from 1 to 20 or 21 to 40 or 41 to 60 trading days after gamification, depending on specification); $Volume_{itb}$ is the trading volume; and $Volatility_{itb}$ is the difference between the high and low prices on day t scaled by the high price. The variables are winsorized at 1% and 99% and standardized by symbol, as such models control for stock fixed effects.

[Table A.8]

Results in Table A.8 highlights two things: (i) a certain portion of the gamification effect goes away with time, and (ii) the power of the test is not enough on a longer horizon to draw reliable conclusions. First, 62% of the gamification effect stays as we move from the first twenty trading

days to the second, as evident from the coefficient in specifications 1 and 2.[28] Second, as we move to later time periods, economic significance stays approximately the same, but statistical significance disappears as more noise comes into the metric due to confounding events.

To summarize, the biggest portion of the gamification effect is permanent and persists even after 60 days of the gamification event; however, drawing reliable conclusions after this mark is hard due to noise in the data.[29]

[28] To calculate it, I divide the estimated coefficient from specification 2 to coefficient from specification 1.

[29] I find similar results for other key variables I use in my paper. These results are available upon request.

Table A.1: Descriptive Statistics: Time-Series

This table reports sample summary statistics computed across sample days. In comparison, Table 2 in the main text computes summary statistics across sample stocks. Panel A includes market capitalization, daily trading volume, and share price. Panel B reports retail trading metrics, including retail traded volume, retail trading imbalance, price improvement amount, percentage of price-improved trades, per-share payment for order flow, retail intraday return, and retail intraday return volatility calculated as squared retail intraday return. Panel C reports liquidity metrics including quoted, effective, and realized spreads, as well as price impact. Panel D reports market-wide metrics that exclude retail trades from the calculation. These include daily trading volume, intraday return, price volatility, and intraday return volatility, with the former computed as the difference between the day's high and low prices scaled by the high price. The data cover the sample period of 2018-2021.
Welch (2022)

	Mean	St. dev.	25th	Median	75th
Panel A: Sample characteristics					
Market capitalization, $B	19.54	3.96	16.53	17.58	22.79
Volume, sh. '000	1,649	212	1,336	1,510	1,862
Price, $	80.89	16.04	68.91	73.59	95.27
Panel B: Retail trading					
Retail volume, '000	182	157.32	23.38	156.04	353.64
Retail imbalance	0.20	0.06	0.11	0.19	0.28
Price improvement, ¢	6.53	1.18	5.01	6.23	8.08
Price improved trades, %	94.32	2.21	92.35	94.75	98.10
Payment for order flow, $\frac{1}{100}$¢	1.05	0.41	0.69	1.10	2.02
Intraday return, bps.	4.46	2.57	2.17	4.12	6.11
Intraday return volatility, bps	0.15	0.08	0.06	0.14	0.24
Panel C: TAQ liquidity metrics, bps.					
Quoted spread	23.93	0.59	23.76	23.84	23.92
Effective spread	13.99	0.52	13.46	13.81	14.05
Price impact	7.42	0.39	7.11	7.36	7.68
Realized spread	6.56	0.30	6.50	6.55	6.60
Panel D: The rest of the market					
Volume, sh. '000	1,467	176	1,375	1,440	1,534
Intraday return, bps.	2.29	1.72	1.58	2.29	2.97
Price volatility, bps.	0.04	0.00	0.04	0.04	0.04
Intraday return volatility, bps	0.06	0.01	0.06	0.06	0.06

Table A.2: The Cross-Section of Retail Traders

The table contains regression coefficient estimates from models without control variables (Panel A) and regression coefficient estimates from models with control variables (Panel B):

$$DepVar_{itb} = \alpha_i + \beta_1 Post_{tb} + \beta_2 Post_{tb} \times Medium_{itb} + \beta_3 Post_{tb} \times Small_{itb} + \beta_4 Volume_{itb} + \beta_5 Volatility_{itb} + \varepsilon_{itb}, \tag{A.9}$$

where $Medium_{itb}$ and $Small_{itb}$ are dummy variables for medium and small-sized retail orders, and all other variables are as previously defined. In this setup, the $Post_{tb}$ dummy captures the effect of large-sized retail orders, while the two interaction terms capture the incremental effects for the other two size categories, representing the effects *in addition to* those of large retail orders. The variables are winsorized at 1% and 99% and standardized by symbol, as such models control for stock fixed effects. Standard errors in parentheses are double-clustered across firms and over time. Asterisks ***, **, and * denote the 0.01, 0.05, and 0.10 levels of statistical significance.

	Retail Volume		Retail Return		Return Volatility		Retail Imbalance	
	[1]		[2]		[3]		[4]	
Panel A: Regressions without control variables								
Post	0.022	**	-0.009	**	0.017	***	-0.005	
	(0.01)		(0.00)		(0.01)		(0.01)	
Post×Medium	0.002		-0.003	*	0.014	***	-0.010	*
	(0.00)		(0.00)		(0.01)		(0.01)	
Post×Small	0.004	*	-0.003	**	0.012	***	-0.012	*
	(0.00)		(0.00)		(0.01)		(0.01)	
Controls	No		No		No		No	
Panel B: Regressions with control variables								
Post	0.010	**	-0.009	**	0.008	**	-0.006	
	(0.00)		(0.00)		(0.01)		(0.01)	
Post×Medium	0.003	*	-0.002	*	0.007	**	-0.009	*
	(0.00)		(0.00)		(0.01)		(0.01)	
Post×Small	0.004	*	-0.003	**	0.007	**	-0.011	*
	(0.00)		(0.00)		(0.01)		(0.01)	
Controls	Yes		Yes		Yes		Yes	

Table A.3: The Cross-Section of Brokers

The table reports regression coefficient estimates from models without control variables (Panel A) and regression coefficient estimates from models with control variables (Panel B):

$$DepVar_{itb} = \alpha_i + \beta_1 Post_{tb} + \beta_2 Post_{tb} \times Large_{tb} + \beta_3 Volume_{itb} + \beta_4 Volatility_{itb} + \varepsilon_{itb}, \tag{A.10}$$

where $Large_{tb}$ is a dummy variable equal to one for brokers with an above-average number of app downloads (i.e., larger clientele size), and all other variables are defined as in Table 7. Additionally, the table contains regression coefficient estimates from models without control variables (Panel C) and regression coefficient estimates from models with control variables (Panel D):

$$DepVar_{itb} = \alpha_i + \beta_1 Post_{tb} + \beta_2 Post \times Mature_{tb} + \beta_3 Volume_{itb} + \beta_4 Volatility_{itb} + \varepsilon_{itb}, \tag{A.11}$$

where $Mature_{tb}$ is a dummy variable for brokers with above-average age, and all other variables are as previously defined. In this setup, the $Post_{tb}$ dummy captures the effect of small (first specification) or young (second specification) brokers, while the interaction term captures the incremental effects for the opposite group, representing the effects *in addition to* those of small (Panels A and B) or young (Panels C and D) brokerage firms. The variables are winsorized at 1% and 99% and standardized by symbol, as such models control for stock fixed effects. Standard errors in parentheses are double-clustered across firms and over time. Given the size of the table, I omit the asterisks. Instead, the coefficient estimates reported in regular font are statistically significant at the 0.01 level, and the coefficient reported in italicized font is statistically significant at the 0.05 level. For statistically insignificant coefficients, I report the result as 0.000.

	Retail Metrics							Liquidity Costs				Market Metrics		
	Vol	PFOF	RetImb	Ret	RetVolat	PrImp	PrImpT	QS	ES	PI	RS	Vol	PrVolat	RetVolat
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]
Panel A: Separation by size, regressions without control variables														
Post	0.000	0.000	0.000	0.000	*0.012*	0.000	0.000	-0.052	-0.027	*-0.009*	*-0.011*	0.000	*-0.013*	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.02)	(0.02)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
Post×Large	0.048	0.030	0.038	-0.015	0.041	0.023	0.235	-0.322	-0.180	-0.099	-0.107	0.054	-0.095	-0.024
	(0.01)	(0.01)	(0.01)	(0.00)	(0.02)	(0.01)	(0.02)	(0.05)	(0.03)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Controls	No	No	No	No	No	No	No	No	No	No	No	No	No	No
Panel B: Separation by size, regressions with control variables														
Post	0.000	0.000	0.000	0.000	*0.006*	0.000	0.000	-0.047	-0.021	0.000	*-0.010*	0.000	-0.018	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)
Post×Large	0.025	0.026	0.039	-0.014	0.034	0.024	0.187	-0.290	-0.188	-0.087	-0.102	0.112	-0.117	-0.021
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.02)	(0.04)	(0.04)	(0.02)	(0.03)	(0.02)	(0.02)	(0.00)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel C: Separation by age, regressions without control variables														
Post	0.030	0.022	-0.032	-0.008	0.030	0.019	0.170	-0.201	-0.123	-0.082	-0.074	0.027	-0.060	-0.016
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.02)	(0.04)	(0.03)	(0.02)	(0.02)	(0.00)	(0.01)	(0.00)
Post×Mature	0.000	*-0.006*	0.012	0.000	0.000	-0.007	-0.031	0.105	0.053	0.030	0.028	0.000	*0.010*	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
Controls	No	No	No	No	No	No	No	No	No	No	No	No	No	No
Panel D: Separation by age, regressions with control variables														
Post	0.012	0.020	-0.032	-0.008	0.015	0.020	0.142	-0.170	-0.112	-0.068	-0.072	0.056	-0.078	*-0.012*
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.00)
Post×Mature	0.000	-0.007	0.012	0.000	0.000	-0.008	-0.018	0.084	0.042	0.023	0.027	0.000	*0.012*	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A.4: The Cross-Section of Stocks

The table reports regression coefficient estimates from models without control variables (Panel A) and regression coefficient estimates from models with control variables (Panel B):

$$DepVar_{itb} = \alpha_i + \beta_1 Post_{tb} + \beta_2 Post_{it} \times Large_{itb} + \beta_3 Volume_{itb} + \beta_4 Volatility_{itb} + \varepsilon_{it}, \tag{A.12}$$

where $Large_{itb}$ is a dummy variable for stocks with above-average market capitalization, and all other variables are defined as in Table 7. Additionally, the table contains regression coefficient estimates from models without control variables (Panel C) and regression coefficient estimates from models with control variables (Panel D):

$$DepVar_{itb} = \alpha_i + \beta_1 Post_{tb} + \beta_2 Post_{tb} \times Low_{itb} + \beta_3 Volume_{itb} + \beta_4 Volatility_{itb} + \varepsilon_{itb}, \tag{A.13}$$

where Low_{itb} is a dummy variable for stocks with below-average beta, and all other variables are as previously defined. In this setup, the dummy captures the effect of small-size or high-beta stocks, while the interaction term captures the incremental effects for the large-size or low-beta category, representing the effects in addition to those of small-size or high-beta stocks. Some results are missing due to data limitations. The variables are winsorized at 1% and 99% and standardized by symbol, as such models control for stock fixed effects. Standard errors in parentheses are double-clustered across firms and over time. Given the size of the table, I omit the asterisks. Instead, the coefficient estimates reported in regular font are statistically significant at the 0.01 level, and the coefficient reported in italicized font is statistically significant at the 0.05 level. For statistically insignificant coefficients, I report the result as 0.000.

	Retail Metrics							Liquidity Costs				Market Metrics		
	Vol	PFOF	RetImb	Ret	RetVolat	PrImp	PrImpT	QS	ES	PI	RS	Vol	PrVolat	RetVolat
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]
Panel A: Separation by market capitalization, regressions without control variables														
Post	0.040		-0.025	-0.009	0.032	0.013	0.136	-0.175	-0.101	-0.070	-0.078	0.032	-0.052	-0.016
	(0.01)		(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.03)	(0.02)	(0.02)	(0.01)	(0.02)	(0.00)
Post×Large	-0.025		0.000	0.000	0.000	0.000	0.000	0.034	0.050	0.031	0.035	-0.018	0.000	0.000
	(0.01)		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.02)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
Controls	No		No	No	No	No	No	No	No	No	No	No	No	No
Panel B: Separation by market capitalization, regressions with control variables														
Post	0.021		-0.026	-0.009	0.016	0.012	0.122	-0.149	-0.092	-0.058	-0.072	0.063	-0.069	-0.012
	(0.01)		(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.04)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.00)
Post×Large	*-0.010*		0.000	0.000	0.000	0.000	0.000	0.022	0.041	0.020	0.029	-0.015	0.000	0.000
	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.02)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
Controls	Yes		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel C: Separation by beta, regressions without control variables														
Post	0.047		-0.027	-0.010	0.034	0.012	0.137	-0.201	-0.121	-0.075	-0.081	0.034	-0.061	-0.020
	(0.02)		(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.04)	(0.03)	(0.03)	(0.02)	(0.01)	(0.02)	(0.00)
Post×Low	-0.032		0.000	0.000	0.000	0.000	0.000	0.079	0.060	0.055	0.057	-0.022	0.020	*0.012*
	(0.01)		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.02)	(0.02)	(0.02)	(0.00)	(0.00)	(0.01)
Controls	No		No	No	No	No	No	No	No	No	No	No	No	No
Panel D: Separation by beta, regressions with control variables														
Post	0.025		-0.026	-0.010	0.017	0.012	0.124	-0.172	-0.105	-0.068	-0.077	0.070	-0.078	-0.014
	(0.01)		(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.04)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.00)
Post×Low	-0.014		0.000	0.000	0.000	0.000	0.000	0.064	0.057	0.044	0.032	-0.029	0.029	-0.014
	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.00)
Controls	Yes		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A.5: Rule 605; Retail Orders Execution

The table contains regression coefficient estimates from models without control variables (Panel A) and regression coefficient estimates from models with control variables (Panel B):

$$DepVar_{itb} = \alpha_i + \beta_1 PostNum_{t-1} + \beta_2 Volume_{itb} + \beta_3 Volatility_{itb} + \varepsilon_{itb}, \tag{A.14}$$

where $DepVar_{itb}$ represents the variable of interest for stock i on month t for a market center b. Variables of interest include the total retail volume executed by all market centers in my sample, the average effective spread of retail orders, the average realized spread of retail orders, and the average price impact of retail orders. $PostNum_{t-1}$ equals the total number of gamification updates that all brokerage firms in my sample introduced one month before; $Volume_{itb}$ is the overall traded volume, calculated from TAQ; and $Volatility_{itb}$ is the difference between the high and low prices scaled by the high price and averaged across month t. Standard errors in parentheses are double-clustered across firms and over time. Asterisks ***, **, and * denote the 0.01, 0.05, and 0.10 levels of statistical significance.

	Retail Volume		Effective Spread		Realized Spread		Price Impact	
	[1]		[2]		[3]		[4]	
Panel A: Regressions without control variables								
PostNum	8.041	***	-0.004	***	-0.001	***	-0.003	***
	(0.56)		(0.00)		(0.00)		(0.00)	
Controls	No		No		No		No	
Panel B: Regressions with control variables								
PostNum	5.914	***	-0.003	***	-0.001	***	-0.002	***
	(0.24)		(0.00)		(0.00)		(0.00)	
Controls	Yes		Yes		Yes		Yes	

Table A.6: Rule 606; Retail Orders Execution in Options

The table contains regression coefficient estimates from the model:

$$OptionsPayment_t = \alpha + \beta_1 PostNum_{t-1} + \varepsilon_t, \tag{A.15}$$

where $OptionsPayment_t$ represents the net payment amount Citadel gets for executing market orders on the retail options market for a month t. $PostNum_{t-1}$ equals the total number of gamification updates that all brokerage firms in my sample introduced one month before. Asterisks ***, **, and * denote the 0.01, 0.05, and 0.10 levels of statistical significance.

	Options Payments	
	[1]	
PostNum	130.833	***
	(20.14)	
Intercept	27,246.22	***
	(1484.83)	

Table A.7: The Drivers of Gamification

The table reports coefficient estimates from the following probit model:

$$Pr(Gamification = 1)_{tb} = \alpha + \beta_1 interest_var_{tb} + \beta_2 Volume_t + \beta_3 Volatility_t + \varepsilon_{tb}, \tag{A.16}$$

where the dependent variable is a binary indicator equal to one if broker b releases gamified update in day t and equal to zero otherwise, $interest_var_{tb}$ is one of the four variables: the number of gamified updates released by the rival brokers in a past month, the number of quarterly earnings announcement by companies in my sample in a current week, dummy variable equal to one if the broker allows zero commission trading on its platform, and dummy variable equal to one if broker allows fractional shares trading on its platform. $Volume_t$ is market-wide traded shares volume, and $Volatility_t$ is market-wide volatility. As previously stated, all variables have been standardized; thus, any changes in the variables indicate deviations from an expected value of zero. The marginal effects are reported in square brackets, and standard errors are in parentheses. Asterisks ***, **, and * denote the 0.01, 0.05, and 0.10 levels of statistical significance.

	[1]		[2]		[3]		[4]	
Gamification by rivals	0.012	**						
	[0.001]							
	(0.01)							
Earnings announcemnts			0.002					
			[0.000]					
			(0.00)					
Zero comission trading					0.037	***		
					[0.004]			
					(0.00)			
Fractional shares trading							0.050	***
							[0.005]	
							(0.00)	
Volume	0.007	*	0.007	*	0.008	*	0.006	
	[0.002]		[0.002]		[0.002]		[0.002]	
	(0.00)		(0.00)		(0.00)		(0.00)	
Volatility	0.003		0.003		0.002		0.004	
	[-0.002]		[-0.002]		[-0.002]		[-0.002]	
	(0.00)		(0.00)		(0.00)		(0.00)	
Intercept	-1.245	***	-1.147	***	-1.233	***	-1.417	***
	(0.00)		(0.00)		(0.00)		(0.00)	

Table A.8: Transitory vs. Permanent Effect of Gamification

The table reports the coefficient estimates from the following model:

$$DepVar_{itb} = \alpha_i + \beta_1 Post_{tb} + \beta_2 Volume_{itb} + \beta_3 Volatility_{itb} + \varepsilon_{itb}, \quad (4)$$

where $DepVar_{itb}$ represents the variable of interest for stock i on day t for a broker b; $Post_{tb}$ is a dummy variable equal to zero in pre-gamified update period (from 1 to 20 trading days before gamification) and one during the post-gamified update period (from 1 to 20 or 21 to 40 or 41 to 60 trading days after gamification, depending on specification); $Volume_{itb}$ is the trading volume; and $Volatility_{itb}$ is the difference between the high and low prices on day t scaled by the high price. The variables are winsorized at 1% and 99% and standardized by symbol, as such models control for stock fixed effects. Standard errors in parentheses are double-clustered across firms and over time. Asterisks ***, **, and * denote the 0.01, 0.05, and 0.10 levels of statistical significance.

	Retail Volume, 1-20 days		Retail Volume, 21-40 days		Retail Volume, 41-60 days	
	[1]		[2]		[3]	
Panel A: Regressions without control variables						
Post	0.025	***	0.019	**	0.020	*
	(0.01)		(0.00)		(0.01)	
Controls	No		No		No	
Panel B: Regressions with control variables						
Post	0.012	***	0.008	*	0.008	
	(0.00)		(0.00)		(0.01)	
Controls	Yes		Yes		Yes	