# Who participated in the GameStop frenzy? Evidence from brokerage accounts

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# Who participated in the GameStop frenzy?

# Evidence from brokerage accounts[*]

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**Abstract**

In January 2021, the GameStop stock was the epicenter of the first case of predatory trading initiated by retail investors. We use brokerage accounts to study who participated in this GameStop frenzy and how they performed. We investigate the extent to which investors' personal and trading characteristics differ from the general population of retail investors. GameStop traders had a history of investing in speculative instruments, including stocks with lottery-like features. They were also more likely to close their positions before the peak of the bubble. At the onset of the frenzy, numerous retail investors also shorted GameStop. Overall, our results indicate that the GameStop frenzy was not a pure digital protest against Wall Street but speculative trading by a group of retail investors, in line with their prior high-risk trading behavior.

**Keywords:** Predatory Trading; Retail Investors; Trading Behavior.

**JEL Classification:** G11, G40, G41.

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## 1. Introduction

In economics, causality usually runs from events to narratives (Shiller, 2020). However, to explain the recent GameStop frenzy, a different theory may be needed. The sharp increase in price and volatility was not a reaction to an economic event but has largely been attributed to the subreddit WallStreetBets and retail investors (Chohan, 2021; Umar et al., 2021). News outlets speak of a modern morality tale, suggesting that retail traders were taking a stand against Wall Street using a self-fulfilling prophecy (Wells and Egkolfopoulou, 2021).

From a research perspective, the event is particularly interesting, as it represents the first case of predatory trading (Brunnermeier and Pedersen, 2005) attributed to retail investors. Predatory trading occurs when investors withdraw liquidity from the market instead of providing it by trading in the same direction as a (distressed) large investor to force the distressed investor to liquidate. Liquidation leads to price overshooting, which allows predators to realize profits. As Brunnermeier and Pedersen (2005) note, predatory trading can even induce distress for a large investor, particularly for a short seller. While there are many documented cases of predatory trading, this may very well be the first case attributed to retail investors. A critical ingredient of a successful predatory attack is that retail predators act in concert and, fundamentally consistent with a simple prisoner's dilemma, do not sell their shares early. Thus, it critically depends on the contagious narrative.

While GameStop retail investors have received immense media attention, we do not know who they are, why they traded GameStop stock, or how they performed. However, as the GameStop frenzy has highlighted, investor positioning and order flow enable retail investors to move stock prices (see also Barber et al., 2009). Thus, it is important to understand behavior at the micro level to increase our understanding of aggregate outcomes at the market level.

In this paper, we focus on retail investors participating in the frenzy and use brokerage data to profile retail investors who participated in trading GameStop shares in January 2021, explore their net performance, and attempt to understand their underlying motives. We find that the profile of retail investors who participated in GameStop trading changed throughout the frenzy as the stock received increasing media attention. Interestingly, we find a substantial number of retail investors who took short positions against GameStop in early January, suggesting the media portrayal of this frenzy as a battle between retail investors and Wall Street to be somewhat incomplete. GameStop traders are more likely to have a past of trading highly volatile and lottery-like stocks, and high-volatility investors were more likely to close their positions prior to the peak of the bubble, implying that the decision to trade GameStop stock is in line with an attraction to gambling in the stock market (e.g., Kumar, 2009).

Our paper sits within the predatory trading literature but also contributes to a growing amount of research on the GameStop frenzy. While some papers model the episode by considering the role of options (Van Wesep and Waters, 2021), the identification of asset price bubbles based on options data (Fusari et al., 2021), and social media (Jarrow and Li, 2021), others have attempted to empirically explore the dynamic linkages between factors such as investor sentiment, volume and returns (Umar et al., 2021; Pedersen, 2021). Moving beyond only considering GameStop, Bradley et al. (2021) find that retail investors follow investment advice provided on WallStreetBets and are able to profit from this advice by earning abnormal returns. Furthermore, Aharon et al. (2021) find no evidence of financial contagion from GameStop to the wider stock market. The GameStop frenzy also included a number of trading restrictions, and Jones et al. (2021) find that stocks subject to these restrictions were associated with strong negative abnormal returns and that retail traders moved from equities to options markets during restrictions. In response to the major impact of GameStop on the stock market, Angel (2021) provides some potential policy implications. We contribute to this evolving discussion by focusing on the alleged instigators of this frenzy, retail investors.

## 2. Data

We use transactional-level brokerage data from a retail broker to provide insights into our research questions. The sample comprises all trades executed with the broker during the period from December 1, 2020, to February 12, 2021. In total, our data include over 65 million trades executed by over 700,000 investors. These investors executed nearly 2 million trades of GameStop stock, with the majority of these trades (almost 96%) coming in late January and early February 2021. The data include the timestamp of each trade, execution price, whether it opens or closes a position, whether the position is a long or a short position, and profit net transaction costs. Investors pay moderate transaction costs via the spread. The data also contain investor-specific characteristics, such as gender, age, self-reported trading experience, income, and liquid assets.

To proxy for investors' trading activities, we count the number of trades an investor executes. As the broker also allows its customers to take short positions, we separately measure investors' short-selling activities with the variable short seller. We estimate the aggregate buy-sell imbalance of all investors who trade with the broker as the fraction of trades that indicate a long position. Investors can take a long position by either buying a stock or by closing a short sale; similarly, investors can take a short position by selling a stock short or by closing a long position.

To classify investors, we also measure investors' preferences to invest in high volatility stocks, in lottery-type stocks (Kumar, 2009), and in cryptocurrencies, as these are perceived to be rather risky (Pelster et al., 2019), and their propensity to engage in short selling. In particular, we define the 50 stocks with the highest volatility of monthly returns over the previous five years as high-volatility stocks. Then, we define all investors who purchased one of these stocks prior to the GameStop frenzy as a high-volatility trader. Following Kumar (2009), we define stocks with below-median prices, above-median idiosyncratic volatility, and above-median idiosyncratic skewness as lottery-type stocks and define all investors who purchased one of these stocks prior to the GameStop frenzy as lottery-type investors. Definitions of cryptotraders and short sellers follow the same logic. Based on the number of trades, average net returns, and volatility of their returns, we rank investors on trading, performance, and return volatility quintiles. We only use trading data prior to the GameStop frenzy (until January 9, 2021) to classify investors' trading preferences. Finally, we classify investors who opened their account later than January 1, 2020, to proxy for the "new generation" of retail investors (e.g., Ortmann et al., 2020; Glossner et al., 2020).

In addition to investors' trading activities, we use several measures to capture public interest in GameStop. We measure the number of subscribers to the subreddit WallStreetBets, given the media suggestion that retail investors coordinated using this subreddit. We also measure Twitter activity on GameStop and Google search volume for GameStop. Finally, we complement our data with stock price data and bid and ask quotes from Refinitiv EIKON and Refinitiv Datastream.

We provide detailed variable descriptions and summary statistics of our data in Table 1. Trading and profitability variables are highly skewed, which we account for by including ranks in our regression analyses.

## 3. Methodology

We use logit regressions to analyze the decision to trade GameStop stock at a particular point in time. The dependent variable is a dummy variable that takes value one when an investor opens (closes) a GameStop position on a particular date and zero otherwise. We use various periods to capture different phases of the GameStop frenzy.

The retail investor who initially promoted GameStop on WallStreetBets did so for an extended period. In particular, he posted a video mentioning GameStop and the opportunity for a short squeeze on July 28, 2020.[1] Several other posts mention a short squeeze on GameStop prior to the market frenzy in January, without clearly affecting the market. The narrative using hashtags such as #gme, #burnshorts, and #wallstreetbets only became a viral economic narrative when activist investor and large shareholder Ryan Cohen, who targeted GameStop in December 2020, gained a seat on the board of GameStop together with two of his nominees, leading to a premarket spike of 8% on January 11 and sparking additional belief in the narrative. This is in line with the notion that some mutations in narratives may lead to higher contagion rates (Shiller, 2020; Salganik et al., 2006) before new contagious narratives cause economic events (Shiller, 2020). Equipped with an "us versus them" theme and a playbook for people to follow, two typical features of contagious narratives (Shiller, 2020), the story of investing in GameStop spread among millions.

Based on Cohen's announcement, we define the first period to be January 11-12. The news led to GameStop being one of the most discussed stocks on WallStreetBets over the next few days. The market frenzy began on January 13, 2021, with shares being up 68.82% at noon. The price increase triggered mainstream media coverage later during the day. Consequently, we define the second time period to be January 13-17. During this period, several retail investors also took short positions in GameStop. We consider these short investors separately from investors who took long positions. Our final two time periods consider the weeks starting on January 18 and January 25. During these periods, media coverage discussing WallStreetBets increased and took off on January 25, with, for example, Bloomberg describing "How WallStreetBets Pushed GameStop Shares to the Moon". Thus, the last period captures investors whose decision to trade GameStop stock was likely driven by extensive media coverage that erupted following the initial price increases. As a result of increased trading and resulting margin requirements, several brokerage services limited their customers' ability to purchase GME shares on January 28. By February 12, trading had decreased significantly, and the share price had dropped to $52.40, still elevated compared to pre-frenzy prices.

[1] According to screenshots of his brokerage account posted by the user, he initially invested in GameStop with a position of 50,000 shares in April 2019.

## 4. Results

We first take a brief look at the aggregate stock market (see also Umar et al, 2021). In line with the notion that predatory trading reduces liquidity when large traders need it most, we observe that the bid-ask spread of the GameStop stock increased significantly in the second half of January 2021. While the average bid-ask spread in 2020 amounted to 1 cent, the average bid-ask spread between January 11 and February 1, 2021 amounted to 129 cents (not tabulated). These figures clearly highlight market illiquidity when liquidity was most needed for large short sellers, a key aspect of predatory trading.

Figure 1 depicts the trading activities of investors, together with attention measures, highlighting that investors significantly increased trading activities prior to the increase in overall attention. Only the last increase in trading coincides with the spike in attention. Figure 2 sheds additional light on trading activities. Key takeaways are the spike in retail short selling on January 13 and that we do not observe an extreme buy-sell imbalance during the frenzy. At its peak, the buy-sell imbalance amounts to 67% (January 27), indicating that many retail investors were not completely caught up in the narrative but likely participated to generate returns.

Table 2 reports summary statistics of characteristics separately for investors who purchased GameStop during the frenzy and those who did not. Investors who traded GameStop stock are more likely to be male, younger, less experienced, and have a history of engaging in risky trading, including high-volatility instruments and lottery-like stocks. We observe that most differences in past trading behavior between those who traded GameStop stock and those who did not decrease over time. Additionally, we observe that 4.5% of investors who participated in the frenzy opened their account with the broker on or after January 13 (untabulated), indicating that the frenzy attracted several new investors to the market.

Table 3 reports odds ratios for logit regressions for each time period.[2] The best predictors of engaging in GameStop trading are investors' historical behavior, particularly trading high-volatility and lottery-type stocks. Males were more likely to trade GameStop in the third and fourth periods, particularly when the new generation of investors was less engaged. During our last time period, investors who had already invested earlier during the frenzy but previously closed their positions participated again. This indicates that they may have experienced seller's remorse after seeing the price rise further. GameStop short sellers are more likely to have a history of short selling and to engage in high-volatility trading behavior in general, including trading cryptocurrencies and stocks with lottery-like features.

Next, we explore the decision to sell GameStop on different days at the height of frenzy in Table 4. Most notably, the new generation of investors shows the best timing in terms of closing their positions during the peak. High-volatility investors and short sellers were more likely to close their positions prior to the peak. Similarly, those who opened accounts with the broker during the frenzy were more likely to sell prior to January 26 or after February 1. Men,

[2] We omit the variable "Account open during frenzy" from the regression analysis because we are not able to proxy for the typical trading behaviors of novel investors. While some of our reported Pseudo $R^2$ statistics are relatively low, this is in line with prior studies using brokerage data (Grinblatt and Keloharju, 2001; Bailey et al., 2011). Since we are not interested in predicting future behavior but in understanding the past, we focus on significance tests in interpreting our results.

already purchasing during later stages, were more likely to hold their GameStop shares throughout the frenzy and are more likely to still be holding them.

Turning to investor performance, in Panel A of Table 5, we report distributions of returns of investors' trading activities in GameStop, split by the time of their purchase. In line with predatory trading, several investors realized both statistically and economically significant profits. For example, the 90th percentile of investors in the second and third time periods realized net returns of 50.3% and 128%, respectively. However, a large share of investors (approximately 30% of the sample) realized losses. The 30th percentile of investors in the second time period realized net losses of 2.3%. Even investors in the first time period just broke even in the 40th percentile. Short sellers, on average and at the median, performed worse than investors who took long positions: approximately 40% of short sellers realized positive returns, with the 90th percentile being 16.1%.

Panel B of Table 5 shows the average return volatility of GameStop positions, again split by the time of purchase. We estimate intraday volatility based on 10-minute returns using the multiplicative component GARCH of Engle and Sokalska (2012). Then, we calculate the average volatility of positions during their holding periods. In line with expectations, we observe that investments during the frenzy were associated with significantly increased levels of volatility. In particular, short sellers experienced significant levels of volatility, with the 10th percentile of short sellers showing higher average volatility than the 90th percentile of investors who purchased GameStop prior to the frenzy.

Last, Table 6 studies who realized positive returns on their GameStop trading separately for long and short positions. Investors with long positions realized positive returns, particularly when they exited prior to or on January 25, had a history of frequent trading in lottery-type stocks, or initially opened their account during the frenzy. Male investors and those who closed their first GameStop position during the frenzy before the peak, only to open a second position later, performed particularly poorly. A notable exception is short sellers, who profited with second positions on the downturn of GameStop.

## 5. Discussion

In this paper, we explored who participated in the GameStop frenzy of January 2021 and how they performed. Early investors in particular had a history of investing in highly volatile stocks with lottery-like features. However, the retail investors' profile changed throughout the month as the frenzy spread to the wider market. Additionally, there are numerous of retail investors who took short positions in GameStop, indicating that initially, retail investors were on both sides of the trades. We also observe frequent buying *and* selling at all times during the frenzy. Consequently, the media portrayal of a fight being between retail investors and Wall Street is somewhat simplistic. Furthermore, while some rationalized retail investors' behavior as a protest against Wall Street, their history of engaging in highly risky behavior and the early closing of their GameStop positions indicates that participation in the frenzy was to some extent fueled by their desire for gambling. In addition, large amounts of media coverage may also have contributed to the extant buying pressure (Barber and Odean, 2008).

With respect to performance, we find males to perform particularly poorly, while those who opened their account during the frenzy, lottery-type investors, and frequent traders, on average, realized gains.

Our paper contributes to the broader literature highlighting recent changes in the behavior of retail investors (e.g., Ortmann et al., 2020; Glossner et al., 2020; Kalda et al., 2021). In particular, we document the first known case of retail investors acting as predators on financial markets, a role that was previously reserved for institutional investors, similar to the role of liquidity providers (Glossner et al., 2020).

As brokerage choice is nonrandom, investors in our sample may not be representative of investors across all brokers. In particular, we cannot rule out that a specific group of investors selects into a particular brokerage service. However, we specifically compare GameStop investors with other investors using the same broker who did not participate in the GameStop frenzy. Thus, we believe that our analysis nonetheless provides valuable insights into who participated in the frenzy.

While we position our paper within the predatory trading literature, we acknowledge that some of the GameStop investors who are part of our sample may not be predatory in nature but may be genuine value investors. Similarly, we only focus on retail investors in this paper and cannot comment on how institutional investors behaved during the frenzy. Nevertheless, we believe that our focus on retail investors is appropriate, as they were identified as causing the short squeeze (Umar et al., 2021). Notwithstanding these limitations, we believe that we provide a valuable contribution to the literature and hope that it spurs future research on this unprecedented case in which retail investors and social media participants engaged in predatory trading practices.

## References


Aharon, D. Y., Kizys, R., Umar, Z., Zaremba, A. (2021). Did David Win a Battle or the War Against Goliath? Dynamic Return and Volatility Connectedness between the GameStop Stock and the High Short Interest Indices. *SSRN*, 3788155.

Angel, J. (2021). Gamestonk: What Happened and What to Do about It. *SSRN Working Paper*, 3782195.

Bailey, W., Kumar, A., Ng, D. (2011). Behavioral biases of mutual fund investors. *Journal of Financial Economics*, 102, 1-27.

Barber, B. M., Odean, T. (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *The Review of Financial Studies*, 21(2), 785–818.

Barber, B. M., Odean, T., Zhu, N. (2008). Do retail trades move markets? *The Review of Financial Studies*, 22(1), 151-186.

Bradley, D., Hanousek Jr., J., Jame, R., Xiao, Z. (2021). Place Your Bets? The Market Consequences of Investment Advice on Reddit's Wallstreetbets. *SSRN Working Paper*, 3806065.

Brunnermeier, M. K., Pedersen, L. H. (2005). Predatory trading. *The Journal of Finance*, 60(4), 1825-1863.

Chohan, U. W. (2021). Counter-Hegemonic Finance: The GameStop Short Squeeze. *SSRN*, 3775127.

Engle, R.F., Sokalska, M.E. (2012). Forecasting intraday volatility in the US equity market. Multiplicative component GARCH. *Journal of Financial Econometrics*, 10(1), 54-83.

Fusari, N., Jarrow, R., Lamichhane, S. (2021). Testing for Asset Price Bubbles Using Options Data. *SSRN Working Paper*, 3670999.

Glossner, S., Matos, P., Ramelli, S., Wagner, A. F. (2020). Where Do Institutional Investors Seek Shelter When Disaster Strikes? Evidence from Covid-19. *CEPR Discussion Paper* No. DP15070.

Grinblatt, M., Keloharju, M. (2001). What Makes Investors Trade? *The Journal of Finance*, 56(2), 589-616.

Jarrow, R., Li, S. (2021). Media Trading Groups and Short Selling Manipulation--Are Media Groups Efficiency Enhancing or Reducing? *SSRN Working Paper*, 3804130.

Jones, C. M., Reed, A. V., Waller, W. (2021). When Brokerages Restrict Retail Investors, Does the Game Stop? *SSRN Working Paper*, 3804446.

Kalda, A., Loos, B., Previtero, A., Hackethal, A. (2021). Smart (Phone) Investing? A Within Investor-Time Analysis of New Technologies and Trading Behavior. *SAFE Working Paper* No. 303.

Kumar, A. (2009). Who gambles in the stock market? *The Journal of Finance*, 64(4), 1889-1933.

Ortmann, R., Pelster, M., Wengerek, S. T. (2020). COVID-19 and Investor Behavior. *Finance Research Letters*, 37, 101717.

Pedersen, L. H. (2021). Game On: Social Networks and Markets. *SSRN Working Paper*, 3794616.

Pelster, M., Breitmayer, B., Hasso, T. (2019). Are cryptocurrency traders pioneers or just risk-seekers? Evidence from brokerage accounts. *Economics Letters*, 182, 98-100.

Salganik, M. J., Dodds, P. S., Watts, D. J. (2006). Experimental Study of Inequality and Unpredictability in an Artificial Cultural Market. *Science*, 311(5762), 854-856.

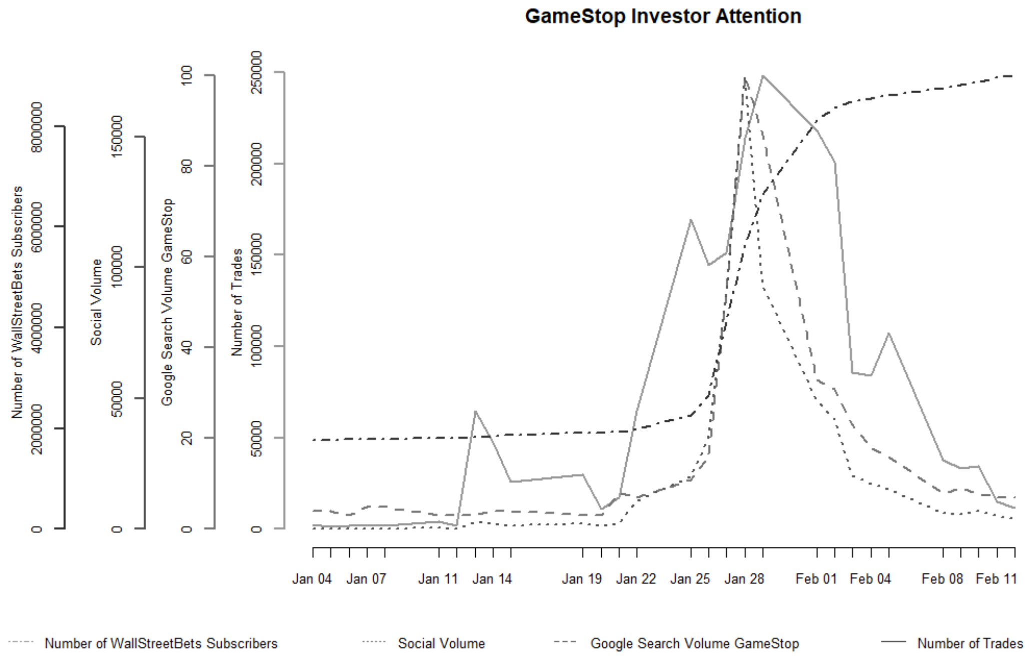
Shiller, R. J. (2020): Narrative Economics, *Princeton University Press*.

Umar, Z., Gubareva, M., Yousaf, I., Ali, S. (2021). A tale of company fundamentals vs sentiment driven pricing: The case of GameStop. *Journal of Behavioral and Experimental Finance*, 30, 100501.

Van Wesep, E. D., Waters, B. (2021). All-in Investors and Unstable Asset Prices. *SSRN Working Paper*, 3785637.

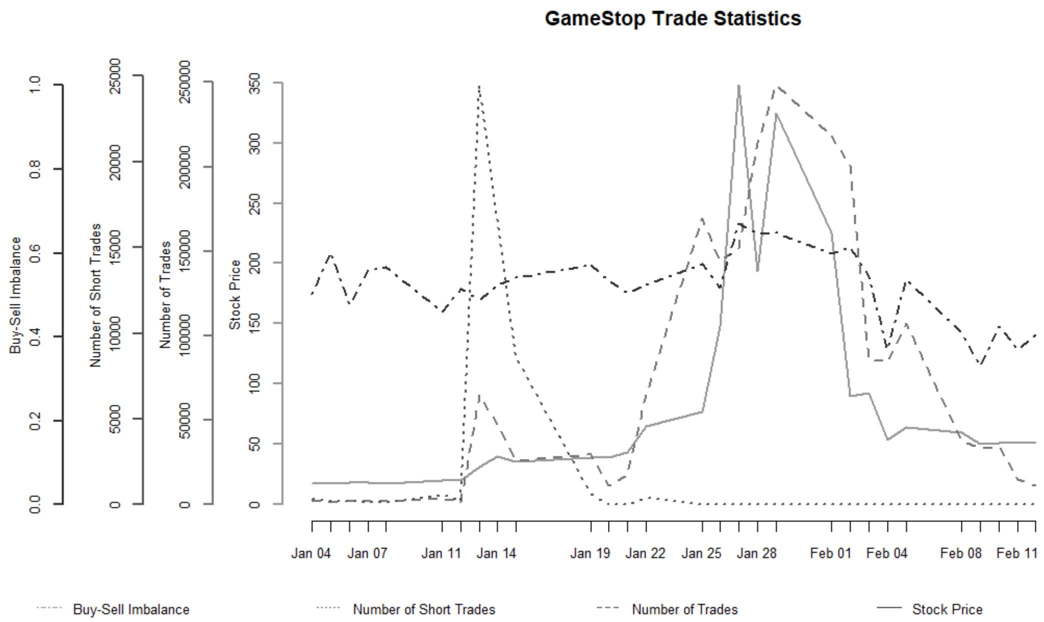
Wells, C., Egkolfopoulou, M. (2020, January 28). GameStop’s Reddit Revolution Echoes Occupy Wall Street Crusade. *Bloomberg News*.

## Figure 1. GameStop investor attention




Notes: The figure shows GameStop investor attention. Attention measures are the number of subscribers to WallStreetBets (dotted and dashed), Tweets with $/#GME - (social volume, dotted), and the Google search volume for GameStop (dashed). The solid line shows the total number of trades in GameStop (solid) that investors execute with the broker on a given day.

## Figure 2. GameStop trade statistics




Notes: The figure shows investors' trading activities in GameStop. The buy-sell imbalance (dotted and dashed) denotes the fraction of long positions taken on a given day, the number of short trades (dotted) denotes the number of short trades in GameStop with the broker, and the number of trades denotes the total number of trades in GameStop (dashed) that investors execute with the broker on a given day. The solid line shows the closing stock price of GameStop.

## Table 1. Summary statistics of trading data

| | N | Mean | St. Dev. | Skewness | Kurtosis | P25 | P50 | P75 |
|---|---|---|---|---|---|---|---|---|
| Male | 714,301 | 0.881 | 0.324 | -2.353 | 6.535 | 1 | 1 | 1 |
| Age | 519,416 | 34.587 | 12.84 | 0.954 | 2.882 | 30 | 30 | 50 |
| Experience | 245,744 | 0.983 | 1.083 | 0.750 | 2.039 | 0 | 0.5 | 2 |
| Wealth | 623,771 | 56,264.94 | 68,765.03 | 2.466 | 30.20 | 10,000 | 50,000 | 50,000 |
| Income | 647,549 | 86,240.67 | 75,972.90 | 1.346 | 15.92 | 50,000 | 50,000 | 200,000 |
| Cryptocurrency trader | 726,570 | 0.599 | 0.49 | -0.403 | 1.162 | 0 | 1 | 1 |
| Lottery stocks trader | 726,570 | 0.222 | 0.416 | 1.337 | 2.788 | 0 | 0 | 0 |
| High-volatility trader | 726,570 | 0.167 | 0.373 | 1.786 | 4.19 | 0 | 0 | 0 |
| Short seller | 726,570 | 0.078 | 0.269 | 3.138 | 10.848 | 0 | 0 | 0 |
| Trades | 726,570 | 35.911 | 132.134 | 24.293 | 1461.088 | 2 | 7 | 25 |
| Realized profit | 726,570 | 0.671 | 9.69 | 97.012 | 25529.03 | 0.000 | 0.000 | 0.115 |
| Return volatility | 726,570 | 5.978 | 19.833 | 25.196 | 1837.869 | 0.000 | 0.000 | 4.770 |
| Account open Jan 1, 2020, to Jan 9, 2021 | 726,570 | 0.587 | 0.492 | -0.352 | 1.124 | 0 | 1 | 1 |
| Account open during frenzy | 726,570 | 0.045 | 0.207 | 4.391 | 20.283 | 0 | 0 | 0 |

Notes: Male is a dummy variable that takes a value of one for male investors, zero for female investors; age denotes the average age of investors collected in discrete age groups; experience reports investors' self-reported trading experience in years; wealth denotes the wealth of investors in USD collected in discrete wealth buckets; income denotes the income of investors in USD collected in discrete income buckets; cryptocurrency trader is a dummy variable that takes a value of one for investors who engaged in cryptocurrency trading at some point prior to January 9, 2021, zero otherwise; lottery stocks trader is a dummy variable that takes a value of one for investors who trade stocks that are classified as lottery stocks according to Kumar (2009) at some point prior to January 9, 2021, zero otherwise; high-volatility trader is a dummy variable that takes a value of one for investors who purchased one of the 50 stocks with the highest volatility of monthly returns over the previous five years at some point prior to January 9, 2021, zero otherwise; short seller is a dummy variable that takes a value of one for investors who engaged in short selling at some point prior to January 9, 2021, zero otherwise; trades denotes the number of trades that investors executed between December 1, 2020, and January 9, 2021; realized profit denotes the average weighted performance of stock investments realized prior to January 9, 2021; return volatility denotes the standard deviation of the performance of stock investments realized prior to January 9, 2021; account open Jan 1, 2020, to Jan 9, 2021, is a dummy variable that takes a value of one for investors who opened their brokerage account between Jan 1, 2020, and Jan 9, 2021, zero otherwise; account open during frenzy is a dummy variable that takes a value of one for investors who opened their brokerage account on or after Jan 13, 2021, zero otherwise. The data are from a retail broker and contain all trades on the platform between December 1, 2020, and February 12, 2021.

**Table 2. Summary statistics of investor characteristics split by investment activity**

| | Investors who do not trade GameStop | Jan. 11-Jan. 12 | Jan. 13-Jan. 17 | Jan. 18-Jan. 24 | After Jan. 25 | Short-sellers |
|---|---|---|---|---|---|---|
| Male | 0.8695 | 0.9111 | 0.8932 | 0.8960 | 0.9122 | 0.9252 |
| | | (5.6698) | (7.8269) | (9.9768) | (53.341) | (15.267) |
| Age | 36.2765 | 33.3632 | 32.5178 | 32.0883 | 30.3680 | 31.1579 |
| | | (8.3472) | (28.706) | (37.136) | (173.42) | (31.506) |
| Experience | 1.0033 | 0.9185 | 0.8885 | 0.9016 | 0.8770 | 0.9356 |
| | | (1.4658) | (5.1917) | (5.2136) | (21.994) | (2.3291) |
| Wealth | 57938.61 | 54059.93 | 52631.05 | 53721.12 | 51660.35 | 51987.33 |
| | | (2.1557) | (7.9411) | (7.098) | (32.908) | (6.3929) |
| Income | 88244.24 | 78915.57 | 77911.15 | 79970.50 | 80789.87 | 75589.99 |
| | | (4.8613) | (14.171) | (12.672) | (35.395) | (12.652) |
| Cryptocurrency trader | 0.6817 | 0.7288 | 0.7195 | 0.6342 | 0.3809 | 0.7494 |
| | | (4.1061) | (8.5774) | (11.37) | (237.87) | (11.298) |
| Lottery stocks trader | 0.2108 | 0.7851 | 0.6453 | 0.5413 | 0.2448 | 0.7139 |
| | | (54.211) | (92.955) | (76.715) | (30.471) | (80.575) |
| High-volatility trader | 0.1396 | 0.7208 | 0.6482 | 0.5475 | 0.2312 | 0.6940 |
| | | (50.256) | (109.23) | (95.001) | (86.496) | (87.193) |
| Short seller | 0.0711 | 0.4456 | 0.3427 | 0.2613 | 0.0925 | 0.6060 |
| | | (29.243) | (58.839) | (50.283) | (28.943) | (79.456) |
| Trades | 31.5579 | 274.8402 | 186.9950 | 154.5082 | 45.8391 | 201.5380 |
| | | (18.462) | (39.955) | (40.382) | (34.334) | (35.791) |
| Trading quintile | 3.1741 | 4.4920 | 4.1892 | 3.7706 | 2.5242 | 4.4502 |
| | | (51.479) | (83.285) | (45.406) | (155.89) | (88.196) |
| Realized profit | 0.7640 | 0.4892 | 0.4835 | 0.4938 | 0.4279 | 0.3783 |
| | | (2.529) | (6.2616) | (6.3019) | (16.204) | (5.7098) |
| Performance quintile | 3.0126 | 3.2984 | 3.3046 | 3.2037 | 2.9611 | 3.2875 |
| | | (7.4041) | (19.783) | (15.487) | (14.218) | (12.803) |
| Return volatility | 5.7273 | 17.7033 | 15.6160 | 13.0103 | 6.4721 | 18.6173 |
| | | (23.029) | (50.179) | (42.729) | (14.743) | (43.255) |
| Return-volatility quintile | 2.9867 | 4.4131 | 4.1777 | 3.8489 | 3.0141 | 4.4226 |
| | | (56.14) | (103.13) | (73.703) | (7.2966) | (100.93) |
| Account open Jan 1, 2020, to Jan 9, 2021 | 0.6624 | 0.7692 | 0.7487 | 0.6550 | 0.3861 | 0.7432 |
| | | (9.8241) | (20.27) | (1.8062) | (217.25) | (13.36) |

Notes: Variable definitions can be found in Table 1. *t*-tests (in parentheses) report results from an equality test of GameStop investors in the given time period versus investors who did not engage in the GameStop frenzy.

## Table 3. Explaining participation in GameStop trading

| | **Model 1** | **Model 2** | **Model 3** | **Model 4** | **Model 5** |
|---|---|---|---|---|---|
| | **Jan. 11-Jan. 12** | **Jan. 13-Jan. 17** | **Jan. 18-Jan. 24** | **After Jan. 25** | **Short sellers** |
| Male | 1.3369 | 0.9571 | 1.3556** | 1.6671*** | 1.1414 |
| | (0.4379) | (0.1062) | (0.1492) | (0.0585) | (0.1909) |
| Age | 0.9911 | 0.9868*** | 0.9765*** | 0.9646*** | 0.9726*** |
| | (0.0061) | (0.0024) | (0.0022) | (0.0007) | (0.0034) |
| Experience | 0.9768 | 0.9365* | 0.9372* | 0.9296*** | 0.9753 |
| | (0.0702) | (0.0274) | (0.0239) | (0.0078) | (0.0368) |
| Log(Wealth) | 1.0000 | 1.0000* | 1.0000 | 1.0000*** | 1.0000 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Log(Income) | 1.0000 | 1.0000 | 1.0000* | 1.0000*** | 1.0000 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Cryptocurrency trader | 0.9853 | 1.1396 | 0.8568** | 0.3827*** | 1.1805 |
| | (0.1604) | (0.0782) | (0.0483) | (0.0066) | (0.1065) |
| High volatility | 3.3382*** | 4.6350*** | 4.7841*** | 2.9982*** | 3.8174*** |
| | (0.5984) | (0.3504) | (0.3216) | (0.0821) | (0.3634) |
| Lottery stocks trader | 2.4521*** | 1.5104*** | 1.6273*** | 1.1790*** | 1.6245*** |
| | (0.5103) | (0.1201) | (0.1143) | (0.0308) | (0.1684) |
| Short seller | 3.0697*** | 2.9904*** | 2.7650*** | 1.4878*** | 7.9554*** |
| | (0.4722) | (0.1955) | (0.1692) | (0.0472) | (0.6632) |
| Trading quintile | 1.4730*** | 1.3697*** | 1.1279*** | 0.8353*** | 1.4679*** |
| | (0.1461) | (0.0494) | (0.0320) | (0.0066) | (0.0780) |
| Performance quintile | 0.9837 | 0.9892 | 0.9600* | 0.9613*** | 0.9937 |
| | (0.0440) | (0.0186) | (0.0160) | (0.0063) | (0.0232) |
| Return-volatility quintile | 1.5487*** | 1.3883*** | 1.2342*** | 1.1252*** | 1.3431*** |
| | (0.1461) | (0.0465) | (0.0327) | (0.0091) | (0.0636) |
| Account open Jan 1, 2020, | 1.0833 | 1.0436 | 0.8057*** | 0.4968*** | 0.8635 |
| to Jan 9, 2021 | (0.1833) | (0.0712) | (0.0502) | (0.0114) | (0.0801) |
| Exit prior to or on January 25 | | | | 240.5926*** | |
| | | | | (27.5071) | |
| Num. obs. | 120998 | 122170 | 122602 | 145297 | 121612 |
| Log Likelihood | -1214.854 | -5827.8561 | -7721.4127 | -52595.4521 | -3405.9117 |
| AIC | 2457.7087 | 11683.7122 | 15470.8253 | 105220.9041 | 6839.8234 |
| LR chi$^2$ | 659.62 | 3480.52 | 3444.45 | 26677.84 | 3061.39 |
| P(> chi$^2$) | <0.0001 | <0.0001 | <0.0001 | <0.0001 | <0.0001 |
| Pseudo $R^2$ | 0.216 | 0.241 | 0.194 | 0.281 | 0.319 |
| c index | 0.891 | 0.854 | 0.832 | 0.785 | 0.906 |

Notes: Models 1 to 4 present odds ratios from logit regressions with the GameStop purchase decision as the dependent variable. The dependent variable takes a value of one if a GameStop position was opened during the specified date and zero otherwise. Model 5 presents odds ratios from a logit regression with the GameStop short decision as the dependent variable. Variable definitions can be found in Table 1. Standard errors in parentheses. Diagnostic tests include the model likelihood ratio chi$^2$ with the corresponding *p*-value, the Nagelkerke pseudo $R^2$, and the c index (i.e., the area under the ROC curve). $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

## Table 4. Explaining selling GameStop throughout the frenzy

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 | Model 7 |
|---|---|---|---|---|---|---|---|
| | **<= Jan 25** | **Jan 26** | **Jan 27** | **Jan 28** | **Jan 29** | **=> Feb 1** | **Not closed vs. closed** |
| Male | 0.7768*** | 0.7834*** | 0.8131*** | 0.9053* | 0.7760*** | 1.0362 | 1.1381*** |
| | (0.0231) | (0.0340) | (0.0439) | (0.0430) | (0.0350) | (0.0328) | (0.0306) |
| Age | 0.9934*** | 1.0084*** | 0.9949*** | 0.9890*** | 0.9927*** | 1.0073*** | 0.9967*** |
| | (0.0007) | (0.0010) | (0.0013) | (0.0011) | (0.0011) | (0.0007) | (0.0006) |
| Experience | 0.9684*** | 1.0103 | 0.9784 | 1.0235* | 0.9654** | 0.9858 | 1.0269*** |
| | (0.0077) | (0.0119) | (0.0140) | (0.0118) | (0.0112) | (0.0073) | (0.0066) |
| Log(Wealth) | 1.0000*** | 1.0000*** | 1.0000 | 1.0000** | 1.0000 | 1.0000 | 1.0000 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Log(Income) | 1.0000*** | 1.0000*** | 1.0000*** | 1.0000*** | 1.0000*** | 1.0000** | 1.0000** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Cryptocurrency trader | 0.9736 | 1.2863*** | 1.4380*** | 1.2976*** | 1.2110*** | 0.7405*** | 1.2116*** |
| | (0.0211) | (0.0441) | (0.0571) | (0.0409) | (0.0375) | (0.0151) | (0.0216) |
| High-volatility trader | 1.2070*** | 1.4145*** | 1.2065*** | 0.8388*** | 0.8950*** | 1.0105 | 0.9170*** |
| | (0.0255) | (0.0465) | (0.0469) | (0.0272) | (0.0296) | (0.0223) | (0.0171) |
| Lottery stocks trader | 1.1355*** | 1.0544 | 0.9906 | 1.0856* | 1.1351*** | 0.8690*** | 1.0650** |
| | (0.0255) | (0.0363) | (0.0401) | (0.0368) | (0.0393) | (0.0200) | (0.0208) |
| Short seller | 1.7111*** | 1.1048*** | 0.9669 | 1.1166*** | 0.8689*** | 1.0900*** | 0.7619*** |
| | (0.0306) | (0.0321) | (0.0350) | (0.0342) | (0.0280) | (0.0237) | (0.0139) |
| Trading quintile | 1.1891*** | 1.0964*** | 1.0392* | 1.0099 | 0.9793 | 1.1841*** | 0.8149*** |
| | (0.0115) | (0.0153) | (0.0161) | (0.0124) | (0.0118) | (0.0094) | (0.0057) |
| Performance quintile | 0.9691*** | 1.0100 | 1.0111 | 1.0454*** | 1.0202* | 0.9202*** | 1.0796*** |
| | (0.0050) | (0.0082) | (0.0098) | (0.0085) | (0.0084) | (0.0052) | (0.0051) |
| Return-volatility quintile | 1.1879*** | 1.0303* | 1.0293* | 1.0257* | 1.0310** | 1.0180* | 0.9463*** |
| | (0.0109) | (0.0134) | (0.0150) | (0.0120) | (0.0120) | (0.0077) | (0.0062) |
| Account open Jan 1, 2020, to Jan 9, 2021 | 1.0090 | 1.1854*** | 1.2347*** | 1.2896*** | 1.1655*** | 1.0226 | 0.8644*** |
| | (0.0193) | (0.0343) | (0.0416) | (0.0366) | (0.0345) | (0.0210) | (0.0149) |
| Account open during frenzy | 1.8546*** | 1.1456 | 0.8180 | 0.6465*** | 0.6074*** | 1.7578*** | 0.5909*** |
| | (0.1082) | (0.1112) | (0.0919) | (0.0557) | (0.0469) | (0.0766) | (0.0236) |
| Num. obs. | 106219 | 81124 | 72263 | 65988 | 55720 | 84820 | 146274 |
| Log Likelihood | -54130.517 | -27120.580 | -21024.849 | -28231.738 | -27463.484 | -58031.207 | -83505.095 |
| AIC | 108291.034 | 54271.159 | 42079.698 | 56493.476 | 54956.967 | 116092.414 | 167040.191 |
| LR $chi^2$ | 7884.58 | 1717.84 | 607.84 | 590.80 | 309.84 | 1261.40 | 4726.14 |
| P(> $chi^2$) | <0.0001 | <0.0001 | <0.0001 | <0.0001 | <0.0001 | <0.0001 | <0.0001 |
| Pseudo $R^2$ | 0.108 | 0.042 | 0.019 | 0.015 | 0.009 | 0.02 | 0.046 |
| c index | 0.681 | 0.633 | 0.594 | 0.578 | 0.553 | 0.566 | 0.615 |

Notes: Models 1 to 6 present odds ratios from logit regressions with the GameStop selling decision as the dependent variable. The dependent variable takes a value of one if the GameStop position was closed on the specified date and zero if it was closed at later point during the frenzy or is still open. Model 7 presents odds ratios from a logit regression with the dependent variable taking a value of one if the GameStop position is still open and zero if it was closed at any point during the frenzy. Variable definitions can be found in Table 1. Diagnostic tests include the model likelihood ratio $chi^2$ with the corresponding *p*-value, the Nagelkerke pseudo $R^2$, and the c index (i.e., the area under the ROC curve). $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

## Table 5. Performance of GameStop investors

### Panel A: Holding period returns, split by time of purchase

| Percentile | Investors who did not participate in GameStop frenzy | Jan. 11-Jan. 12 | Jan. 13-Jan. 17 | Jan. 18-Jan. 24 | After Jan. 25 | Short sellers |
|---|---|---|---|---|---|---|
| 10% | -7.08 | -7.42 | -21.5 | -12.3 | -82.6 | -50.7 |
| 20% | -2.2 | -2.76 | -7.62 | -2.58 | -70.3 | -47 |
| 30% | -0.114 | -0.375 | -2.3 | 0.26 | -48.8 | -16.6 |
| 40% | 1.04 | 0.42 | 0.305 | 1.6 | -26.5 | -6.93 |
| 50% | 2.84 | 1.49 | 1.81 | 3.94 | -12.9 | -1.09 |
| 60% | 5.57 | 3.44 | 4.44 | 8.58 | -3.42 | 1.23 |
| 70% | 10 | 6.88 | 9.18 | 19.1 | 0.5 | 3.83 |
| 80% | 17.4 | 14.6 | 18 | 42.6 | 3.04 | 7.91 |
| 90% | 37 | 44 | 50.3 | 128 | 10.9 | 16.1 |

### Panel B: Avg. volatility of open positions (in 10-minute intervals)

| Percentile | Investors who did not participate in GameStop frenzy | Jan. 11-Jan. 12 | Jan. 13-Jan. 17 | Jan. 18-Jan. 24 | After Jan. 25 | Short sellers |
|---|---|---|---|---|---|---|
| 10% | 0.821 | 0.804 | 1.99 | 2.02 | 1.53 | 3.16 |
| 20% | 0.942 | 0.951 | 2.32 | 2.38 | 1.98 | 3.74 |
| 30% | 0.992 | 1.07 | 2.59 | 2.6 | 2.42 | 4.13 |
| 40% | 1.03 | 1.19 | 2.92 | 2.85 | 2.94 | 4.57 |
| 50% | 1.16 | 1.37 | 3.39 | 3.25 | 3.6 | 5 |
| 60% | 1.45 | 1.61 | 4.16 | 4.39 | 4.28 | 5.99 |
| 70% | 1.85 | 2.05 | 5 | 5.15 | 4.82 | 7.26 |
| 80% | 2.31 | 2.42 | 5.41 | 5.54 | 5.34 | 9.43 |
| 90% | 2.57 | 3.08 | 6.23 | 6.33 | 6.44 | 11.2 |

Notes: This table reports the performance implications of GameStop investments. Panel A reports holding period returns in percent, split by the time of purchase. For positions that are still open at market close on Feb. 12, 2021, we calculate holding-period returns to this date. Panel B shows the average intraday volatility of GameStop positions, split by the time of purchase. Intraday volatility is based on 10-minute returns estimated using the multiplicative component GARCH of Engle and Sokalska (2012).

## Table 6. Explaining profitable GameStop investments

| | **Model 1** | **Model 2** |
|---|---|---|
| | **Long positions** | **Short positions** |
| Male | $0.7778^{***}$ | 0.7284 |
| | (0.0186) | (0.1251) |
| Age | $1.0064^{***}$ | 0.9973 |
| | (0.0006) | (0.0036) |
| Experience | 1.0071 | 0.9718 |
| | (0.0061) | (0.0329) |
| Log(Wealth) | 1.0000 | 1.0000 |
| | (0.0000) | (0.0000) |
| Log(Income) | $1.0000^{***}$ | 1.0000 |
| | (0.0000) | (0.0000) |
| Cryptocurrency trader | $0.8953^{***}$ | 0.9847 |
| | (0.0148) | (0.0934) |
| High-volatility trader | 1.0258 | 0.9903 |
| | (0.0173) | (0.0843) |
| Lottery stocks trader | $1.0907^{***}$ | 1.0767 |
| | (0.0192) | (0.1033) |
| Short seller | $1.0609^{***}$ | 1.1799 |
| | (0.0164) | (0.1061) |
| Trading quintile | $1.1747^{***}$ | 1.0097 |
| | (0.0079) | (0.0635) |
| Performance quintile | $1.0317^{***}$ | 0.9785 |
| | (0.0043) | (0.0191) |
| Return-volatility quintile | $0.9541^{***}$ | 1.0197 |
| | (0.0060) | (0.0599) |
| Second GameStop position | $0.7039^{***}$ | $1.3923^{***}$ |
| | (0.0167) | (0.1075) |
| Exit prior to or on Januar 25 | $3.3712^{***}$ | $0.7953^{*}$ |
| | (0.0792) | (0.0785) |
| Account open during frenzy | $1.2592^{***}$ | 1.1825 |
| | (0.0506) | (1.2025) |
| Account open Jan 1, 2020, to Jan 9, 2021 | $1.0609^{***}$ | $0.8148^{*}$ |
| | (0.0162) | (0.0686) |
| Num. obs. | 145334 | 3961 |
| Log Likelihood | -89545.9915 | -2725.5661 |
| AIC | 179125.9830 | 5485.1323 |
| LR $chi^2$ | 12022.92 | 39.91 |
| P(> $chi^2$) | <0.0001 | 0.0008 |
| Pseudo $R^2$ | 0.109 | 0.013 |
| c index | 0.669 | 0.559 |

Notes: Models 1 and 2 present odds ratios from a logit regression with the dependent variable taking a value of one if the GameStop position was closed for a gain (or was a paper gain on Feb 12, 2021) and zero if it was closed for a loss (or was a paper loss on Feb 12, 2021). Variable definitions can be found in Table 1. Diagnostic tests include the model likelihood ratio chi2 with the corresponding p-value, the Nagelkerke pseudo $R^2$, and the c index (i.e., the area under the ROC curve). $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$