# The Impact of Zero-Commission Platforms on Retail Trading Behavior

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**Introduction**

Over the past decade, zero-commission trading platforms have drastically altered the retail investing landscape and scope of reach. Through the removal of traditional cost and knowledge barriers associated with investing, platforms, such as Robinhood, have brought millions of new participants into the investing scene and reshaped the way investors interact with financial markets. These platforms introduced simple, gamified user interfaces that make investing more appealing, and greatly influence their investors' participation. While the monumentally transformed ease of access in investing has been widely celebrated, it has also prompted growing concern surrounding behavioral consequences and market quality as a result. Experts suggest that the design of these zero-commission apps, distinguished by simplified information displays, reward-based incentives, and social trading cues, transcends merely facilitating transactions. These characteristics shape investor behavior in ways that influence and promote short-term perspectives, speculative trading, and herd dynamics, all of which are witnessed especially among inexperienced users (Barber et al., 2022; Eaton et al., 2021; Langvardt & Tierney, 2022).

While early analysis highlighted the role of zero-commission trading platforms in lowering barriers to entry in the investing world, new light has revealed the obstructive effects from platform design within these applications (Jones, 2021). Robinhood has been in the center of attention in regard to gamification mechanics, such as confetti for completing a trade, scratch tickets, and the featured “Top Movers” list, all of which nudge users toward behavior resembling gambling instead of investing. Studies have shown that loyal Robinhood traders disproportionately invest in volatile, trending stocks and momentum-herding behavior that has no fundamental backing (Barber et al., 2022; Grawert, Freibauer, & Rieger, 2024). However, there are limitations among these studies, particularly regarding causality. Most do not fully take self-selection bias into account, which raises the question of whether these platforms cause speculative behavior, or attract users predisposed to it.

While previous research demonstrates that retail traders destabilize markets through attention-driven behavior, less attention has been paid to how these effects differ across types of stocks, specifically small-cap stocks (Liang, Najand, & Selover, 2024). Small-cap stocks are generally less liquid and receive less analyst coverage, making these more vulnerable to the influence of inexperienced, speculative traders. It has also been found that herding behavior is more prominent in small-cap equities leading to frequent negative returns when compared to large-cap stocks where investor behavior is more knowledge-backed and rational (Lakonishok, Shleifer & Vishny, 1992; Frey, Walter & Herbst, 2014). This distinction between small and large-cap stocks is critical for analyzing how platform-induced behavior may amplify the risk and volatility of certain segments of the market.

Our paper and analysis build on the negative impact of Robinhood trading on short-term stock price volatility, with greater focus on small-cap stocks. Utilizing a longitudinal panel dataset of over 3.5 million daily stock observations from May 2018 to August 2020, we analyze whether stocks listed on Robinhood are associated with increased price fluctuations, independent of other observable factors. We leverage a random-effects regression model to quantify the effect of Robinhood trading on intra-month volatility, applied through a 20-day rolling standard deviation of daily returns. Additionally, we control for key stock-level characteristics including trading volume, daily returns, aggregate volatility, and test for nonlinear effects and heterogeneity across market capitalization. Our analysis reveals that stocks listed on Robinhood exhibit significantly higher short-term volatility than comparable equities, with the effect strongest in small-cap stocks. With all this in mind, **do zero-commission trading platforms systematically lead to poor investment outcomes for retail investors, with the effect magnified in stocks with a market capitalization below $1 billion?** *We hypothesize that zero-commission trading platforms amplify short-term price volatility in small-cap stocks by promoting speculative trading, herding tendencies, and attention-driven investing. Through gamification, ease of access, and limited financial data integration, these platforms encourage impulsive decision-making, which disproportionately affects inexperienced investors, reinforcing short-term trading habits that undermine long-term financial outcomes and contribute to broader market instability.*

## Literature Review

Zero-commission trading platforms have reshaped investment behavior, particularly regarding trading frequency and speculative activity. Using a longitudinal approach, Grawert, Freibauer, and Rieger track how trading behavior evolves, revealing that investors on platforms such as Robinhood engage in riskier, short-term trading strategies (Grawert, Freibauer, Rieger, 2024). These platforms make market access more easily available to everyone and actively shape investor behavior in ways that encourage focusing on short-term results. This aligns with existing literature such as Eaton et al. (2021) and Jones (2021), which demonstrate that zero-commission platforms lower barriers to entry and attract noise traders who are prone to speculative trading. However, this study fails to account for self-selection bias, limiting its ability to prove causation between app use and speculative trading. Investors predisposed to speculation might flock to these platforms rather than the platforms themselves shaping their behavior. If gamified mechanics reinforce speculative trading, then platform design might be a stronger driver of market instability rather than commission-free access. While the study presents evidence that long-term engagement with trading apps leads to more risk-taking, there should be further research to determine whether these effects continue to exist in investors who shift to traditional brokerage firms or if they are specific to the app environment.

Using data from Robinhood outages, Barber, Huang, Odean, and Schwarz further explore the possible consequence of gamification by showing that the design of the app itself influences the behavior of Robinhood traders. The app design gamifies the investment experience, allowing users to scratch off fake lottery tickets for rewards such as a free share of stock (Barber et al., 2022). The app also displays simplified information, with only five charting indicators compared to TD Ameritrade's 489 (Barber et al., 2022). Such a minimalistic interface reduces friction in decision-making, encouraging users to make less informed trades and leading to attention-based trading and herding behavior. Barber et al. used a regression discontinuity design to show that Robinhood's "Top Mover" list influenced trading behavior. They found that Robinhood users invested more intensely in "Top Mover" stocks, regardless of whether they faced extreme gains or losses (Barber et al., 2022). The authors found that this trend did not replicate across other platforms, showing how platform design can manipulate the investment choices of inexperienced traders.

Chapkovski, Khapko, and Zoican (2024) take this further by examining the impact of gamification in trading platforms on retail investor behavior through an online experiment. Research shows that investors with lower financial knowledge and experience prefer trading platforms with gamification elements, such as Robinhood. Gamification leads to a 5.17% increase in trading volume among these groups, attributing 70% of the increase to the self-selection of traders who already prefer gamified platforms and demonstrate higher trading activity (Chapkovski, 2024). Furthermore, the article by Langvardt and Tierney (2022) examines the regulatory challenges and ethical concerns posed by gamified investing in apps like Robinhood. These trading apps employ hedonic, game-like features that utilize behavioral psychology to encourage frequent and excessive trading. However, Tierney and Langvardt view this game-like appeal as a form of conflicted financial advice, leading to maladaptive financial behavior among retail investors (Langvardt, 2022).

Aside from the effects of gamification on the behavior of investors on these platforms, their behavior regarding new information is also explored. These investors often engage in speculative trading with little information, basing their decisions around general consensus rather than real information. Liang, Najand, and Selover use empirical trading data to show how retail traders engage heavily in earnings-related momentum trading, increasing market volatility (Liang, Najand, Selover, 2024). Unlike Welch (2022), who argues that Robinhood traders provide market liquidity during downturns, this study demonstrates that retail investors actually add noise by engaging in uninformed trading around earnings events. The study finds that attention-driven trading around earnings announcements creates price distortions, reinforcing the idea that retail investors act as noise traders. Additionally, as identified by Peress and Schmidt, trading activity by noise traders decreases during major distraction events, which plays a crucial role in short-term market fluctuations and quality. Furthermore, if these investors are acting without justification, they are more likely to focus on short-term results than long-term gains, potentially leading to worse long-term results. While this study provides strong evidence for the behavior of retail investors, one drawback is that the study assumes all retail investors act as one homogeneous group. Investors might have differences in trading strategies or financial literacy, meaning that they may overlook nuances in trading. The study also fails to account for the role of social media in amplifying hype around earnings announcements, meaning there is a gap in understanding how online discourse affects short-term volatility rather than solely the release of recent earnings. Eaton et al. shows the potential impact of these differences, since Robinhood traders have a different impact on the market than typical retail traders.

An important aspect to dive into when determining whether zero-commission platforms lead to poor investment outcomes for retail investors is the amount of information that is available to supplement their trading decisions. Havakhor, Rahman, Zhang, and Zhu explore how limited financial data access affects retail investment behavior directly related to these investors' outcomes. This study uses the shutdown of Yahoo! Finance's API in 2017 as a natural experiment to compare changes in trading activity between stocks that were disproportionately followed by retail traders and those that were not. The study isolates the effect of reduced financial data access on retail trading behavior by analyzing daily trading volume and return predictability. This study found that retail trading volume decreased by 8.6%-10.5% following the shutdown (Havakhor, Rahman, Zhang, Zhu, 2024). The findings demonstrate that limiting retail investors’ access to easily available data causes them to trade less frequently and make more informed decisions, since researching trades takes longer without readily accessible information. This further shows that commission-free platforms, like Robinhood, that have intentionally simplified investment interfaces fail to equip their users with the necessary financial literacy and insights, thus worsening investment outcomes. Zero-commission platforms support impulsive traders rather than informed decision-makers, ultimately leading to worse long-term performance, especially for small-cap stocks where this information is more limited.

To look more closely into how this behavior differs between large-cap stocks and small-cap stocks, one study investigates the herding behavior of individual investors on a leading Social Trading Platform (STP) by analyzing daily portfolio data from January 2021 to June

2023. Using solidified herding measures (Lakonishok, Shleifer & Vishny, 1992; Frey, Walter & Herbst, 2014), the research finds that herding behavior is more prominent in small-cap stocks than in large-cap stocks. This behavior leads to negative returns in small-cap stocks but positive returns in large-cap stocks. The authors link this discrepancy to information availability, market liquidity, and risk perception differences. The study suggests that in small-cap stocks, excessive herding contributes to price distortions and increased volatility, while in large-cap stocks, herding appears to be more rational and results in better-coordinated investment decisions. These findings reinforce the idea that retail investors in small-cap stocks may engage in speculative trading that undermines their long-term investment outcomes.

## Conceptual Framework

Our analysis relies on behavioral finance theory and market microstructure theory. Behavioral finance theory claims that investors are not rational actors and are often influenced by cognitive biases and emotional responses rather than purely stock information. Platforms like Robinhood, by gamifying the investment experience, actively amplify biases that promote speculative and momentum-driven trading, particularly among inexperienced retail investors. Small-cap stocks are particularly vulnerable to attention-driven trading. Smaller stocks tend to have lower liquidity and less analytical coverage, making them more susceptible to price distortions caused by uninformed trading. Trading platforms that reduce friction, simplify information, and reward frequent transactions shift traders' focus away from long-term value investing toward short-term speculation.

With all this in mind, *we hypothesize that zero-commission trading platforms amplify short-term price volatility in small-cap stocks by promoting speculative trading, herding* *tendencies, and attention-driven investing. Through gamification, ease of access, and limited financial data integration, these platforms encourage impulsive decision-making, disproportionately affecting inexperienced investors and reinforcing short-term trading habits that undermine long-term financial outcomes and contribute to broader market instability.*

**Empirical Methodology**

Our analysis uses a panel dataset constructed from historical daily stock data from May 9, 2018, to August 13, 2020, containing over 3.5 million daily stock observations. To determine which stocks to analyze, we downloaded historical popularity data for stocks traded on Robinhood using a now-defunct tracking website called Robintrack. This popularity data provided us with approximately 9,000 stocks traded on Robinhood across the approximately two-year period of available data. Historical stock data was scraped using the Yahoo Finance API (yfinance), run from within Stata using its Python integration. To maintain data integrity, the Python code was written to remove any stocks with significant errors. This could be missing data, inconsistencies in reporting, or an inability to find any data on the ticker at all. After running our Python code, we were left with 6,545 stocks, meaning around 2,500 stocks were eliminated for data inconsistencies.

Each observation corresponds to one stock on a given trading day. The Yahoo Finance API directly pulled daily open and close prices, trading volume, and market capitalization. We also calculated several variables directly in our Python code before importing the data into Stata. These include daily return, which represents the day-over-day percentage change in closing price; rolling volatility, represented by a 20-day rolling standard deviation of daily returns; and aggregate volatility, the standard deviation of daily returns across the full period.

After importing the stock data into Stata, we created a dummy variable to represent that a stock was traded on Robinhood over the period. Since we pulled our stock selection from Robinhood trading data, each stock was automatically assigned “robinhood” = 1. We then compiled a small list of low beta stocks, like the S&P 500, that best represent the movement of the market as a whole and changed their dummy variable to “robinhood” = 0. With this construction, we can broadly compare the collective movement of Robinhood stocks in comparison to the market as a whole. To improve our regression, we calculated several quadratic and interaction terms. We generated squares of the volume, daily return, and market capitalization variables to capture potential nonlinear effects. We also generated interaction variables between the “robinhood” dummy variable and market capitalization as well between “robinhood” and volume to test for heterogeneous effects. Figure 1 describes the nature of each variable included across all our regressions.

In Figure 2, summary statistics show a mean daily return of 0.0463%, mean rolling volatility of 2.44%, and mean aggregate volatility of 3.10%, with notable variation across the dataset. The dummy variable “robinhood” equals 1 for stocks available on the platform and 0 otherwise; this variable comprises 94% of the sample, indicating a skew toward retail-traded equities. Missing data, particularly for rolling volatility (3.8% missing), reflects the requirement for 20 prior trading days of return data, and may bias the sample toward longer-listed or more stable stocks.

**Figure 1: Variable Descriptions**

| Variable Name | Description | Unit / Format |
|---|---|---|
| Ticker, ticker_id | The stock's trading symbol | String, encoded |
| Date, stdate | The trading date for the observation | Date (YYYY-MM-DD), encoded date |
| Open | Stock's opening price on that date | US Dollars |
| Close | Stock's closing price on that date | US Dollars |
| Volume | Number of shares traded during the day | Integer |
| daily_return | Percent change in closing price from previous day ((Close_t - Close_t-1)/Close_t-1) | Percent |
| rolling_vol | 20-day rolling standard deviation of daily returns | Percent |
| agg_vol | Standard deviation of all daily returns for the stock | Percent |
| marketcap | Total number of shares multiplied by current share price | US Dollars |
| robinhood | Dummy variable representing whether a stock was listed on Robinhood | Integer |
| volume_sq | Squared values of Volume | Integer |
| dr_sq | Squared values of Daily Return | Percent |
| mc2 | Squared values of Market Capitalization | US Dollars |
| mcrob | Market Capitalization * Robinhood | US Dollars |
| volrob | Volume * Robinhood | Integer |

**Figure 2: Summary Statistics**

| VARIABLES | (1) N | (2) mean | (3) sd | (4) min | (5) max |
|---|---|---|---|---|---|
| open | 3.446e+06 | 7,816 | 1.076e+06 | -0.0292 | 3.104e+08 |
| close | 3.446e+06 | 7,728 | 1.068e+06 | -0.0293 | 3.085e+08 |
| volume | 3.446e+06 | 1.175e+06 | 9.083e+06 | 0 | 2.512e+09 |
| daily_return | 3.439e+06 | 0.0463 | 4.339 | -94.51 | 1,977 |
| rolling_vol | 3.314e+06 | 2.440 | 3.607 | 0 | 442.5 |
| agg_vol | 3.446e+06 | 3.082 | 3.055 | 0.00357 | 96.85 |
| marketcap | 2.338e+06 | 1.856e+10 | 1.067e+11 | 185 | 3.130e+12 |
| robinhood | 3.446e+06 | 0.939 | 0.239 | 0 | 1 |
| ticker_id | 3.446e+06 | 3,308 | 1,900 | 1 | 6,591 |
| stdate | 3.446e+06 | 291.4 | 164.3 | 1 | 570 |
| volume_sq | 3.446e+06 | 8.388e+13 | 6.710e+15 | 0 | 6.308e+18 |
| dr_sq | 3.439e+06 | 18.83 | 3,284 | 0 | 3.910e+06 |
| mc2 | 2.338e+06 | 1.173e+22 | 2.506e+23 | 34,225 | 9.798e+24 |
| mcrob | 2.338e+06 | 1.011e+10 | 6.528e+10 | 0 | 2.879e+12 |
| volrob | 3.446e+06 | 792,464 | 5.055e+06 | 0 | 9.141e+08 |
| Number of ticker_id | 4,252 | 4,252 | 4,252 | 4,252 | 4,252 |

A limitation of our construction is that we manually reassign a subset of large-cap, low-volatility stocks—many of which are traded on Robinhood—to the control group. While this creates a more stable benchmark of the overall market for comparison, it introduces a selection bias by systematically excluding less volatile Robinhood stocks from the treatment group. This may inflate our estimate of volatility associated with Robinhood activity. We expect the bias to be small, since only a small fraction of the 6,500 stocks were reassigned to the control group. Future research should explore alternate matching techniques or stratified sampling to avoid this concern.

To estimate the impact of Robinhood trading on short-term volatility, we used a random-effects generalized least squares (GLS) regression model using Stata's "xtreg, re" command to create three different models, each with additional independent variables. The dependent variable across all three models is rolling_vol, the 20-day rolling standard deviation of returns, which captures intra-month price fluctuation. Our selection of a random effects model was motivated by the time-invariant nature of the robinhood variable, which would be absorbed by fixed effects. The random-effects framework enables estimation of both within-stock and between-stock variation while preserving our variable of interest.

**Results:**

Several different model specifications were created to examine the impact of added control and interaction terms. The first regression simply captures the relationship between Robinhood status and volatility:

$$rolling\_vol = \beta_0 + \beta_1 robinhood_i + \epsilon_{it}$$

Figure 3 shows the results of that regression. This model shows that Robinhood stocks exhibit a statistically significant ($p < 0.001$) increase in short-term volatility of 0.466%. However, the model fits very poorly overall, with an $R^2$ within of 0.0000, an $R^2$ between of 0.0032, and an overall $R^2$ of 0.0009. This shows that, obviously, there are many other factors that explain the variation in the model beyond just whether a stock is listed on Robinhood.

Figure 3: Results for Model 1

| rolling_vol | Coefficient | Std. err. | z | P>\|z\| | [95% conf. | interval] |
|---|---|---|---|---|---|---|
| robinhood | .4662458 | .1021299 | 4.57 | 0.000 | .2660749 | .6664166 |
| _cons | 2.021419 | .0991833 | 20.38 | 0.000 | 1.827023 | 2.215814 |

The second regression model added important stock characteristics as control variables. This model now includes trading volume, daily return, market capitalization, and aggregate volatility, leading to a new equation:

$$rolling\_vol = \beta_0 + \beta_1 robinhood_i + \beta_2 volume_{it} + \beta_3 daily\_return_{it} + \beta_4 marketcap_{it} + \beta_5 agg\_vol_{it} + \epsilon_{it}$$

Figure 4 shows the regression output for the second model. In this model, the "robinhood" coefficient drops to 0.365%, but is still highly significant. Since control variables that influence volatility were added to the model, it makes sense that the amount of variation explained by a stock's Robinhood status would decrease. The model's fit substantially improved, with an $R^2$ within of 0.0222, an $R^2$ between of 0.7815, and an overall $R^2$ of 0.1817. The addition of basic stock characteristics to the model helps explain the variation between different stocks, or why the rolling volatility of individual stocks is different on the same day. While this model doesn't explain much of the variation within individual stocks, it is a significant increase from the first model (0.0000 to 0.0222).

Figure 4: Results for Model 2

| rolling_vol | Coefficient | Std. err. | z | P>\|z\| | [95% conf. | interval] |
|---|---|---|---|---|---|---|
| robinhood | .3642176 | .0486195 | 7.49 | 0.000 | .2689253 | .45951 |
| volume | 3.44e-08 | 4.36e-10 | 78.83 | 0.000 | 3.35e-08 | 3.53e-08 |
| daily_return | .0991781 | .0004759 | 208.42 | 0.000 | .0982454 | .1001108 |
| marketcap | -2.16e-12 | 1.32e-13 | -16.29 | 0.000 | -2.42e-12 | -1.90e-12 |
| agg_vol | .4905495 | .0038929 | 126.01 | 0.000 | .4829195 | .4981795 |
| _cons | .7958695 | .0477436 | 16.67 | 0.000 | .7022938 | .8894453 |

The final regression model added several nonlinear and interaction terms. The new model includes the squares of volume, daily returns, and market capitalization, which help capture the nonlinear effects of these variables. The final regression equation is below.

$$rolling\_vol = \beta_0 + \beta_1 robinhood_i + \beta_2 volume_{it} + \beta_3 volume\_sq_{it} + \beta_4 daily\_return_{it}$$

$$+\beta_5 dr\_sq_{it} + \beta_6 marketcap_{it} + \beta_7 mc2_{it} + \beta_8 mcrob_{it} + \beta_9 volrob_{it} + \beta_{10} agg\_vol_{it} + \epsilon_{it}$$

Figure 5 shows the result of the final regression. In this model, the "robinhood" coefficient dropped slightly to 0.286%, but is still statistically significant with $p < 0.001$. Based on this model, stocks traded on Robinhood experience an increase in short-term volatility of about 0.29 percentage points, holding all else equal. Volume and daily return continue to have strong positive effects, but their squared terms are both significant and have opposite signs, showing that these variables have diminishing marginal effect on rolling volatility. At lower levels of trading, liquidity constraints increase volatility, while higher volume appears to stabilize price movements. Similarly, larger price swings—regardless of direction—drive increased volatility. The coefficient on market capitalization is still negative, but its squared term is both positive and significant, suggesting a U-shaped relationship between size and volatility. This reinforces the idea that large-cap firms with deeper liquidity and institutional coverage are less affected by short-term speculative trading but implies that there may be outliers to this trend on the high end that cause the U-shape relationship.

The interaction term between volume and "robinhood" is positive and highly significant, indicating that Robinhood stocks react more strongly to volume surges. The interaction term between marketcap and "robinhood" is negative, but is only marginally significant, with a p-value of 0.064. The fit of Model 3 improves slightly from the previous model, with an $R^2$ within of 0.0356, an $R^2$ between of 0.7640, and an overall $R^2$ of 0.1884. This shows that this model explains more of the variation within individual stocks than any of our previous models.

Figure 5: Results for Final Model

| rolling_vol | Coefficient | Std. err. | z | P>\|z\| | [95% conf. | interval] |
|---|---|---|---|---|---|---|
| robinhood | .2857945 | .0448138 | 6.38 | 0.000 | .197961 | .373628 |
| volume | 5.12e-08 | 9.64e-10 | 53.08 | 0.000 | 4.93e-08 | 5.30e-08 |
| volume_sq | -2.96e-17 | 6.35e-19 | -46.58 | 0.000 | -3.08e-17 | -2.83e-17 |
| daily_return | .0496978 | .0005634 | 88.21 | 0.000 | .0485936 | .050802 |
| dr_sq | .00011 | 6.98e-07 | 157.47 | 0.000 | .0001086 | .0001113 |
| marketcap | -4.24e-12 | 3.07e-13 | -13.84 | 0.000 | -4.84e-12 | -3.64e-12 |
| mc2 | 7.27e-25 | 1.15e-25 | 6.31 | 0.000 | 5.01e-25 | 9.53e-25 |
| mcrob | -4.38e-13 | 2.37e-13 | -1.85 | 0.064 | -9.03e-13 | 2.57e-14 |
| volrob | 2.73e-08 | 1.10e-09 | 24.90 | 0.000 | 2.51e-08 | 2.94e-08 |
| agg_vol | .4857606 | .0033313 | 145.82 | 0.000 | .4792313 | .4922899 |
| _cons | .8679144 | .044647 | 19.44 | 0.000 | .780408 | .9554209 |

The results from our random-effects regression confirm the hypothesis that zero-commission trading platforms like Robinhood are associated with elevated short-term volatility, particularly in smaller-cap stocks. The coefficient on the "robinhood" dummy variable indicates that, holding other factors constant, stocks listed on Robinhood exhibit significantly higher 20-day rolling volatility than the market as a whole. This finding supports prior evidence of herding and speculative behavior among retail investors using these platforms.

These results are consistent with the behavioral finance literature on noise traders and speculative bubbles. As documented by Barber et al. (2022) and Eaton et al. (2021), platforms like Robinhood attract attention-driven, inexperienced investors who often act on momentum rather than fundamentals. Our findings show that this behavior leads to meaningful increases in short-term volatility, particularly in less-liquid market segments.

The model's explanatory power is highest in between-stock variation ($R^2$ between = 0.7640), which aligns with our focus on platform-level differences across stock categories. While $R^2$ within = 0.0356 indicates modest explanatory power over time, this is expected given the persistent nature of volatility in financial markets.

## Discussion and Conclusion

Our analysis indicates zero-commission trading apps such as Robinhood have reshaped short-run price movements in U.S. stock market. Using a panel of over 3.4 million daily stock observations from May 2018 through August 2020, a random-effects GLS model shows that stocks classified as tradable on Robinhood experience a 0.29 percentage-point increase in the 20-day rolling standard deviation of returns, a 12 percent jump relative to the sample average of 2.44 percent. This effect is statistically significant at the 1% level and robust to multiple model specifications. It is strongest for small-capitalization firms, where limited liquidity makes prices more sensitive to retail order imbalances. The finding expands on the behavioral narrative in the research paper of Barber (2022) and Eaton (2021) where gamified trading interfaces steer inexperienced investors toward momentum trades, replacing fundamental analysis with herd behavior and so amplifying transitory price pressure . Our results show that while normal levels of trading can help make markets more stable, sudden spikes in trading, like those caused by Robinhood's 'Top Mover' alerts, can actually scare off the professional traders who help keep prices steady. When that happens, the market becomes more chaotic, which ends up hurting the same retail investors who caused the surge in the first place

While Welch (2022) finds that Robinhood users can actually help stabilize the market during big crashes, our results show that during regular trading periods, they tend to increase short-term volatility. The effects we observe are not uniform: market capitalization, trading volume, and periods of market stress materially alter the magnitude of Robinhood's impact on volatility. Features that gamify trading, such as confetti animations, trending stock lists, and simplified data displays, appear to encourage impulsive trading behavior. Enhancing platform designs by including longer-term performance views, volatility warnings, or alerts about retail crowding could potentially mitigate these short-term destabilizing effects.

On the technical side, our methodology relies on random-effects GLS estimation, which allows us to capture both within-stock and between-stock variation without absorbing the time-invariant Robinhood classification. However, it assumes no hidden correlation between the random effects and explanatory variables. One limitation is that we manually reassigned a subset of low-volatility, large-cap stocks into the control group, which may introduce a small selection bias, albeit affecting only a small portion of the sample. Additionally, since our dataset ends in mid-2020 and excludes approximately 2,500 delisted stocks, our results may be somewhat biased toward larger, more successful firms.

Future research should look at more recent data, test other free trading platforms like Webull or Public, and explore whether these patterns apply to retail investing in general or are specific to Robinhood's app design. It would also be helpful to connect individual investor behavior with long-term investment performance to see if these short-term swings actually lead to worse outcomes over time. Overall, our findings suggest that while zero-commission trading apps have made investing more accessible, they've also added extra risk, especially for smaller, more vulnerable stocks. This highlights the need for smarter app design and more regulation to keep markets stable as markets become more accessible to everyday users.

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