Gamification of Stock Trading: Losers and Winners*

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Abstract. Gamification of stock trading is a novel practice by brokers to incorporate game-like features to increase clients' engagement with trading. This study examines how the market reacts to the introduction of 142 gamification features in the mobile trading apps of 17 major U.S. brokers. I find that the gamification of trading can be viewed as a double-edged sword. It alters and worsens retail traders' strategy by reducing their returns and increasing return volatility. However, it also reduces costs and risks for liquidity providers by making retail order flow less toxic, leading to a positive effect for the rest of the market.

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

JEL: G11; G12; G14.

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1. Introduction

Gamification acts as a catalyst to significantly boost human engagement in a given task. 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)). 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 about the regulation of brokers strategies in the U.S. to enhance clients' engagement (SEC (2021)) call for a market microstructure study of gamification.

I add to this literature by analyzing updates of major U.S. brokers' mobile trading apps. The updates are typically accompanied by developers' notes about the purpose of an update. Based on these notes, I identify updates that are associated with gamification of a trading process. The results suggest that gamified updates drive retail traders to take more risks and diminish their returns. In the meantime, trading costs decrease, and market quality improves for the rest of the market.

The sample of app updates made by brokerage firms comes from MobileAction (`https://www.mobileaction.co/`), which stores the data for all apps in the App Store starting from 2018. I collected a sample of updates for 17 major U.S. brokers' mobile trading apps from 2018 to 2021. In total, 142 updates introduced new game-like features into the apps.

The results show that gamified updates increase retail trading volume yet do not substantially change the number of brokerage app users. These findings suggest that gamification enhances retail trading volume by increasing the engagement of existing app users. Unfortunately, gamification weakens the trading strategy of retail traders. It diminishes intraday retail trading return and increases return volatility. There is a bright side, however.

Gamification makes retail order flow less toxic for the counterparts of retail traders, i.e., liquidity providers. First, a decrease in retail return following gamification implies a decrease in adverse selection costs. Second, retail volume imbalance decreases post gamified updates, which makes inventory management easier for liquidity providers.

Eventually, these benefits go beyond market makers and disperse to the rest of the market. Transaction costs, proxied by quoted, effective, realized spreads, and price impact, decrease post gamified updates. Moreover, market quality improves, which is captured by an increase in traded volume and a decrease in market-wide price and return volatility.

The aforementioned results have substantial economic significance. The cumulative effect of all gamified updates in the sample is an increase in retail traded volume by 21.07% and a decrease in retail return by 27.78%. The overall market benefits from these changes, as the effective spread declines by 16.55%, and trading volume, besides retail trading volume, goes up by 12.23%.

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 lured 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) show 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.

The partial answer to this incongruity may lie in the heterogeneity of retail traders. Eaton, Green, Roseman, and Wu (2021) find that properties of retail order flow are different for clients of different brokers. Overall, whether retail traders are informed or not remains an open question. While some studies show that retail traders generate positive returns (Boehmer, Jones, Zhang, and Zhang (2021)), others demonstrate that retail traders act more like noise traders (Peress and Schmidt (2020)). My findings illustrate that retail traders generate positive intraday returns on average, but this property is highly malleable and can be altered by gamification. As a result, retail traders act more noisily and contribute to market liquidity (Glosten and Milgrom (1985); Kyle (1985)).

The study also contributes to the literature that examines retail herding. Retail traders tend to trade in the same direction in response to market-wide events (Barber, Odean, and Zhu (2008); Barber, Lin, and Odean (2021)). Such a trading strategy creates additional inventory costs for market makers, who act as counterparties in these trades (Ho and Stoll (1981); Grossman and Miller (1988); Hendershott and Menkveld (2014)). The antidote to herding is noisier trades. For example, Cookson, Engelberg, and Mullins (2023) show that disagreement among retail investors leads to greater liquidity because such traders are relatively balanced on both sides of an order book. The current research indicates that gamification forces retail traders to act more noisily, which makes their order flow less toxic. In line with the theory of Baldauf, Mollner, and Yueshen (2023), market makers utilize this shift to improve exchange execution, as manifested in improved market-wide liquidity metrics.

This paper also discusses retail brokerage firms. In today's market, they act as intermediaries between retail traders and wholesalers. The current practice, known as payment for order flow, allows brokerage firms to collect retail order flow and sell it to wholesalers for 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 (2022)). Then these orders are executed off-exchange (Menkveld, Yueshen, and Zhu (2017); Buti, Rindi, and Werner (2017)). Since the amount of the premium paid to brokerage firms depends on the traded volume they are able to collect (Bryzgalova, Pavlova, and Sikorskaya (2023)), it is in their best interest to maximize retail trading on their platforms (Egan (2019); Heimer and Simsek (2019)). To do so, brokers introduce new rational and behavioral features into their platforms. Two examples of rational features are zero-commission trading (Jain, Mishra, O'Donoghue, and Zhao (2020)) and fractional shares trading (Bartlett, McCrary, and O'Hara (2022)). In contrast, behavioral features include practices that increase the propensity of retail traders to execute extra trades, such as push notifications (Arnold, Pelster, and Subrahmanyam (2022); Moss (2022)) and gamification.

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 only documented cases of the use of gamification are in the banking sector (Rodrigues, Oliveira, and Costa (2016); Baptista and Oliveira (2017)). This study contributes to the literature by analyzing how new game-like features, introduced by brokerage firms, affect their clients, i.e., retail traders. Chapkovski, Khapko, and Zoican (2021) conducted an experiment on traders using a trading platform with and without game-like features. Their study shows that gamification elements increase traders' engagement, prompt them to take excessive risks, and conduct noisier trading. The results of this study confirm these findings in an empirical setting.

2. Data and metrics

The study data come from four main sources: (i) MobileAction (`https://www.mobileaction.co/`), (ii) AppTweak (`https://www.apptweak.com/en`), (iii) the Trade and Quote (TAQ) database provided by the New York Stock Exchange, and (iv) Center for Research in Security Prices (CRSP).

2.1 Brokerage apps updates and number of downloads

MobileAction is a company that helps mobile apps promote themselves 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. For this study, I obtained apps activity data of 17 major brokerage firms in the U.S. from 2018 to 2021. I use two pieces of information: (i) date of an update, and (ii) description of an update. On average, each app updates every 13 days or 112 times during the analyzed time frame. The vast majority of these updates (93%) are routine bug fixes, while the rest (7%) may 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 search to identify updates that have the highest likelihood of being associated with the gamification of app design. Specifically, I define an update as potentially gamified if it contains one of the following words: *design*, *color(s)*, or *font(s)*. For example, one update from Fidelity mentioned "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.[1] Following this rationale, I selected all app updates that changed the design of an app based on the update description. In total, I have identified 142 such updates. 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 an overestimation of the number of gamified updates, since change of an app design did not always lead to more game-like features in an app. Indeed, if some updates changed the app design in a way that did not alter the behavior of clients of the app, 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 a quantitative and data science approach to help its 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

[1] https://www.reddit.com/r/fidelityinvestments/comments/n0fvgz/meet_the_new_fidelity_mobile_beta_trading/

obtained the number of downloads for 17 brokerages apps from 2018 to 2021. On average, each app had $2,361$ downloads from new users. This number varied 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.

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 (2023). The former identification algorithm relies on the fact that, in today's market, 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 (2023) contribute to an algorithm by switching the signing strategy from the sub-penny amount to the prevalent quoted spread midpoint during a trade, which significantly decreases the signing error of retail trades.

In this study, I use four retail trading metrics: (i) retail volume, (ii) retail imbalance, (iii) retail intraday return, and (iv) retail intraday return volatility. Retail volume $retail\_volume_{it}$ 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 total buy and sell retail shares volume scaled by the total retail shares volume. Formally,

$$retail\_imbalance_{it} = \left|\frac{buy\_vol_{it} - sell\_vol_{it}}{retail\_volume_{it}}\right|, \tag{1}$$

where buy_vol_{it} and $sell\_vol_{it}$ are the total sell and buy retail shares volume. Retail intraday return is the traders' profit plus the value of the end-of-day holdings scaled by total dollar volume traded by retailers. Formally,

$$retail\_return_{it}=[(\$\_sell\_vol_{it}-\$\_buy\_vol_{it})+(buy\_vol_{it}-sell\_vol_{it})\times close\_price_{it}]/(0.5\times\$\_vol_{it}), \quad (2)$$

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 $\$\_vol_{it} = \$\_sell\_vol_{it} + \$\_buy\_vol_{it}$. I divide $\$\_vol_{it}$ by two to avoid double counting. Finally, retail intraday return volatility is calculated as squared retail intraday return, i.e., $return\_volatility_{it} = retail\_return^2_{it}$.

2.3 Liquidity metrics

I obtained liquidity metrics from the TAQ database. I computed quoted and effective spreads as well as the two components of the latter, that is, 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 $quoted\_spread_{it} = \dfrac{best\_ask_{it} - best\_bid_{it}}{midpoint_{it}}$, 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., $midpoint_{it} = \dfrac{best\_ask_{it} + best\_bid_{it}}{2}$. Further, to measure trading costs incurred by the liquidity demanders, I computed the *effective spread* as twice the signed difference between the traded price and the NBBO midpoint at the time of the trade: $effective\_spread_{it} = 2 \times (price_t - midpoint_t)$, where $price_t$ is a trade price. Next, to assess the levels of adverse selection, I computed 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* was 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) show that this algorithm performs well in modern markets. All variables are scaled by the corresponding quote midpoints. When computing daily aggregates, I weight quoted spreads by the time they are outstanding and weight all trade-related metrics by the corresponding trading volume. To compute price impacts, I use 15-second horizons.

2.4 The rest of the market

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

$$return_{it} = [(\$\_sell\_vol_{it} - \$\_buy\_vol_{it}) + (buy\_vol_{it} - sell\_vol_{it}) \times close\_price_{it}] / (0.5 \times \$\_vol_{it}), \tag{3}$$

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 $\$\_vol_{it} = \$\_sell\_vol_{it} + \$\_buy\_vol_{it}$. I divide $\$\_vol_{it}$ by two to avoid double counting. Finally, intraday return volatility is calculated as squared intraday return, i.e., $return\_volatility_{it} = return_{it}^2$. For all three metrics, I exclude retail trades identified by BJZZ algorithm.

2.5 Sample

To define the sample, I began with all common equities traded in the TAQ in January 2018, which is the beginning of the sample period. The sample included stocks that survived the entire

2018-2021 period and those that had non-zero traded volume for each trading day in a time-series. The final sample consists of 1404 stocks.

Table 2 reports the summary statistics. The average stock has about $20 billion in market capitalization and trades close to 1.6 million shares a day at a price of $81. The quoted and effective spreads are 23.93 and 13.99 bps, with a price impact of 7.42 bps and a realized spread of 6.56 bps. In line with the previous literature, retail traders generate positive intraday return, which is 4.46 bps in the sample. The average retail imbalance is around 20%, and the retail trading volume is close to 0.2 million shares a day, which is 1.25% of the overall volume.

[Table 2]

Such a small ratio of retail to overall volume may seem trivial. To put this number into context, a couple of caveats about the BJZZ retail trading identification algorithm are worth mentioning. While today's stock market witnesses the all-time high participation 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 Barber, Huang, Jorion, Odean, and Schwarz (2023) finds that this number is lower for more recent years, around 35%, and even lower for low cap stocks, which constitute a substantial portion of the stock sample for this study. Despite the hardship of the BJZZ algorithm to identify retail trades, i.e., a high Type II error, its Type I error is small, and its ability to capture shifts in retail trading has been confirmed in the previous literature (Boehmer, Jones, Zhang, and Zhang (2021); Baig, Blau, Butt, and Yasin (2023)). Thus, even though the BJZZ algorithm poorly identifies *level* values of retail trading, its ability to capture *changes* in retail trading is sufficient to infer meaningful results.

3. Empirical results

3.1 Methodology

I conduct my analysis in three steps. First, I illustrate the variable of interest around updates with a figure. 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.[2] The potential pitfall for an interpretation in such a setup is confounding events. If a concurrent event drives results during gamified updates, it may lead to an omitted variable bias. One example of such a confounding event is the default smartphone animation that users see when they update any app. This animation might capture their attention and encourage them to visit an app and do some trades. Such a trading decision would be irrelevant to the content of an update but rather with the fact itself that an update has happened. To resolve this concern, I include a control group in the figures and regressions. I define the control group as updates that only involve a bug fix and do not introduce any changes in app design. The control group is then matched with the gamified updates group by broker. This setup allows me to control for brokerages' updates fixed effects. These include the above-mentioned default animation of an update, the strategic timing of updates by brokerage firms, or any temporal technical disruptions caused by updates, etc. Finally, variables of interest are winsorized at 1% and 99% and standardized by stock.

Univariate results report the average value of the variable of interest 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 $Post_t$, 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. Further analysis includes a regression setup with volume and volatility as control variables, as they might be correlated with $Post_t$ and could drive

[2] The results are robust to alternative event-window length. See 3.5.

changes in the dependent variable. Formally, I specify this type of linear regression as follows:

$$DepVar_{it} = \alpha_i + \beta_1 Post_t + \beta_2 Volume_{it} + \beta_3 Volatility_{it} + \varepsilon_{it}, \tag{4}$$

where $DepVar_{it}$ represents some variable of interest for stock i on day t; $Post_t$ is a dummy variable equal to one after the gamified update period and zero before the gamified update period; $Volume_{it}$ is the trading volume; and $Volatility_{it}$ 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:

$$\Delta DepVar_{ijt} = \alpha_{ij} + \beta_1 Post_t + \beta_2 \Delta Volume_{ijt} + \beta_3 \Delta Volatility_{ijt} + \varepsilon_{ijt}, \tag{5}$$

where $\Delta DepVar_{ijt}$ is the difference between the gamified updates and the bug fix updates computed for stock i, broker j, and day t; and $\Delta Volume_{ijt}$ and $\Delta Volatility_{ijt}$ controls are the differences between the volume and volatility estimates for stock i, broker j, and day t.[3] 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 A.1 and Table A1), 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 per

[3]To calculate the difference between gamified updates and bug fix updates for a variable, I first compute the average value of the variable by stock, event day, and broker, using data from all bug fix updates. I then subtract this average from the values associated with the gamified updates. For example, broker introduced bug fix updates 50 times, and the average retail volume for AAPL stock on the first day after these updates was 2,500. Broker also introduced gamified updates on different dates, with retail volumes of 10,000 and 20,000 on the first day after these updates. $\Delta RetailVolume$ for the first gamified update would be 7,500 (10,000 - 2,500). For the second gamified update, $\Delta RetailVolume$ would be 17,500 (20,000 - 2,500).

post-gamified period time window, which is 4.10 in the sample.

3.2 Retail trading metrics

3.2.1 Retail volume. I begin the analysis by examining the effects of trading gamification on retail volume. The experiment conducted by Chapkovski, Khapko, and Zoican (2021) shows that game-like features intensify trading. Figure 1 (sub-figure 1) illustrates these effects. In line with the previous literature, I capture an increase in retail traded volume post-gamified update.

[Figure 1]

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, columns 1 and 2). Finally, the DiD setting shows a similar increase of 0.012 standard deviations.

[Table 3]

In terms of economic significance, the average gamified update increases retail volume by 0.15%, and the cumulative effect from all gamified updates in the sample is an increase of retail volume by 21.07%. This increase could come from two potential sources: (i) an increase in the number of retail traders or (ii) an increase in trading intensity by existing retail traders. The next section sheds light on the primary source of an increase in retail trading volume.

3.2.2 Number of retail traders. In the experiment by Chapkovski, Khapko, and Zoican (2021), the authors directly control for the number of participants. Such a setup allows the authors to equate changes in trading volume with changes in trading intensity by an average participant. In an empirical setup, however, I cannot observe the number of retail traders before and after gamified updates. Thus, to draw any conclusion about trading intensity, I should confirm that the number of retail traders stays approximately the same before and after gamified updates. To explore this concern, I analyze the number of app downloads by new users before and after gamified updates. If such updates attract new retail traders to a market, we should expect an increase of app downloads. Figure A1 does not show any evidence of this. The dynamic of app downloads around gamified updates does not change in comparison to the control group and for pre- and post-event periods. Moreover, regressions in the univariate, gamified group only, and the DiD settings show that the number of downloads do not change significantly before and after gamified updates (Table 3, columns 3 and 4). Thus, in line with Chapkovski, Khapko, and Zoican (2021), the findings show that an increase in retail traded volume is driven by an increase in trading intensity by existing clients of these apps rather than by new users. Overall, the results show that gamified updates drive retail traders to increase the *quantity* of trading. This leads to a question: do gamified updates change the *quality* of trading?

3.2.3 Retail return and volatility. The vast majority of investors consider two key characteristics as a cornerstone to assess their investment performance: (i) return on investment and (ii) return volatility. These two factors capture an intuitive idea of *risk and reward* that is fundamental in economics. This section of the paper measures how trading gamification affects these metrics for retail trades. Figure 2 plots intraday return and intraday return volatility for 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 2]

The regression results corroborate this finding (Table 4, columns 1, 2, 3, and 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 with 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 deviatons in the DiD setup. These changes have a remarkable economic significance. Each gamified update decreases the retail return by 0.20% and increases the return volatility by 0.12%. The cumulative effect from all gamified updates in the sample is 27.78% for the retail return and 17.59% for the return volatility.

[Table 4]

The findings show that gamification harms retail traders. Their performance deteriorates in two dimensions: their trading strategy become less rewarding and more risky. In the meantime, today's stock market is a highly complex and interconnected system where changes in the trading strategy of one party often lead to changes in the trading of its counterparty. The next sections explore if there is evidence to support such a claim.

3.2.4 Retail imbalance.

Previous literature indicates that retail traders are somewhat informed (Boehmer, Jones, Zhang, and Zhang (2021); Welch (2022)) and tend to herd (Barber, Odean, and Zhu (2008); Barber, Lin, and Odean (2021)). Both features impose additional costs on market makers who act as a counterpart to retail traders. The preceding section demonstrates that gamified updates make the retail trading strategy less toxic for market makers by reducing the retail return from trading. In this section, I test whether the second channel, herding, also changes due to gamification.

The experiment by Chapkovski, Khapko, and Zoican (2021) shows that gamification makes the trading strategy of retail traders noisier. To test this in an empirical setting, I analyze how the retail trading volume imbalance changes after gamified updates. Figure 1 (sub-figure 2) plots the retail imbalance before and after gamified updates and the 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 1 percentage point (Table 4, columns 5 and 6).

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 decrease in the retail imbalance of 0.10% per update, amounting to a cumulative decrease of 13.60% due to all gamified updates in the sample.

Despite gamification negatively impacting retail trading performance, it simplifies trading for market makers who act as a counterparty in these transactions. Gamification makes the retail order flow less toxic by reducing its return, and it makes it noisier by decreasing its order imbalance. Both features are favorable for market makers and should ultimately decrease their trading costs (Glosten and Milgrom (1985); Kyle (1985)).[4] Next, I test whether these benefits remain with market makers or transfer further, creating positive externalities for the rest of the market.

3.3 Market-wide liquidity

3.3.1 Quoted and effective spreads. To test if gamification changes market-wide liquidity, I examine two liquidity proxies: (i) quoted spread and (ii) 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 are actually incurred by market participants. Thus, effective spread accounts for the fact that trades are often timed to periods when liquidity is relatively cheap.

[Figure 3]

Both liquidity metrics decline following gamified updates (Figure 3). The univariate setting shows a decrease in quoted and effective spreads by 0.02 bps and 0.03 bps, respectively (Table 5, columns 1, 2, 3, and 4). In a regression setting, these values are 0.163 and 0.089 standard

[4] At first glance, it might seem counter intuitive 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, while intraday retail return volatility is more concerned with the timing of trades rather than their direction. This means that even if retail imbalance declines, intraday retail return volatility can still rise if retail investors time the market well at one point and then fail to do so at another.

deviations, respectively. Finally, the DiD setup shows a more modest but still significant decline in spreads by 0.130 and 0.064 standard deviations. These numbers translate to a decline in quoted and effective spreads of 0.15% and 0.12% per update or by 20.76% and 16.55% cumulatively across all gamified updates in the sample.

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, I decompose effective spread into its components, (i) price impact and (ii) realized spread, to see how these are changing post-gamified updates.

3.3.2 Price impact and realized spread. The previous findings show that trading gamification decreases retail return, which should decrease 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 considered a proxy of order processing costs, both of these variables are expected to decrease post-gamified updates.

In line with this argument, the results show that price impact and realized spreads decreased in the post-gamified period (Figure A2). Price impact and realized spread declined by 0.02 and 0.01 bps in the univariate setup (Table 5, columns 5, 6, 7, and 8). The regressions analysis run on gamified updates and the DiD setup have corresponding decreases of 0.072, 0.040, and 0.054, 0.054 standard deviations, respectively. On average, each gamified update decreases the price impact by 0.10% and the realized spread by 0.07%. Taken together, all gamified updates in the sample decrease the price impact by 14.05% and the realized spread by 10.21%.

The results show that market makers benefit from gamified updates from two channels. First, gamification decreases retail return, leading to lower adverse selection costs for liquidity providers. Second, order processing costs, proxied by realized spread, also decline due to increased noise in retail trading after gamified updates. Ultimately, these benefits extend beyond market makers and are distributed to the rest of the market in the form of decreased trading costs, which confirms a theory of Baldauf, Mollner, and Yueshen (2023) that market makers intermediate heterogeneous order flows, trading off the expected spread revenue against inventory costs. In the next section, I analyze additional dimensions of market quality.

3.4 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 as a result of gamification. The lower trading costs identified in the previous section as a consequence of 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 form expectations. 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 that adverse selection declines post-gamified updates, I expect that volatility may also decline.

Figure A3 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.

Both price and return volatility decrease after the gamification update, as shown in Figure A4 and in the univariate results in Table 6. 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.

[Table 6]

On average, each gamification update is associated with a 0.09% increase in traded volume, a 0.09% decrease in price volatility, and a 0.04% decrease in return volatility. The cumulative effect of 142 updates leads to a 12.23% increase in traded volume, a 14.64% decrease in price volatility, and a 5.03% decrease in return volatility. These results suggest that gamification is associated with greater price and return stability and also potentially with greater gains from trade, as more market participants may enter the market to engage in asset exchange.

3.5 Robustness

3.5.1 Various event windows. In section 3.1, I mentioned that the results are robust to varying the length of event windows. In the main sample, 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 line 1 referencing the base regression case with a 20 trading days event windows.

[Table 7]

First, I examine several adjustments to the event windows. In line 2 of Table 7, I shortened the length of 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.

3.5.2 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 theoretically should bias the results upward. To mitigate these effects, in Table 7, line 4, I regress every variable of interest on a 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.

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 suggest that it may be useful to account for possible serial dependence in the dependent variable and error terms. Following this suggestion, I detrend using the polynomial and an additional AR(1) term. Besides detrending, I follow my standard data cleaning and adjustment procedures. Line 5 in Table 7 shows that the results obtained using this approach remain similar to those in the main text.

3.5.3 Placebo test. An alternative method to confirm that the results are not driven by background trends 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 exactly 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. Formally,

$$\Delta DepVar_{i,t,t-1} = \alpha_{i,t} + \beta_1 Post_t + \beta_2 \Delta Volume_{i,t,t-1} + \beta_3 \Delta Volatility_{i,t,t-1} + \varepsilon_{i,t,t-1}, \tag{7}$$

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

3.5.4 Tick constrained stocks. One limitation of the BJZZ retail trading identification algorithm is its reliance on the amount of sub-penny price improvement. As the bid-ask spread for a given stock increases, the reliability of inferences based on price improvement decreases. Consequently, Barber, Huang, Jorion, Odean, and Schwarz (2023) notes that stocks with bid-ask spreads constrained by 1 tick should have the highest BJZZ identification rate. Although my main results show statistical significance, it is still of interest to examine the effect of the gamification of stock trading on the most liquid stocks in my sample.

From my initial sample of 1,404 stocks, I selected those that traded with a 1-tick spread for more than half of the total trading hours on the exchange for each trading day from 2018 to 2021. The final sample consists of 63 of the most liquid stocks in the market. The results for these stocks are reported in line 9 of Table 7. The retail metrics results are consistent with the main text. Additionally, I find that the gamification of stock trading does not affect market-wide metrics, except for volume, likely due to the already exceptional market quality, which is largely independent of the gamification of stock trading.

3.5.5 Canadian control group. One concern in using bug fix updates as a control group is the timing of these updates. Since gamified updates and bug fix updates happen at different times, there is a potentially high chance of violating the parallel trend assumption of the DiD setup. To alleviate this concern, I plot bug fix updates along with gamified updates for all figures in this paper. That said, 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 use a control sample of stocks that trade in Canada, matched with the main U.S. sample by market capitalization and trading volume. The Canadian data have daily granularity and resemble CRSP data.[5] 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) show 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:

$$\Delta DepVar_{it} = \alpha + \beta_1 Post_t + \beta_2 \Delta Volume_{it} + \beta_3 \Delta Volatility_{it} + \varepsilon_{it}, \tag{8}$$

where $\Delta DepVar_{it}$ is the difference between the spread proxies (i.e., EOD and AR) computed for a day t that falls into the event window for a pair of stocks i that includes a U.S. sample stock and its matched Canadian counterpart, $Post_t$ is a dummy variable equal to one after the gamified update and zero before, and $\Delta Volume_{it}$ and $\Delta Volatility_{it}$ controls are the differences between the U.S. and Canadian volume and volatility estimates. As before, this regression standardizes all non-dummy variables by stock and uses standard errors clustered by stock and day. Table 7 line 10 reports the $Post$ coefficient estimates. The findings are similar to those obtained with the previous specifications. These results allow us to suggest with added confidence that changes in the dependent variables are driven by gamified updates and not by model misspecification.

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

4. Conclusion

Starting from the informational revolution, humanity has gained an unprecedented ability to capture, quantify, and quickly update myriad characteristics of its activity. These data can be neatly grouped and presented back to humans using eye-catching infographics, stylized visualization, and forward-projected trends. For a human, such a tool might turn even the most mundane task into a fun and addictive process resembling a game, from which the word *gamification* gets its root.

The gamification of trading is a recent trend among brokerage firms to integrate game-like features into their trading apps with the purpose of increasing client 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 that are associated with gamification of the trading process in these apps.

First, gamification harms a major group of clients of these trading apps, i.e., retail investors. While retail trading volume goes up, intraday return declines and return volatility increases post gamification update. In line with the previous literature, I find that gamification increases the *quantity* but decreases the *quality* of trading for retailers.

Even though gamification adversely affects retail traders, it creates a positive effect for market makers who take the opposite side in these trades. The results show that retail volume imbalance decreases post gamified update, indicative of the reduced toxicity of retail order flow. This new ease to handle retail order flow for market makers transfers to the rest of the market through reduced trading costs and improved market quality. Trading costs are proxied by quoted, effective, and realized spreads, as well as by price impact, and market quality improvement manifests in increased traded volume other than retail volume and decreased stock price volatility and market-wide return volatility.

Whether gamification of trading is an ethical practice is still an open question. Starting in

2021, the Securities and Exchange Commission has routinely conducted speeches and public comment requests about this topic for further market regulation. This research shows that there is no easy answer to this question, and like almost everything in this world, gamification of trading has its dark side and its bright side.

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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. In Panel A, these include market capitalization, daily trading volume, and share price. Panel B reports retail trading metrics, including retail traded volume, retail trading imbalance, intraday return, and intraday return volatility calculated as squared intraday return. Panel C reports liquidity metrics computed from the TAQ, including quoted, effective, and realized spreads as well as price impact. Panel D reports market-wide metrics that exclude retail trades from 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 compute 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
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 and App Downloads

This table contains the univariate results (Panel A), gamified group regression results (Panel B), and difference-in-differences regression results (Panel C) that measure the effects of gamified updates on retail traded volume and number of daily app downloads. 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:

$$DepVar_{it} = \alpha_i + \beta_1 Post_t + \beta_2 Volume_{it} + \beta_3 Volatility_{it} + \varepsilon_{it}, \tag{4}$$

where $DepVar_{it}$ represents the variable of interest for stock i and day t; $Post_t$ is a dummy variable equal to one during the post-gamified update period and zero during the pre-gamified update period; and $Volume_{it}$ is the trading volume; and $Volatility_{it}$ is the difference between the high and low prices on day t scaled by the high price. Panel C reports the coefficient estimates from the following model:

$$\Delta DepVar_{ijt} = \alpha_{ij} + \beta_1 Post_t + \beta_2 \Delta Volume_{ijt} + \beta_3 \Delta Volatility_{ijt} + \varepsilon_{ijt}, \tag{5}$$

where $\Delta DepVar_{ijt}$ is the difference between gamified updates and bug fix updates computed for stock i, broker j, and day t; and $\Delta Volume_{ijt}$ and $\Delta Volatility_{ijt}$ controls are the differences between the volume and volatility estimates for stock i, broker j, and day t. 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 level of statistical significance.

	Retail Volume				App Downloads			
	[1]		[2]		[3]		[4]	
Panel A: Univariate results								
Pre	177,764				1,914			
Post	180,508	***			1,916			
Panel B: Gamified group								
Post	0.025	***	0.012	***	0.000		0.001	
Panel C: DiD results								
Post	0.025	***	0.012	***	0.014		0.015	
	(0.00)		(0.00)		(0.01)		(0.01)	
ΔVolume			0.650	***			0.032	***
			(0.00)				(0.00)	
ΔVolatility			0.129	***			0.043	***
			(0.00)				(0.00)	
Intercept	0.001		0.002		-0.008		-0.008	
	(0.00)		(0.00)		(0.00)		(0.00)	

Table 4: Retail Metrics: Return, Volatility, and Imbalance

This table contains the univariate results (Panel A), gamified group regression results (Panel B), and difference-in-differences regression results (Panel C) that measure the effects of gamified updates on retail intraday return, retail intraday return volatility, 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:

$$DepVar_{it} = \alpha_i + \beta_1 Post_t + \beta_2 Volume_{it} + \beta_3 Volatility_{it} + \varepsilon_{it}, \tag{4}$$

where $DepVar_{it}$ represents the variable of interest for stock i and day t; $Post_t$ is a dummy variable equal to one during the post-gamified update period and zero during the pre-gamified update period; and $Volume_{it}$ is the trading volume; and $Volatility_{it}$ is the difference between the high and low prices on day t scaled by the high price. Panel C reports the coefficient estimates from the following model:

$$\Delta DepVar_{ijt} = \alpha_{ij} + \beta_1 Post_t + \beta_2 \Delta Volume_{ijt} + \beta_3 \Delta Volatility_{ijt} + \varepsilon_{ijt}, \tag{5}$$

where $\Delta DepVar_{ijt}$ is the difference between gamified updates and bug fix updates computed for stock i, broker j, and day t; and $\Delta Volume_{ijt}$ and $\Delta Volatility_{ijt}$ controls are the differences between the volume and volatility estimates for stock i, broker j, and day t. 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 level of statistical significance.

	Retail Return		Return Volatility		Retail Imbalance	
	[1]	[2]	[3]	[4]	[5]	[6]
Panel A: Univariate results						
Pre	4.63		0.14		0.20	
Post	4.57 ***		0.15 ***		0.19 ***	
Panel B: Gamified group						
Post	-0.011 ***	-0.011 ***	0.030 ***	0.015 ***	-0.020 **	-0.020 **
Panel C: DiD results						
Post	-0.008 ***	-0.008 ***	0.030 ***	0.015 ***	-0.020 ***	-0.020 ***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
ΔVolume		-0.001		0.017 ***		-0.050 *
		(0.00)		(0.00)		(0.00)
ΔVolatility		0.000		0.292 ***		-0.035 ***
		(0.00)		(0.00)		(0.00)
Intercept	-0.001	-0.001	-0.001	0.000	0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)

Table 5: Liquidity Costs

This table contains the univariate results (Panel A), gamified group regression results (Panel B), and difference-in-differences regression results (Panel C) that measure the effects 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:

$$DepVar_{it} = \alpha_i + \beta_1 Post_t + \beta_2 Volume_{it} + \beta_3 Volatility_{it} + \varepsilon_{it}, \tag{4}$$

where $DepVar_{it}$ represents the variable of interest for stock i and day t; $Post_t$ is a dummy variable equal to one during the post-gamified update period and zero during the pre-gamified update period; and $Volume_{it}$ is the trading volume; and $Volatility_{it}$ is the difference between the high and low prices on day t scaled by the high price. Panel C reports the coefficient estimates from the following model:

$$\Delta DepVar_{ijt} = \alpha_{ij} + \beta_1 Post_t + \beta_2 \Delta Volume_{ijt} + \beta_3 \Delta Volatility_{ijt} + \varepsilon_{ijt}, \tag{5}$$

where $\Delta DepVar_{ijt}$ is the difference between gamified updates and bug fix updates computed for stock i, broker j, and day t; and $\Delta Volume_{ijt}$ and $\Delta Volatility_{ijt}$ controls are the differences between the volume and volatility estimates for stock i, broker j, and day t. 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 level of statistical significance.

	Quoted Spread		Effective Spread		Price Impact		Realized Spread	
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Panel A: Univariate results, bps								
Pre	22.64		14.04		7.59		6.42	
Post	22.62***		14.01***		7.57***		6.41***	
Panel B: Gamified group								
Post	-0.179***	-0.163***	-0.104***	-0.089***	-0.088***	-0.072***	-0.057***	-0.054***
Panel C: DiD results								
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 contains the univariate results (Panel A), gamified group regression results (Panel B), and difference-in-differences regression results (Panel C) that measure the effects 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:

$$DepVar_{it} = \alpha_i + \beta_1 Post_t + \beta_2 Volume_{it} + \beta_3 Volatility_{it} + \varepsilon_{it}, \tag{4}$$

where $DepVar_{it}$ represents the variable of interest for stock i and day t; $Post_t$ is a dummy variable equal to one during the post-gamified update period and zero during the pre-gamified update period; and $Volume_{it}$ is the trading volume; and $Volatility_{it}$ is the difference between the high and low prices on day t scaled by the high price. Panel C reports the coefficient estimates from the following model:

$$\Delta DepVar_{ijt} = \alpha_{ij} + \beta_1 Post_t + \beta_2 \Delta Volume_{ijt} + \beta_3 \Delta Volatility_{ijt} + \varepsilon_{ijt}, \tag{5}$$

where $\Delta DepVar_{ijt}$ is the difference between gamified updates and bug fix updates computed for stock i, broker j, and day t; and $\Delta Volume_{ijt}$ and $\Delta Volatility_{ijt}$ controls are the differences between the volume and volatility estimates for stock i, broker j, and day t. 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 level 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: Gamified group																
Post	0.025	***	0.051	***	-0.001		-0.000		-0.050	***	-0.066	***	-0.013	***	-0.009	***
Panel C: DiD results																
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:

$$\Delta DepVar_{ijt} = \alpha_{ij} + \beta_1 Post_t + \beta_2 \Delta Volume_{ijt} + \beta_3 \Delta Volatility_{ijt} + \varepsilon_{ijt}, \tag{5}$$

where $DepVar_{ijt}$ represents the retail volume (Vol), retail intraday return (Ret), retail intraday return volatility (RetVol), 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 each stock i, broker j, on day t, and all other variables as defined previously. The first line reports the *Post* coefficient for the base case, which is 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 next 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* coefficient for time-detrended variables and the polynomial time-detrend of order 2 with an autoregressive parameter AR(1) (see 3.5.2). Line 6 omits the year 2020 (COVID year). Line 7 reports regression coefficients only for the year 2020 (COVID year). Line 8 reports the difference between the *Post* coefficients of gamified updates and placebo event dates exactly one year before the actual gamified update occurred (see 3.5.3). Line 9 reports results only for the sample of tick constrained stocks. Finally, line 10 reports the differenced *Post* coefficient between U.S. stocks and matched Canadian stocks before and after gamified updates (see 3.5.5). Some results are missing due to limitations in Canadian data. 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 coefficients that are statistically insignificant, I report the result as 0.000. Intraday market returns are excluded from the table because they do not exhibit statistically significant changes in any of the models. Results for this variable are available upon request.

	Retail Metrics			Liquidity Costs				Market Metrics		
	Vol	Ret	RetVolat	QS	ES	PI	RS	Vol	PrVolat	RetVolat
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
1. Base case	0.012	-0.008	0.015	-0.130	-0.064	-0.040	-0.054	0.051	-0.066	-0.010
	(0.00)	(0.00)	(0.00)	(0.02)	(0.02)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
2. 15 days around event	0.013	-0.007	0.015	-0.117	-0.059	-0.040	-0.051	0.059	-0.051	*-0.008*
	(0.00)	(0.00)	(0.00)	(0.02)	(0.02)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)
3. 25 days around event	0.014	-0.008	0.019	-0.091	-0.057	-0.038	-0.058	0.057	-0.058	-0.009
	(0.00)	(0.00)	(0.00)	(0.02)	(0.02)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)
4. De-trend	0.09	-0.006	0.015	-0.123	-0.052	-0.031	-0.040	0.056	-0.065	-0.010
	(0.00)	(0.00)	(0.00)	(0.02)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)
5. Polynomial + AR(1))	0.08	*-0.005*	0.015	-0.106	-0.048	-0.030	-0.037	0.056	-0.067	-0.010
	(0.00)	(0.00)	(0.00)	(0.02)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)
6. No COVID period	0.10	-0.008	*0.011*	-0.154	-0.066	-0.045	-0.065	0.042	-0.045	*-0.008*
	(0.00)	(0.00)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
7. COVID period	0.18	-0.007	0.022	-0.080	-0.053	-0.031	-0.044	0.074	-0.078	-0.016
	(0.00)	(0.00)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
8. Placebo test	0.013	-0.009	0.014	-0.108	-0.062	-0.042	-0.054	0.055	-0.067	-0.012
	(0.00)	(0.00)	(0.00)	(0.02)	(0.02)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
9. 1 tick constrained stocks	0.014	*-0.004*	*0.009*	0.000	0.000	0.000	0.000	*0.015*	0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)
10. Canadian control				-0.142	-0.075			0.050	-0.062	
				(0.03)	(0.02)			(0.01)	(0.01)	

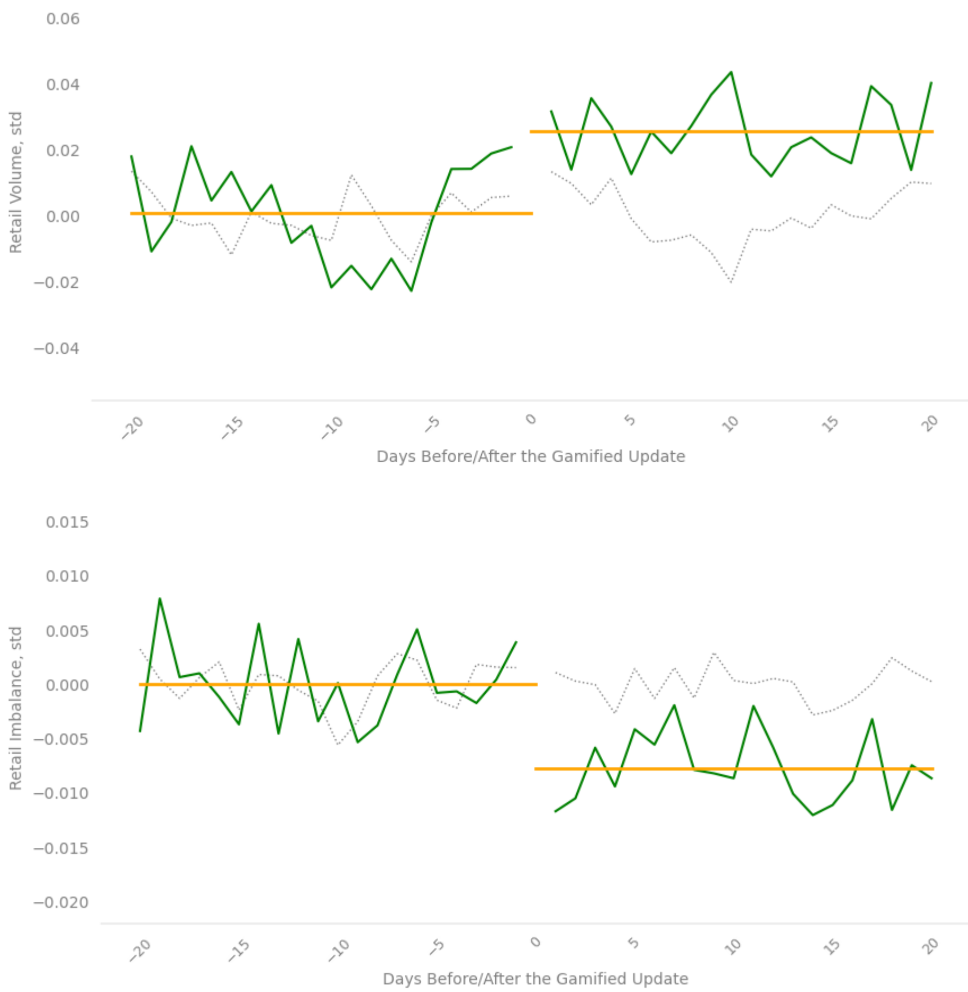

Figure 1. Retail Trading Metrics Around App Updates
This figure plots the retail traded volume and retail volume imbalance over a period of 20 trading days before and after gamified updates (green solid line) and bug fix updates (gray dotted line). Variables are standardized for each stock and then averaged across stocks.

Figure 2. Retail Trading Metrics Around App Updates
This figure plots the retail intraday return and retail intraday return volatility over a period of 20 trading days before and after gamified updates (green solid line) and bug fix updates (gray dotted line). Variables are standardized for each stock and then averaged across stocks.

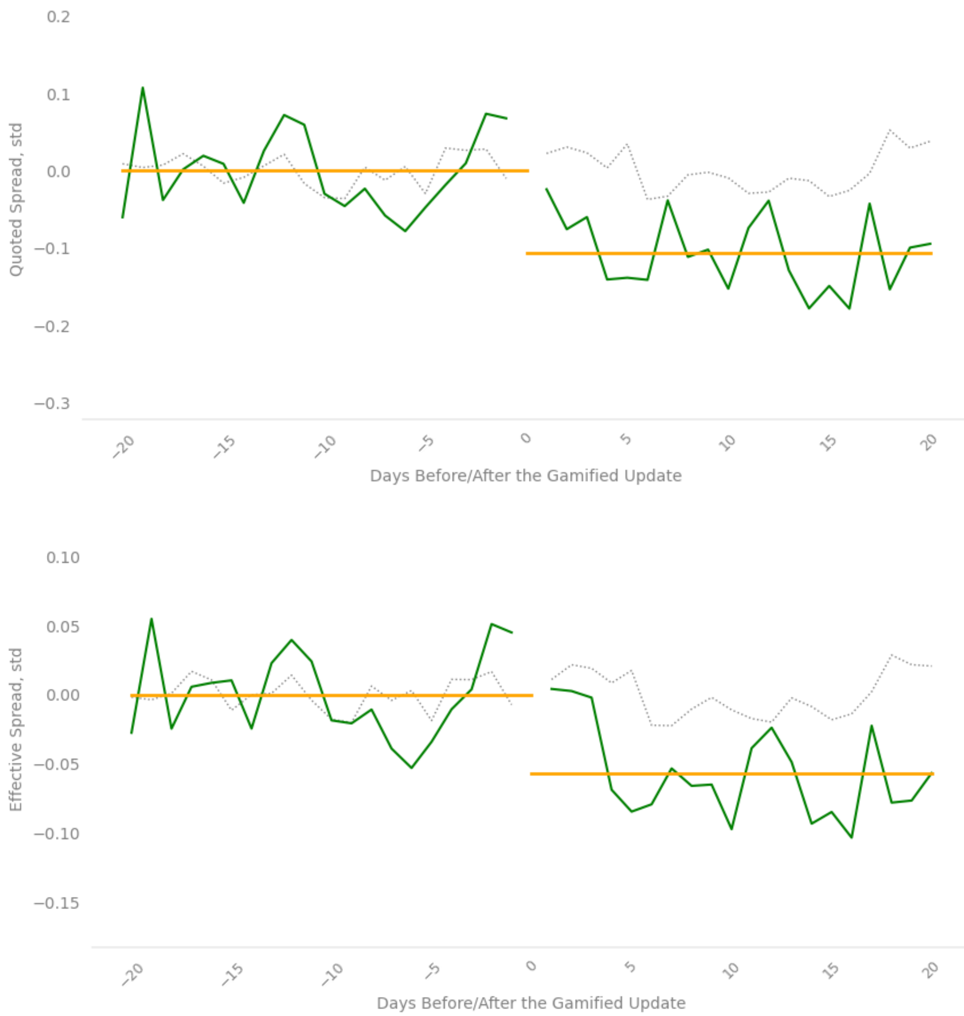

Figure 3. Liquidity Metrics Around App Updates
This figure plots the quoted spread and effective spread over a period of 20 trading days before and after gamified updates (green solid line) and bug fix updates (gray dotted line). Variables are standardized for each stock and then averaged across stocks.

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 75.19 when computed via this method. We report these standard deviations, along with the other summary statistics in Table A1.

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 (2021) shows that gamification has the strongest 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 it is that 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:

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

where $Medium_{it}$ and $Small_{it}$ are dummy variables for medium and small-sized retail orders, and all other variables are as previously defined. In this setup, the $Post_{it}$ 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 for large retail orders.

The results in Table A2 show that the effects of gamification are more pronounced in medium and small-sized trades, confirming the experimental findings of Chapkovski, Khapko, and Zoican (2021). This indicates that the main group affected by the gamification of stock trading are less experienced investors who trade in smaller amounts.

A.3 Robintrack

The main analysis explores the effect of stock trading gamification using market-wide retail trading metrics. Although the effect of stock trading gamification is strong enough to produce statistically significant results in such a noisy setup, it is still valuable to demonstrate this effect in a context with a more direct channel. Unfortunately, brokerage-specific retail trading data is not available for the majority of firms in my sample. However, Robinhood is an exception.

Robinhood provided public updates on the total number of users holding each stock on their website, with updates occurring approximately every hour. I obtained data on the breadth of ownership among Robinhood investors from Robintrack, a platform that utilized the Robinhood API to monitor and record investor interest in stocks with non-zero holdings. Robintrack began collecting this data in July 2018, and continued until August 2020.

The Robintrack dataset includes hourly snapshots of stock-level investor positions. Following the methodologies of Eaton, Green, Roseman, and Wu (2021) and Barber, Huang, Odean, and Schwarz (2022), my analysis focuses on data recorded between 9:00 AM and 4:00 PM EST on trading days identified by the Center for Research in Securities Prices (CRSP). Using this data, I examine how frequently Robinhood users change their positions following gamified updates. Although Robinhood has updated its app more frequently than other brokers (see Table 1), most of these updates do not provide detailed information about their content, with descriptions reading as follows:

Here's what's under the hood in our latest update:

- Bug fixes and improvements

Only two Robinhood updates in my sample mention changes to the app's design, which could potentially include gamification elements. Robinhood released the first such update on May 12, 2020, and the second on April 12, 2021. The second update occurred after Robintrack had stopped collecting data from Robinhood. The first update, however, is well-suited for studying the effect of stock trading gamification on Robinhood's retail traders, as indicated by the following update description:

Here's what's under the hood in our latest update:

- New fonts and colors

- New design elements

To examine how Robinhood retail trading strategies change following a gamified update, I calculate the number of times Robinhood users start and stop holding a position for a given hour, day, and stock. Consistent with the setup described in the main text, I analyze trading activity around 20 trading days of the gamified update. Figure A5 illustrates the dynamics of changes in stock holdings among Robinhood users.

[Figure A5]

The bars represent the actual values of position changes, while the lines indicate the time trends during the pre- and post-gamified update periods. The results show that engagement among Robinhood retail traders decreases during the pre-gamified period and begins to increase during the post-gamified period, as reflected by the negative time trend slope before the update and the positive slope after. Both time trend slopes are statistically significant from zero.[6] Consistent with my previous findings, I observe that gamification intensifies retail trading, as evidenced by the increased frequency of stock position changes among Robinhood users. However, this result is suggestive and should be interpreted cautiously due to several limitations: (i) the analysis is based only on one gamified update; (ii) the analysis is confounded by market perturbations during COVID-19; and (iii) there is no data available on position changes within each hour of the Robintrack snapshots.

[6]Results are available upon request.

Table A1: 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. In Panel A, these include market capitalization, daily trading volume, and share price. Panel B reports retail trading metrics, including retail traded volume, retail trading imbalance, intraday return, and intraday return volatility calculated as squared intraday return. Panel C reports liquidity metrics computed from the TAQ, including quoted, effective, and realized spreads as well as price impact. Panel D reports market-wide metrics that exclude retail trades from 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.

	Mean	St. dev.	25^{th}	Median	75^{th}
Panel A: Sample characteristics					
Market capitalization, $B	19.54	3.96	16.53	17.58	22.79
Volume, sh. '000	1,649	461	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	75.19	125.38	156.04	225.64
Retail imbalance	0.20	0.08	0.13	0.19	0.26
Intraday return, bps.	4.46	4.41	3.17	4.19	5.29
Intraday return volatility, bps	0.15	0.02	0.15	0.15	0.15
Panel C: TAQ liquidity metrics, bps.					
Quoted spread	23.93	1.64	23.59	23.72	23.88
Effective spread	13.99	1.62	13.37	13.73	14.11
Price impact	7.42	1.77	6.46	7.06	7.87
Realized spread	6.56	0.60	6.40	6.49	6.59
Panel D: The rest of the market					
Volume, sh. '000	1,467	100	1,401	1,440	1,509
Intraday return, bps.	2.29	1.72	1.58	2.29	2.97
Price volatility, bps.	0.04	0.02	0.03	0.03	0.04
Intraday return volatility, bps	0.06	0.01	0.06	0.06	0.06

Table A2: 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):

$$DepVar_{it} = \alpha_i + \beta_1 Post_{it} + \beta_2 Post \times Medium_{it} + \beta_3 Post \times Small_{it} + \beta_4 Volume_{it} + \beta_5 Volatility_{it} + \varepsilon_{it}, \quad (9)$$

where $Medium_{it}$ and $Small_{it}$ are dummy variables for the medium and small size retail orders, and all other variables are as previously defined. In this setup, the $Post_{it}$ dummy absorbs the effect for the large size retail orders, and the two interaction variables capture the incremental effect for the other two size categories, that is the effects *in addition to* the large retail orders effect. 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 level 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	

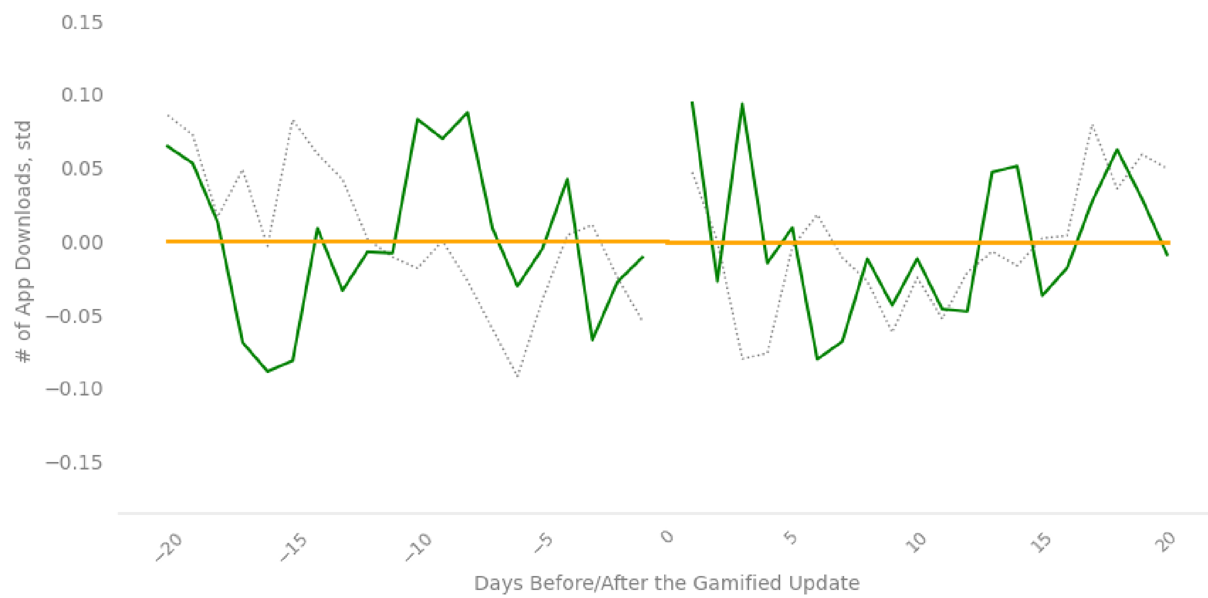

Figure A1. App Downloads Around App Updates
This figure plots the number of daily app downloads over a period of 20 trading days before and after gamified updates (green solid line) and bug fix updates (gray dotted line). Variables are standardized for each stock and then averaged across stocks.

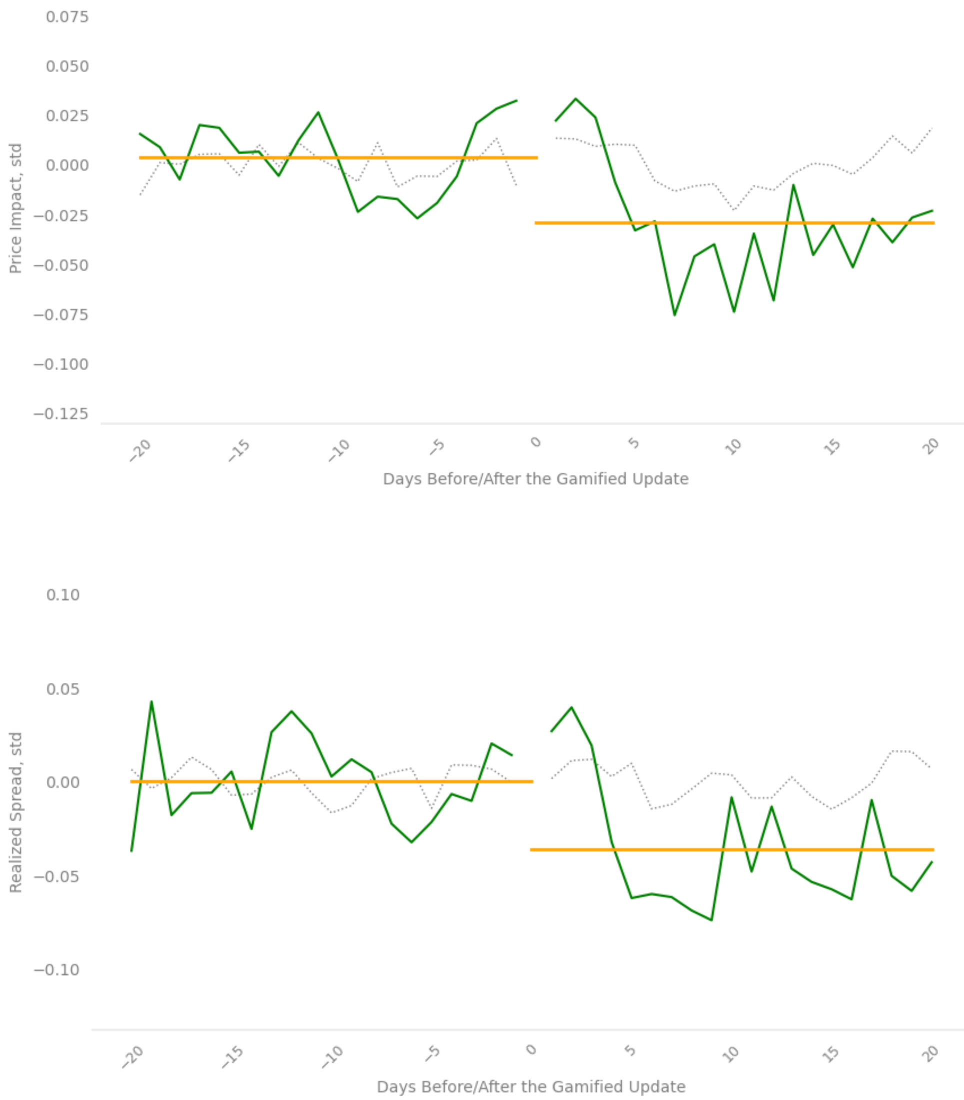

Figure A2. Liquidity Metrics Around App Updates
This figure plots the price impact and realized spread over a period of 20 trading days before and after gamified updates (green solid line) and bug fix updates (gray dotted line). Variables are standardized for each stock and then averaged across stocks.

Figure A3. Market Volume and Return Around App Updates
This figure plots the overall volume minus retail volume and volatility over a period of 20 trading days before and after gamified updates (green solid line) and bug fix updates (gray dotted line). Variables are standardized for each stock and then averaged across stocks.

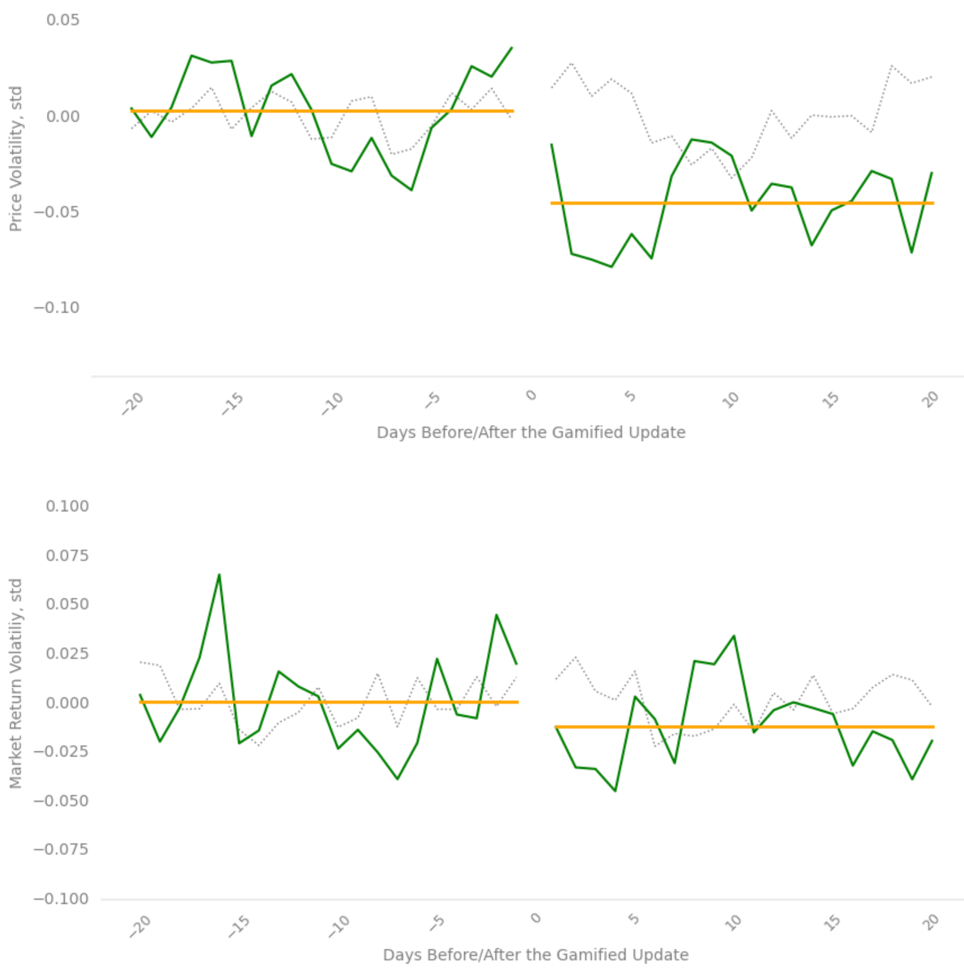

Figure A4. Market Price and Return Volatility Around App Updates
This figure plots the price and market intraday return volatility over a period of 20 trading days before and after gamified updates (green solid line) and bug fix updates (gray dotted line). Variables are standardized for each stock and then averaged across stocks.

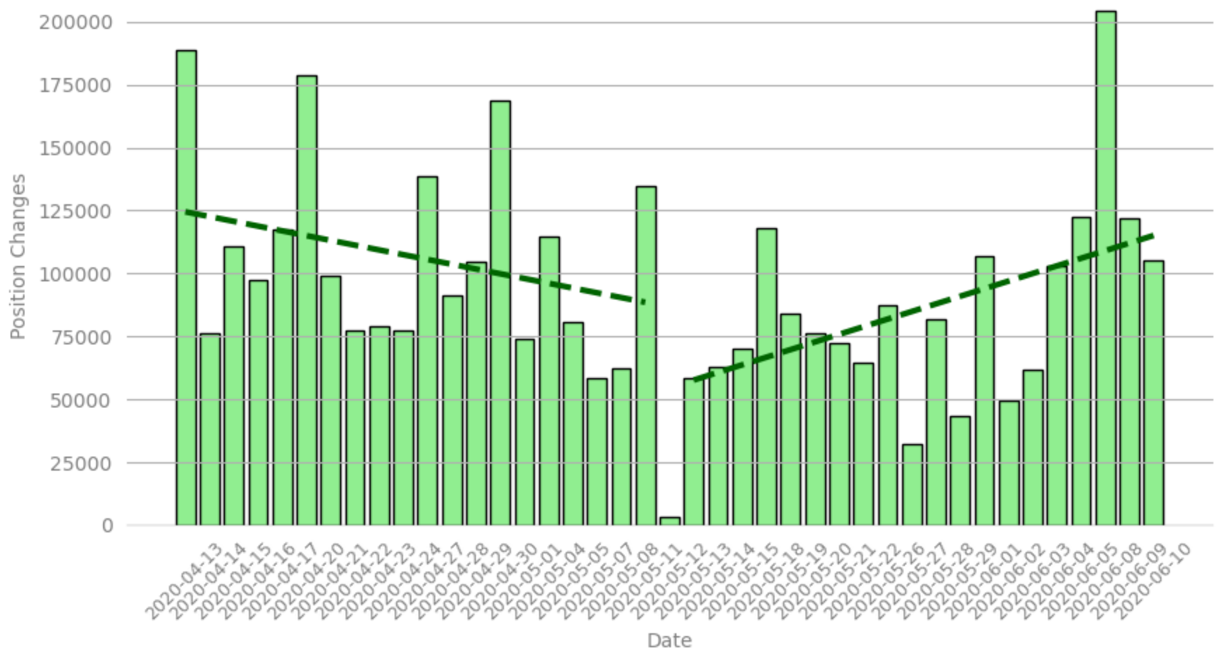

Figure A5. Number of Stock Holding Position Changes of Robinhood Traders Before and After Gamified Update
This figure plots the number of stock holding position changes of Robinhood traders before and after gamified update over a period of 20 trading days. The bars represent the actual values of position changes, while the lines indicate the time trends during the pre- and post-gamified update periods.