An Anatomy of Retail Option Trading

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Abstract

The recent surge in retail option trading has sparked concerns about trading motives and significant losses. To evaluate these concerns, we offer the first trader-level analysis of modern retail option trading by introducing a novel data set of $15 billion in retail stock and option trades. Option trades constitute over one-third of all trades, are concentrated in a few underlyings, especially the S&P 500 index, and are dominated by short-term purchases. Surprisingly, option trades incur relatively small losses despite wide bid-ask spreads. Retail investors use options to participate in high-priced underlyings, with limited evidence of leverage or skewness-seeking in realized trade returns. While our average retail investor is relatively sophisticated, results remain robust across investor subsamples.

1 Introduction

Retail traders account for a substantial portion of stock trading volume, attracting significant public and regulatory attention. While retail stock trading has been extensively studied (Barber and Odean (2013)), the COVID-19 pandemic saw an influx of new investors. These newcomers, often influenced by social networks, are drawn to complex markets like options. The Options Clearing Corp reports a 35% increase in option trading volume between 2020 and 2021, largely attributed to growth in retail trading, which far outpaced the increase in stock trading volume.[1] Indeed, Bryzgalova, Pavlova, and Sikorskaya (2022) estimate that "retail trading recently reached over 60% of total market volume" in options, with retail brokers earning more from option trading than stock trading. This surge in retail option trading has raised widespread concerns. Some argue it resembles gambling, potentially resulting in significant losses (e.g., de Silva, Smith, and So (2023)). The wide bid-ask spreads in options could lead to large losses for active traders (e.g., Muravyev and Pearson (2020)). These concerns have prompted calls for stricter regulation of retail option trading (e.g., FINRA Regulatory Notice 22-08).

We evaluate these concerns through the first comprehensive study of modern retail investor behavior in the option market, using detailed trader-level data on both option and stock trades. Our data allow us to analyze *individual* behavior, profitability, and trading motives, thus extending the growing literature on U.S. retail option trading that relies on proxies of *aggregate* retail behavior.[2]

We obtain our data from a trading journal provider. Trading journals are popular among investors for their advanced performance tracking and verification tools. Users link their brokerage accounts, allowing automatic and verified trade import. To maintain verified trade status, users cannot selectively import trades. The journal exclusively supports retail brokers, such as TD Ameritrade, which we confirm through reported broker IDs. The data set contains 5,182 traders who made 2.4 million parent trades (including 0.9 million option trades) worth about $15 billion between 2020 and 2022. Average trade sizes of $8,798 for stocks and $2,006 for options suggest that the journal tracks investors' primary trading accounts. Each parent trade consists of child trades

[1] For example, WSJ on September 26, 2021, https://www.wsj.com/articles/individuals-embrace-options-trading-turbocharging-stock-markets-11632661201

[2] For example, Bryzgalova et al. (2022) and Hendershott, Khan, and Riordan (2022) assume that all option trades submitted into single-leg auctions are retail. Eaton, Green, Roseman, and Wu (2023), de Silva et al. (2023), and Lipson, Tomio, and Zhang (2023) use the "customer" category of daily option volume (in the Options Open-Close Volume Summary data set), but this category includes both retail and institutional trades.

that open and then close the initial position, or occasionally an option expiration record. Thus, we observe detailed data on modern retail trading of stocks, options, or both. We assess how our findings generalize from journal users to other retail investors after presenting the main results.

We document several stylized facts about retail option trading. First, we confirm the growing popularity of options among retail investors. Option trading activity nearly matches stock trading activity by the end of our sample. The share of option trades in our data increases from 23% in January 2020 to 49% in December 2022. Strikingly, a quarter of all investors in our data trade only options and not stocks in a given month. Thus, despite the spotlight on retail stock trading, retail option trading is gaining comparable importance in our data.

Second, retail investors in our data trade many stocks, but their option trading is concentrated in a few names. The ten most-traded option underlyings represent 60% of all option trades, with 26% linked to the S&P 500 index. Option trading becomes more concentrated as the top-ten share increases from 47% in 2020 to 74% in 2022. In contrast, stock trades are dispersed, and the ten most popular stocks represent only 9% of all stock trades, with Tesla and AMC at the top. A trader-level analysis shows that investors tend to trade different stocks but the same option underlyings. Despite thousands of stocks having listed options, retail option trading is heavily concentrated in a few underlyings. Therefore, a traditional *per-stock* analysis across all optionable stocks could present a skewed perspective.

Third, our analysis of trade characteristics reveals that retail investors in our data primarily use options for short-term speculation. A typical retail option trade involves a purchase of a one-day call or put option linked to the S&P 500 index held for only an hour. Naked option selling is rare as option purchases dominate sales by 7-to-1. Indeed, many brokers either prohibit or require special permission for naked option selling. Thus, option purchases mainly open new positions, while option sales mainly close existing positions. Furthermore, retail investors tend to trade on short-term price swings. The median option maturity decreases from four days in 2020 to less than a day in 2022. Thus, our retail investors primarily trade zero days to expiration (0DTE) options in 2022, contributing to their popularity (Beckmeyer, Branger, and Gayda (2023)). Finally, the holding period is highly skewed, with a 3.5-day average but only a half-hour median. This observation challenges fixed holding horizons assumed by prior studies of retail trading profitability.

We evaluate concerns about retail losses. Retail investors break even on their stock trades, consistent with small bid-ask spreads and unpredictable returns. On the option side, an average option trade in our data earns a -0.9% return, which is small compared to typical option bid-ask spreads of 5% to 10% and is comparable to trading fees. Retail traders likely rely on limit orders to avoid paying the spread. Option trade profitability varies from -5% to 1% across subsamples. Naked option sales are the exception and earn 20% on average, which is consistent with Bryzgalova et al. (2022). These findings suggest that concerns about large retail losses in options may be overstated. Our profitability estimates contrast with Bryzgalova et al. (2022) and de Silva et al. (2023), who report losses of 3% to 9% per trade based on aggregate retail proxies. The difference arises from the proxy limitations, differences in analysis units, endogenous holding periods, and investor sophistication. The "single-leg auction" proxy considers only market orders that cross the spread, while the "open-close" proxy lacks trade prices, affecting profitability calculations. Both proxies assume a fixed holding period (e.g., one day) and analyze an average stock. However, retail option trading is concentrated in few underlyings, with highly skewed holding periods.

Retail investors in our data primarily trade options to participate in high-priced underlyings. Indeed, the price of a median stock trade is $8, whereas the underlying price of a median option trade is much higher at $262 (excluding S&P 500 trades). Retail traders favor options over stocks for high-priced stocks, even within the same trader or stock, controlling for size, volatility, and other characteristics. Hence, traders appear to seek an affordable alternative to buying high-price stocks. Indeed, the capital needed to buy a hundred shares at $262 is 15 times larger than a median stock trade. Traders in our data can achieve the same position by buying seven shares instead of a hundred and thus rarely require fractional shares.[3] Evidence from stock splits further supports the affordability hypothesis. As a stock becomes more affordable to trade post split, investors in our data increase their propensity to trade the stock relative to options on the stock by about 10%.

Embedded leverage is often considered a primary reason for option trading, as a long option can generate higher profits than a similar investment in the underlying, given favorable price movements. Surprisingly, retail investors in our data achieve only modest realized leverage from option trading. The realized leverage would be evident if absolute dollar profits were higher for option trades than stock trades. While option purchases do generate about $110 larger absolute dollar profit than

[3]Most of the brokers in our data set do not allow fractional shares, and even for those who do, we confirm the large difference between the underlying price for option and stock trades.

stock trades—a statistically significant difference with or without trader fixed effects—this amount is economically small, accounting for only 1.3% of an average stock trade size. Although options inherently offer higher leverage than stocks, retail option trades are 4.4 times smaller on average. These offsetting effects result in modest realized leverage on option trades.

Similarly, preference for positive skewness, often associated with gambling behavior, is *not* a major driver of retail option purchases in our data.[4] Long option positions held until expiration can generate lottery-like payoffs with large potential profits and limited losses. But we find that this payoff skewness does not translate into positive skewness in traders' profits. We first assess the asymmetry in the distribution of dollar trade profits. Stock trades show a symmetric P&L distribution. Option trades also display an almost symmetric P&L distribution. For option purchases, the 10th and 90th percentiles are -\$296 and \$217 respectively, indicating slight negative skewness, with similar results in the tails of the distribution.[5] With the same trader, realized dollar return skewness of both option and stock trades is negative and not statistically different (at the level of 1%). An option trade's profit deviates from the theoretical option payoff due to short holding periods. Also, retail traders in our data have a tendency to realize gains earlier than losses on option purchases, which adds negative skewness.

Our analysis reveals that covered calls, protective puts, and other concurrent stock-option positions are rare among our retail traders. For example, covered calls constitute less than 0.2% of all option trades. Despite being taught in every derivatives course and promoted by brokers, retail investors in our data overwhelmingly prefer simple single-leg strategies. We estimate that at most 15% of all option trades represent popular multi-leg ("complex") option trades. This suggests that retail investors use complex strategies less frequently than non-retail investors, as at least one-third of all option trades are complex (Li, Musto, and Pearson (2023)). All previous results remain robust when complex trades are excluded.

While this paper offers, to our knowledge, the first trader-level analysis of modern retail option trading, it focuses on investors who opted to use a trading journal. These traders may be relatively more sophisticated than other retail investors since they find a journal valuable, trade relatively

[4]For example, Boyer and Vorkink (2014) note that options provide large ex ante skewness and find more negative returns for options with larger ex ante skewness (i.e., more out-of-the-money).

[5]Even percentage returns, instead of dollar profits, are slightly negatively skewed until -100% returns become binding for option purchases at the 1st percentile. Percentage returns become positively skewed for more extreme percentiles.

often and in large size, and short more. Our study complements prior research on "unsophisticated" Robinhood investors by examining a sample of (presumably) more sophisticated retail investors in modern stock and options markets. We assess the extent to which the results could generalize to other retail investors. We first show a strong positive correlation between stock trading imbalance in our data and established measures of retail imbalance, such as the change in the number of Robinhood investors holding a stock (Barber et al. (2022), Eaton et al. (2022)) and the Boehmer, Jones, Zhang, and Zhang (2021) retail order imbalance, controlling for the Lee and Ready (1991) imbalance. Option volume in our data is positively related to the retail option measure of Bryzgalova et al. (2022), controlling for total option volume. Finally, TD Ameritrade's trading activity in our data increased relative to other brokers after TD introduced zero-commission trading.

Our analysis reveals significant heterogeneity among retail investors, such as holding periods ranging from less than an hour to weeks. We exploit this heterogeneity to validate our findings across various trader characteristics. Since active traders, who dominate retail volume, are more likely to use trading journals, we confirm our findings for less active traders, as measured by trade count and holding period. We further explore how results vary across brokers, average trade sizes, option usage, and other trader subsamples. By employing trader fixed effects, we confirm that our key results are robust to individual investor characteristics, reducing concerns about sample-specific biases. Finally, to address a potential bias from journal sign-up being influenced by past performance, we analyze trades before and after the sign-up date. Our results appear robust, yet our findings should be interpreted with caution because we only observe a subset of retail investors.

Overall, our main findings arise from the unique trader-level nature of our data. This granularity enables us to compare option trades to stock trades by the same investor, and precisely measure realized trade profitability, leverage, and skewness, accounting for actual holding periods.

Related Literature. A growing literature studies retail trading in options using aggregate proxies for retail trading. Option retail trading exploded in popularity recently (Bryzgalova et al. (2022)), but retail trading proxies suggest that retail investors suffer large losses (de Silva et al. (2023), Bryzgalova et al. (2022), Beckmeyer et al. (2023)). Retail trading also can affect implied volatility (Eaton et al. (2023)) and underlying stock volatility (Lipson et al. (2023)). Lakonishok et al. (2007) find that the least sophisticated investors were chasing dot-com bubble by buying calls on growth stocks. Our study provides the first detailed analysis of how modern retail investors jointly trade options and stocks, leveraging trader-level data to offer new insights into profitability and trading motives. Our findings nuance the common concern that retail investors view options as lottery tickets or leverage sources, resulting in large losses.

To our knowledge, only Bauer, Cosemans, and Eichholtz (2009) study trader-level behavior and performance in options prior to our work. These authors show that clients of a Dutch online broker from 2000 to 2006 primarily gambled with options and incurred large losses. Our results for trade motives and performance in the modern U.S. sample differ significantly. Hu, Kirilova, Park, and Ryu (2023) find that most retail investors in KOSPI 200 options hold simple one-sided positions, which is consistent with our results for the U.S. options market.

Our study of joint retail trading in stocks and options contributes to the literature on retail stock trading.[6] Kogan et al. (2023) show that retail investors trade crypto differently than stocks. Similarly, we find that retail investors in our data trade options differently than stocks, which is a much closer asset class. Retail option trading is concentrated in a few option underlyings (indices and high-price technology stocks) but their stock trading is spread across many tickers (mostly low-price stocks). Moreover, despite the proliferation of option trading, retail traders rarely combine option and stock positions in the same underlying (e.g., very few covered calls). Thus, profitability and other analyses can be conducted separately on stock and option trades.

We also find that stock trades break even on average, and their profit distribution is symmetric. Even if traders seek positive skewness, they do not achieve it, consistent with Fedyk (2022). Finally, retail short selling in our data is more prevalent and profitable compared to the earlier sample studied by Kelley and Tetlock (2017).

2 Data and Descriptive Statistics

2.1 Novel Data Set

In this section, we introduce a novel data set of retail trading. We obtain our data from a popular trading journal provider. Investors use a trading journal to track and analyze their trades.[7] Third-

[6]This literature is extensive. Barber and Odean (2013) summarize earlier work that includes seminal papers such as Barber and Odean (2000, 2001). More recent studies (e.g., Welch (2022); Barber et al. (2022); Eaton et al. (2022); Ozik, Sadka, and Shen (2021); Chapkovski, Khapko, and Zoican (2021); Dyhrberg, Shkilko, and Werner (2022); Kogan et al. (2023)) shed light on the behavior of the new generation of retail investors.

[7]We use the terms investor, trader, and account interchangeably.

party trading journals often offer more advanced features than the analytical tools provided by brokers. For example, these journals allow users to import trade data automatically from many retail brokers, tag and filter trades, and generate a range of reports to help them analyze and improve their trading performance. Once users connect their broker or trading platform, trades are automatically verified and imported into the journal, ensuring that the data in the journal accurately reflects the trader's actual activity.

The trading journal that we use makes customer trades public by default, which the overwhelming majority of users do not change. Thus, anyone can observe their trading journals. We extract users' profile and trade history for 5,182 traders. A typical profile includes basic user information such as an id number, nickname, self-reported location, and account-creation and last-login dates. Users can also follow each other but few do so.[8] This suggests that traders primarily use the journal to monitor their performance.

Importantly, a user profile also includes verified data on up to 1,000 consecutive round-trip "parent" trades made by a trader in her brokerage account. The trade history often predates the journal creation, and about 43% of trades are made after account creation. Even if a user stops logging into the journal, trades continue to be automatically loaded. We later use the post-creation trades to compare trade performance pre and post account creation in Section 4.

Each parent trade involves opening and closing a position in a stock or option. A parent trade reports detailed information such as the symbol (e.g., "TSLA" or "SPY—210707P00433000"), whether the opening trade is short or long, the broker ID (e.g., "TD"), entry and exit dates, percentage return, and dollar return (for some trades). We require all of our trades to be matched to CRSP by ticker and date except for S&P 500 option trades, which are matched separately to the index. Before matching, the data set contains about 2.2 million parent trades between 2020 and 2022.[9] We are able to match 2.1 million parent trades, or about 95% of trades, which indicates that most trades are in U.S. stocks and options. Some of the unmatched trades are in futures and mostly associated with accounts specialized in trading futures. We also exclude a small number of trades in cryptocurrencies. The lack of crypto trading is not surprising as major retail brokers

[8] 76% of accounts do not follow any account, and 87% of accounts do not have any follower.

[9] Some of the collected trades occur before the 2020-2022 sample period, but there are only few of them. We also collected the data for 2022 trades that were closed in 2023 to avoid potential biases due to missing uncompleted trades at the end of the sample.

didn't facilitate crypto trading during our sample, and retail traders have to go directly to crypto exchanges. Thus, almost all investors in our data trade only U.S. stocks and options. Furthermore, we compare the order of reported return on stock parent trades to the stock's CRSP return over the holding period. This comparison flags accounts with abnormal reported returns. For example, we exclude few accounts for which option trades are mistakenly reported as stock trades .

The data set includes the percentage return on each parent trade but does not report trade size and price. We separately collect additional information for a random sample of about 50% of all traders. This additional data set contains parent order size as well as child trades behind a parent trade. Each parent trade includes one or more child trades that open (or increase) the initial position, followed by one or more child trades that close (or decrease) the position or, occasionally, an option expiration record. Child trades report time stamps up to a second (e.g., "09:43:06 AM"), trade direction ("SHORT" or "LONG"), price, and size. They also confirm parent trade information about the symbol, contract parameters, enter and exit dates, holding period, percentage and dollar gains. We use the reported price of child trades to compute the average price of each parent trade. In total, the data set includes 1,311,816 (794,692) stock (option) parent trades, including 704,041 (343,320) trades with complete price and size information. The 1.3 million parent stock trades are worth about 11.9 billion dollars (counting buy and sell sides only once) and the 0.8 million option parent trades are worth about 8.8 billion dollars.

Overall, the data set let us provide the first direct look into how modern retail investors trade stocks and especially options.

2.2 Basic Trade Statistics

We first examine descriptive statistics at the trader level. Table 1 reports characteristics of stock and option trades in our data set by trader in Panel (A) and by trader-month in Panel (B). The results are broadly consistent across the two panels. Out of the 5,182 investors in our data set, 4,783 trade at least some stocks and 2,720 trade at least some options. About half of all investors do not trade options, but about a tenth of all investors trade options exclusively.

An average investor trades 98 unique stocks and 42.5 unique option underlyings over her tenure in our data set (Panel (A)) and 13.8 stocks and 9.2 underlyings over a typical month (Panel (B)). The pattern is similar but less dramatic for the median investor. Thus, option trading is more concentrated than stock trading, which we further explore later. Also, modern retail investors in our data set trade many symbols and frequently adjust the set of symbols they trade. This result contrasts with the conventional wisdom that retail investors only trade a handful of familiar symbols (Barber and Odean (2000)). Investors are much more exposed to new investments through social media and their broker than in the age of over-the-phone trading. Finally, an average investor makes 26.1 stock trades and 15.2 option trades per month with substantial variation across investors.

Most of our analyses are at the trade level. Table 2 reports descriptive statistics for stock trades in Panel (A) and option trades in Panel (B). Our data set contains 1,525,497 round-trip parent stock trades and 889,967 option trades. This is more than in the classic data set of Barber and Odean (2000), which contains less than one million round-trip stock trades and a negligible number of option trades, which they exclude.

Table 2 shows that trade size is substantial, even though we winsorize dollar trade size at 0.01% and 99.9% to avoid potential reporting mistakes. Stock trades have an average (median) trade size of $8,798 ($1,620). Option trades have an average (median) trade size of $2,006 ($337). These trade averages are quite close to the trader and trader-month averages reported in Table 1, though trade size varies across investors. For comparison, an average stock purchase in the Barber and Odean (2000) data set is $11,205, which is about twice as large as in our data after adjusting for inflation. In contrast, the eToro investors studied by Kogan et al. (2023) have an average trade size of $311 and account balance of $987.[10] Thus, our data set primarily contains regular active retail investors rather than investors who put a few hundred dollars in their secondary "play" account. Indeed, TD Ameritrade, the most popular brokerage in our data, has an average account size of $243,000 as of Q1 2022, which appears consistent with the average trade size that we observe.[11] The large dollar trade size suggests that the journal features investors' primary trading accounts.

The data contain trades from eight distinct brokers, in contrast to prior studies that typically rely on data from a single broker (most notably, Barber and Odean (2000)). Broker heterogeneity is important because brokers cater to different retail clienteles.

Retail investors are very heterogeneous. Therefore, no data set can be perfectly representative

[10] Barber and Odean (2000) analyze a now widely-used data set of 78,000 investors (66,465 of whom have positions in common stocks) at a large discount brokerage firm between 1991 and 1996. Kogan et al. (2023) analyze 200,000 non-US investors who trade stocks and crypto between 2015 and 2019.

[11] https://brokerchooser.com/education/news/data-dashboard/brokerage-account-sizes

of retail trading. How appropriate a given data set depends on a particular research question. For our data set, active traders are more likely to use the journal than buy-and-hold investors. Since these investors disproportionately contribute to stock and option volumes, this makes them the appropriate group to focus on when characterizing a typical retail trade. Furthermore, we confirm our main results for trader subsamples and fixed effects that hope to capture retail heterogeneity.

3 Stylized Facts about Retail Trading

This section documents stylized facts about the trading behavior of modern retail investors in stocks and options. To preview, a typical retail option trade in our data involves the purchase of a one-day call or put option linked to the S&P 500 index held for only an hour.

First, we confirm the increasing popularity of options among retail investors. Figure 1 Panel (A) shows that the proportion of option trades relative to all trades increased from 23% to 49% between 2020 and 2022. By the end of our sample period, retail investors traded options nearly as frequently as stocks. On the extensive margin, Panel (B) reveals that the proportion of accounts trading options increased from 29% to 51%. Interestingly, despite a spike in retail trading activity during the COVID-19 pandemic, the ratio of option-to-stock retail trading remained stable, as shown in Figure 1. Finally, Panel (C) documents an increase from 15% to 38% in the proportion of investors trading only options (and not stocks) from 2020 to 2022. This notable trend suggests that many retail investors have become sufficiently comfortable with option trading to deviate from "traditional" stock trading. While previous studies have documented the rise in retail option trading, our study provides important context by demonstrating that the proportion of option trading by retail investors has increased relative to stock trading, both in aggregate and within individual investors. The 'options-only' trend highlights a significant shift in retail trading behavior.

Second, while retail investors trade a wide array of stocks, their option trading is concentrated in a select few names. Figure 2 displays the top ten most actively traded stocks and options underlyings in our dataset. Option trades are notably concentrated, with the ten most traded option underlyings accounting for as much as 60% of all option trades. This concentration has intensified over time, with the share of the top ten underlyings rising from 47% to 74% from 2020 to 2022. Challenging conventional wisdom, ETF and index options, often associated with institutional trading, dominate retail option activity. SPY and SPX options alone constitute 26% of all retail option trades. The remaining top options are primarily linked to QQQ and major technology stocks, reflecting retail investors' focus on liquid, high-price underlyings. In contrast, stock trades are more dispersed, with the ten most popular stocks accounting for only 9% of all trades. Tesla and AMC top the list, accounting for 2.1% and 1.8% of all stock trades, respectively. The remainder of the top list is made up of esoteric high-risk investments including a 3x leveraged version of QQQ (TQQQ), Game Stop (GME), and a Chinese electric vehicle maker (NIO). This dichotomy in trading patterns suggests that retail investors approach options and stocks with distinctly different strategies and preferences.

The contrast in stock-option trade concentration can be attributed to variations among traders. Investors trade different stocks but the same option underlyings. Table 1 shows that a median investor trades seven distinct stocks and five distinct underlyings in a month, but over her tenure, she trades 51 stocks versus only 25 option underlyings. Thus, traders are more likely to try new stocks but are more reluctant to switch option underlyings. Furthermore, there must be significant overlap in option underlyings across accounts to generate the concentration in Figure 2.

Table 2 also shows that purchases (i.e., trades that open new long position) constitute 87% of option trades, while sales account for only 13%, resulting in a 7-to-1 buy-sell ratio. Thus, naked option selling is rare. This is not surprising, as many brokers either prohibit or require special permission for naked option selling. Consequently, option purchases predominantly open new positions, while option sales primarily close existing ones. Interestingly, while the majority of stock trades establish long positions, short sales constitute 36% of all stock trades. This suggests that retail short selling is more prevalent than previously thought.

Table 2 also documents other interesting facts. For single stock options, call trades outnumber put trades by about 2-to-1. However, the put-call ratio is almost balanced for index and ETF options. Relatedly, naked option sales are also concentrated in index and ETF options, suggesting that retail investors differentiate between equity and index options. Most trades occur in at-the-money (ATM) or slightly out-of-the-money (OTM) options.

Retail investors tend to bet on short-term price swings, with the median option maturity of their trades decreasing from four days in 2020 to just one day in 2022. 0DTE constitute 23% of all option trades, and they became increasingly popular towards the end of the sample period.

88% of stock trades are day trades (i.e., closed on the same day as opened), whereas 68.8% of option trades are day trades. For a subset of trades with detailed trade timestamps, the median holding period is 0.12 hours for stocks and 0.54 hours for options. The holding period distribution is extremely right-skewed with average holding times of 64.1 and 82.8 hours for stock and option trades, respectively. We will explore this heterogeneity in holding period to confirm our main results for subset of longer-horizon investors.

4 Why Do Investors Trade Options?

This section explores potential motivations behind options trading. Our data allow us to evaluate concerns regarding retail losses and gambling tendencies in options. We consider alternative explanations: retail investors are attracted to options due to their low price and high embedded leverage. Furthermore, we assess the prevalence of complex multi-leg option strategies.

4.1 Profitability

We start by studying the profitability of retail option trades. Based on a sample of nearly 890,000 parent option trades, Table 2 reveals that an average (median) option trade yields a return of −0.9% (1.0%). These moderately negative returns include broker commissions and liquidity costs from crossing the bid-ask spread. In fact, the returns' magnitude is comparable to typical option trading commissions. For example, TD Ameritrade charges $0.65 per option contract, paid both on entry and exit. For an average trade of 6 contracts and $2,006, this commision translates to about 0.4% of trade value. Notably, the observed losses on retail option trades are much smaller than typical option bid-ask spreads, which range from 5% to 10% or more. Perhaps, retail traders avoid paying the spread by employing limit orders. Finally, our profitability estimates indicate that concerns regarding substantial retail losses in options may be somewhat overstated. They also contrast with prior literature, which documents losses ranging from 3% to 9% per option trade, which are based on aggregate retail proxies that predominantly rely on market orders.

We examine variation in trade profitability across trade categories in Table 3. Returns are winsorized at the 0.01% and 99.99% levels to mitigate the impact of extreme option return outliers on sample averages. The results are similar for unwinsorized returns, though statistical significance is weaker. We regress option trade returns on a constant and indicators for short-sale trades, call option trades, 0DTE options, index/ETF option trades, backfilled trades, TD Ameritrade broker (the most popular in our sample), and an active investor indicator (more than 500 trades). The backfilled indicator equals one for trades completed before the account creation date.

The first column of Table 3 sets the baseline: an average option trade earns a -0.93% return with a -3.57 t-statistic. We then explore profitability variations in option trade subsamples using univariate regressions, later supplementing with multivariate analysis controlling for time trends and fixed effects. We document several dimensions in which option trade profits deviate from the average. Most notably, naked option sales (only 13% of all option trades) are profitable, earning a 20% return. In contrast, option purchases lose 3.95% on average. This finding is broadly consistent with Bryzgalova et al. (2022), who find that option sales are more profitable than option purchases. Index/ETF option trades earn a -3% return versus a 0.15% return for single-stock option. This finding goes against the hypothesis that retail investors use options to gamble and lose on individual stocks. 0DTE option trades lose 4.5% more than other option trades (t-statistic of -10), while non 0DTE trades earn 0.19%. 0DTE options have much lower prices and thus much larger relative bid-ask spreads that can lead to larger loses. We find no statistically significant differences between brokers or between calls and puts.

We further examine how the above trade categories jointly relate to profitability after controlling for date and trader fixed effects. Trader fixed effects are especially useful as they highlight within-trader variation in profitability. The last three columns of Table 3 report the results that are generally consistent with the univariate analysis and are robust across fixed effect specifications. For example, naked option sales earn a 29% (incremental) return with controls and fixed effects, which is similar to the 24% unconditional incremental return. Profitability results for 0DTE and index option trades become less dramatic after adding controls. With all controls, 0DTE trades lose -2.95% more than other trades compared to -4.7% in a univariate regression. We compare specifications with and without trader fixed effects to estimate clientele effects. We find no marked differences except that within a trader, index trades perform similarly stock option trades.

The results in Table 3 also helps us assess two potential data limitations. First, do more active traders, who are more likely to sign up for the journal, perform differently than less active traders? More active traders (with more than 500 trades) earn a 0.27% higher return per trade, but the difference with less active traders is not statistically significant (a 0.58 t-statistic). Another concern is that traders are more likely to start a trading journal after a period of above-average performance, which then reverts back to the mean after the journal creation. Fortunately, we observe the account creation date, and almost half of the trades in our sample date from the pre-journal period. In a univariate regression, backfilled option trades lose on average -0.54% versus -1.25% for non-backfilled trades, and the difference is not statistically significant at conventional levels. With controls, the difference between backfilled and non-backfilled trades drops to 0.27%. The difference increases to 0.52% with a 1.47 t-statistic once trader fixed effects are included. Finally, with both trader and date fixed effects, the difference increases to 1.21% with a t-statistic of 2.85. While the backfill bias appears relatively small in our data set, we confirm our main results in the sample of non-backfilled trades in the corresponding sections.

Overall, while option returns are expectedly volatile, their averages are relatively small in most subsamples. One exception is large gains from naked option selling. The average trade returns that we document stand in stark contrast to systematic catastrophic losses from retail option trading alluded to in the prior literature and popular press.

In Table 4, we study average returns for stock trades and how they depend on trade characteristics. As for the option return analysis, we winsorize stock returns at 0.01% and 99.99% and regress stock trade returns on a constant and the same indicator variables as for option trades (obviously without call and 0DTE indicators). The intercept-only regression reveals that an average stock trade is profitable with a 0.13% return and a 3.3 t-statistic. However, the positive profitability is entirely driven by short-sales that earn a 0.61% return per trade, while stock purchases earn a -0.14% return (t-statistic of -2.3). This result is consistent with short-sellers being informed. Interestingly, ETF trades earn a 0.23% lower return than single stock trades. The stock trade returns are slightly lower for active traders but this is not statistically significant (with t-statistics of -1.44). However, there is evidence of backfill bias for stock trades. Backfilled stock trades earn a 0.27% higher return, while non-backfilled trades earn zero return -0.02%). Finally, clients of TD Ameritrade earn a -0.01% return while clients of over brokers earn a 0.17% return. This result highlight the importance of accounting for broker heterogeneity as brokers tailor to particular clienteles. Overall, most categories of stock trades (except for short sales) earn a near-zero return.

4.2 Option Affordability

Turing to trading motives, we show that retail investors are drawn to options trading primarily due to their low price. Simply put, options let investors bet on high-priced stocks. Table 2 unveils a striking disparity: a median stock trade has a price of \$8, while the underlying price of a median option trade is much higher, reaching \$262 (S&P 500 option trades excluded). This striking price difference is not only observed across different types of trades but also within individual traders. Consequently, it appears that investors look for a more cost-effective substitute for stock purchases. The capital required for a median stock trade is substantially less than the amount needed to buy a hundred shares at \$254. Investors can buy 7-10 shares to get similar exposure but prefer buying options instead.

We further confirm the affordability hypothesis in a regression analysis that documents differences in characteristics between option and stock trades. An indicator variable is set to one for option trades and zero for stock trades. We then regress this indicator on stock characteristics measured at the end of the last month. The characteristics include log of stock price, idiosyncratic volatility and skewness (relative to the Fama-French model estimated on the past month of daily data), maximum daily return over the previous month, CAPM beta, and log of market capitalization. Month-year fixed effect control for general market trends. Trader fixed effects (in some specifications) help us study how the same investor chooses between stocks and options. The sample includes all trades except for ETF and index-linked trades because we do not observe market capitalization for them. This exclusion works against the affordability hypothesis because retail investors frequently trade ETF options, and ETFs often have high prices.

The results in Table 5 confirm that option trades have a much higher underlying stock price than stock trades. Log stock price remains highly significant even controlling for trader fixed effects with a coefficient of 0.048 and t-statistics of 23. Option trades concentrate in large cap stocks, which is expected because many small-cap stocks have few and highly illiquid options. But stock price remains significant even after controlling for market capitalization and other characteristics. Interestingly, volatility, skewness, max return, and beta are not strongly associated with the choice of trading options over stock and often in the unexpected direction, even though these characteristics are motivated by theories of investor attention and skewness preference. The last column of the table shows that, once we include stock fixed effects, stock price is the only characteristics that remains significantly associated with trading an option over the underlying stock.

Stock splits provide an opportunity to establish a more causal relation between stock prices and retail trading patterns. The affordability hypothesis suggests that the propensity to trade options relative to the underlying stock should decrease after a stock split, as the reduced stock price makes direct trading more accessible to retail investors.[12]

To test this hypothesis, we analyze trading activity in the 60 days before and after stock splits, excluding the seven days around the event to mitigate the potential impact of short-term attention-driven trading. We start with all stock splits and then restrict the sample to events with sufficient trading activity in our data. Specifically, we select stock split events that exhibit at least 100 stock and option trades in our data both before and after the split, resulting in 11 split events.[13] For each split event, we construct a two-stock control group with similar pre-split price, number of option trades, and number of stock trades. We employ a difference-in-differences panel design, where the first difference compares stocks that had a split (treatment sample) with similar stocks that did not (control sample), and the second difference compares split stocks before and after the event.

Table 6 presents regression results for the propensity to trade stocks or options on indicators for the post-split period. The first two columns examine how retail activity in stocks and options separately changes after a split. For the stock trade sample, column (1) regresses an indicator variable for treated (i.e., split) stock trades on a post-split indicator, controlling for event fixed effects. Stock trades are 11.7% more likely post split for event stocks relative to control stocks. The increased stock activity is statistically significant with a 1.99 t-statistic. This is consistent with the view that a split-induced decrease in stock price makes it more affordable and attracts more retail stock trading. Similarly, column (2) analyzes option trades, regressing an indicator for treated option trades on a post-split indicator, controlling for event fixed effects. A treated stock exhibits 6.4% fewer option trade in the post-split period compared to option trades in matched stocks, albeit the decrease is not statistically significant (a 1.69 t-statistic). Thus, retail trading activity increases in the underlying stock following a split, while option trading activity remains

[12]We thank Svetlana Bryzgalova for suggesting this test. Bryzgalova et al. (2022) examine micro-sized trading activity in option auctions surrounding the stock splits of Apple (AAPL) and Tesla (TSLA) on August 28, 2020.

[13]The tickers included are AAPL, AMZN, GME, NVDA, TSLA, GOOG, SHOP, and TQQQ. This filter excludes reverse splits, which typically occur in low-price stocks with minimal option trading activity. Our results remain robust when including the days around the split event.

relatively unchanged or decreases.

After establishing these results, we focus on joint stock and option trading. Column (3) of Table 6 examines the substitution between stock and option trading after a stock split. We regress an indicator variable for option trades (one for option trades and zero for stock trades) on indicators for post-split trades, treated trades, and their interaction; as before, we also control for event fixed effects. In the pre-split period, the propensity to trade options relative to stocks between treated and matched stocks does not change significantly. However, supporting the affordability hypothesis, the interaction term between post-split and treated indicators is negative (-9.9%) and highly statistically significant (a -4.41 t-statistic). This finding suggests that as stocks become more affordable to trade directly, some investors shift their trading activity from options to the underlying stocks.

4.3 Embedded Leverage

High embedded leverage is often considered a primary reason for trading options. A long option theoretically provides embedded leverage, potentially yielding larger profits than the same investment in the underlying stock, given a favorable price movement. Indeed, Table 8 confirms that options purchases offer more extreme percentage returns than stocks, 35% vs. 5%, respectively, at the 90th percentile, or about 7-to-1 leverage for the same dollar investment. However, we find that retail investors in our data set *do not* fully utilize this embedded leverage. An average option trade is 4.4 times smaller than an average stock trade ($2,006 vs. $8,798 as shown in Table 2), which also holds within trader. This smaller trade size offsets most of the potential leverage effect.

To assess realized leverage, we compare absolute dollar profits between option and stock trades. If leverage were a driving force behind option trading, we would expect substantially higher absolute dollar profits from option trades. Our analysis reveals that option trades do generate larger absolute dollar profits than stock trades, but the difference is economically small. Specifically, Table 7 presents a within-trader regression analysis, controlling for trader and date fixed effects. Option trades generate absolute dollar gains that are $110 to $120 higher than stock trades. While this difference is statistically significant, it represents only about 1.3% of the average stock trade size. This effect is economically modest and broadly comparable to the leverage effect investors can achieve simply by trading stocks on margin (2-to-1 leverage).

Interestingly, retail investors size their trades to reflect that option trades are riskier than stock trades and that option sales are riskier than option purchase. Specifically, option purchases are $4,783 smaller than stock purchases when controlling for trader and date fixed effects, compared to the $6,178 difference for all option trades. This suggests that retail traders adjust their position sizes based on the perceived risks.

In summary, while options inherently offer higher leverage potential, the combination of smaller trade sizes and modest differences in absolute dollar profits results in only modest realized leverage for retail option trades in our data. This finding challenges the common assumption that leverage is a primary motivation for retail option trading.

4.4 Preference for Positive Skewness

Do retail investors utilize options for to seek positive skewness, often associated with gambling? Long option positions can yield a lottery-like payoff, characterized by substantial potential profits and limited losses. If the primary motivation of investors is gambling, their trading *dollar profits* should display positive skewness. We perform two tests showing that option trades do not exhibit the positive dollar profit skewness typically associated with gambling behavior.

In our initial test, Table 8 evaluates the asymmetry in the distribution of dollar trade profits. The P&L distribution for stock trades is nearly symmetric. For instance, the 10th and 90th percentiles for stock purchases are -$109 and $91, respectively. This result also holds for more extreme percentiles and trade subsamples. Interestingly, the distribution for option trades is also nearly symmetric, or even slightly left-skewed. This pattern persists even when we restrict the sample to option purchases. For this subset, the 10th and 90th percentiles are -$296 and $217, respectively. If anything, the P&L distribution leans slightly to the left. This trend continues as we examine further into the tails of the distribution, comparing the 1st and 99th percentiles (-$3,502 and $2,523) or the 0.5th and 99.5th percentiles (-$6,915 and $5,051). The results are robust for the sample of non-backfilled trades reported in the last panel of the table: the 10th and 90th percentiles are -$309 and $227.

While investors are primarily concerned with *dollar* profits, we also investigate the skewness in option *relative* profits or returns. Table 8 shows that the 10th and 90th return percentiles for option purchases are -71% and 35%, respectively. Thus, at moderate percentiles, the option return distribution exhibits slight left-skewness, which does not support gambling preferences. However, option returns cannot fall below -100% for option purchases, which becomes binding for more extreme percentiles, resulting in positive skewness. For instance, the 1st and 99th return percentiles for option purchases are -100% and 187%, respectively. The discrepancy between dollar and percentage results suggests that the distribution of trade size likely counterbalances the positive skewness in percentage returns. Larger trades tend to be associated with less skewed percentage returns. For example, large option trades held for a few hours would not result in significant positive skewness.

In the second test, we compute realized skewness per trader separately for option and stock purchases as the adjusted Fisher–Pearson standardized moment coefficient. That is, for each investor, we compute the realized skewness for option trade return and the realized skewness for stock trade returns. Thus, we get two skewness values per investor if the investor trades both stocks and options or one value if the investor only trades stocks or options. We then use a regression analysis to test for differences in the skewness of stock and option trades.

In Table 9, we regress return skewness on an option trade indicator and fixed effects. The left part of the panel shows that the percentage return skewness is higher for option trades than for stock trades, which is highly statistically significant. This result holds when we control for investor fixed effects. The right part of the panel, however, shows that the *dollar* return skewness of option and stock trades is not statistically different, and the difference is economically small. Again, this result holds when we control for investor fixed effects.

4.5 Trader and 0DTE Subsamples

To address potential sample bias and enhance the generalizability of our findings, we conduct a comprehensive subgroup analysis. We evaluate how our main results vary across eight distinct trader subsamples, categorized by trading style, size, activity level, and instrument preference. We distinguish between day-traders and longer-horizon traders based on whether their median trade duration exceeds one day. To capture differences in trading capacity, we separate large and small traders using a median trade size threshold of $200 and $5,000, respectively. We also differentiate between active and inactive traders, using median monthly trade counts of less than 10 and more than 30. Finally, we contrast traders who specialize exclusively in options with those who trade both stocks and options. We pick the thresholds so that each subsample is sufficiently populated.

Within each trader sample, we compute the key statistics characterizing our main results. The statistics include average price for stock trades, average underlying price for option trades (excluding index option trades), average fraction of trades in top 10 most popular stocks and options (among the traders' sample under consideration), median dollar return skewness for stock and option trades, and median of traders' average stock and option returns. For example, we compute average return for each trader and then take a median across all traders in a subsample.

Table 10 shows that our main results are broadly robust across these trader subsamples. First, retail traders use options as an affordable way to trade high-priced stocks. Within all the trader samples, average price for stock trades is much smaller than the underlying price for option trades. The smallest price gap is for multi-day traders with a \$97.3 average stock price and a \$307.2 average underlying price. Second, for all the trader samples, the option trading is concentrated in few underlying symbols, while stock trading is dispersed across many symbols. Top ten symbols typically account for 50-70% of all option trades. Multi-day traders are the exception with 33% of option trades in the top ten symbols, which is still much more concentrated than their stock trades (11%). Next, in all traders' samples, traders do not exhibit preference for positive skewness. The dollar P&L is slightly negatively skewed with similar magnitude for stock and option trades. For example, dollar return skewness for multi-day traders is -0.25 for stock trades and -0.14 for option trades. Finally, in terms of average trade return, small traders, who are presumably less sophisticated, lose the most per option trade (-3.4%). In contrast, multi-day traders lose only 0.9% per option trade and break even on their stock trades.

There are growing concerns that the surge in 0DTE trading could potentially trigger market instability and even a stock market crash. We do not directly address these policy concerns but instead explore our main results for 0DTE trades, 23% of all option trades in our dataset. As suggested by option pricing theory, short-term options exhibit higher embedded leverage and have lower prices. Consequently, as Table IA.3 shows, the average trade size for 0DTE trades is much smaller, at \$1,068, compared to \$2,268 for the other trades. A vast majority of 0DTE trades (93.3%) start with an option purchase, while naked option sales are rare. As for the profitability, 0DTE trades, on average, lose 4.6% per trade, whereas the other trades earn zero return. This result indicates that losses in retail options are predominantly concentrated in 0DTE options. Lastly, the underlying price for 0DTE trades is higher (\$563 vs. \$360, excluding S&P), consistent with retail investors preferring shorter-term options with lower prices to affordably trade in high-priced stocks.

Trader heterogeneity, a key aspect highlighted in studies on specific retail investor groups like Robinhood users (Welch (2022); Fedyk (2022)), is crucial. Importantly, despite magnitude variations, our main results remain robust across investor groups.

4.6 Complex Option Strategies

Finally, we provide the first look into how often retail investors employ "complex" option strategies. These strategies are important because about one third of all option trades (in OPRA) are qualified as "complex" based on OPRA trade flags during our sample period (Li et al. (2023)). Undergraduate textbooks and practitioners emphasize that options can be used as lego block to construct customized payoff profiles. But do retail investors use complex strategies?

Specifically, we consider five types of popular complex strategies: call spread, put spread, volatility spread, covered call, and protective put. These strategies are covered extensively in textbooks and retail broker tutorials. If an investor buys a call and a put on the same stock on the same day, we label this trade as a volatility spread. Similarly, if an investor buy a call and sell a call with different strike prices on the same day, we label this trade as a call spread. Put spread is defined similarly. For covered call and protective put, the account must trade the stock and the option on this stock on the same day.

We likely overestimate the fraction of option-only strategies if, for instance, an investor buys a call in the morning, sells it by mid-day, and then buys a put in the afternoon. We currently classify complex trades using only trade date, which is available for all parent trades, but not trade intraday timestamps, which are available only for about half of traders. Finally, we could underestimate the fraction of covered call if the investors already owns the stock, but this assumption does not seem to be too restrictive given that most trades have a short horizon.

We find that retail investors are less likely to use complex strategies than the other investors. Table 11 reports descriptive statistics on complex strategies across accounts. The table reveals that multi-leg strategies are uncommon. Up to 16% of all option trades potentially qualify as complex trades, which is less frequent than one-in-three share of complex trades among all OPRA trades. Volatility spreads represent about 9.1% of all trades, while call and put spreads each represent about 3.3%. Covered calls and protective puts are even more rare. Even at 90th percentile across all accounts that trade options, covered calls and protective puts jointly account for about 0.3% of all option trades.

Overall, while educational resources advertise complex strategies as an essential part of option trading toolbox, retail investors prefer simple strategies that involve trading one option at a time.

5 Validation and Comparison with Aggregate Retail Measures

Due to the reluctance of brokers to disclose client trading data, previous studies on retail option trading have relied on aggregate proxies to identify certain option trades as likely being retail. For instance, Bryzgalova et al. (2022) utilize the "single-leg auction" flag for option trades in Options Price Reporting Authority (OPRA, the analog of TAQ for options), which accounts for about one third of all OPRA trades. Notably, these trades are exclusively market orders that cross the spread and incur large trading costs. Alternatively, de Silva et al. (2023) employ the "customer" category of daily signed volume in the open-close data, which is self-reported by investors and could represent a range of investors from retail investors to professional hedge funds. About three quarters of all option trades are classified as customer trades. However, the exact percentage of the single-leg auction or customer trades that are genuinely retail remains an open question.

Our trader-level data present several benefits over the aggregate measures. We can *directly* observe retail trading, eliminating concerns about potential contamination by institutional trading. We observe the entire life-cycle of the trade from the position opening to its closing. Furthermore, our data include all orders, not just market orders as in the case of single-leg auctions, which affects profitability estimates. Most crucially, we can examine the heterogeneity across investors and their interactions with stocks and options, an analysis that is not feasible with aggregate measures. The limitation of our data is that active retail traders are more likely to use a trading journal. Thus, our findings should be extrapolated to the full universe of retail traders, which likely shows substantial heterogeneity, with caution.

We conduct several tests to validate the retail nature of our data. First, the stock trade imbalance in our data set is positively correlated with popular measures of retail stock trading. We compute the stock trade imbalance as the difference between the number of buy and sell parent trades, aggregated over a week or a month. Since retail trades in our data are sparse relative to the full stock-day cross-section, we require at least one trade to compute the imbalance measure. We also compute the imbalance at the weekly and monthly levels to alleviate sparsity concerns. We benchmark our imbalance measure against two popular measures of retail stock trading: the change in the number of Robinhood users holding a stock using the RobinTrack data (Barber et al. (2022); Eaton et al. (2022); Welch (2022)), and the retail trade imbalance in TAQ using the BJZZ algorithm (Boehmer et al. (2021)).[14] Availability of RobinTrack data limits the sample period for this test to January 2020 to August 2020. We contrast the retail imbalances with regular trade imbalance computed using the Lee and Ready (1991) algorithm, which reflects all investor types.

Table 12 reports regressions of the stock trade imbalance in our data set on the Robinhood popularity change, the BJZZ retail imbalance, and the Lee-Ready overall imbalance. We standardize each variable within stock to make them comparable and include date fixed effects. In individual regressions in the first three columns, each of these imbalance measures are positively and significantly correlated with the imbalance from our data. For example, a one standard deviation (within stock) increase in the Robinhood popularity corresponds to a 0.26 standard deviation increase in our weekly trade imbalance. Interestingly, once all three proxies are included in the joint regression, the Lee-Ready imbalance becomes statistically insignificant while the BJZZ imbalance and Robinhood popularity remain strongly significant. This result shows that stock trade imbalance measured from our data set captures trading by retail investors rather than general investors. Reassuringly, weekly and monthly imbalances produce similar results. The results are also similar when the stock order imbalance includes the exit leg of each parent trade.

The second validation test establishes a positive correlation between option trade volume in our data and the proxy for retail option volume proposed by Bryzgalova et al. (2022). They classify option trades flagged as single-leg auction trades in OPRA as retail and share an aggregated retail option volume series by stock-day on their website. In order to isolate retail volume and mitigate the influence of non-retail activity, we control for total option volume obtained from OPRA.

Table 13 reports panel regressions of retail option trade count at the weekly or monthly frequencies on single-leg auction volume controlling for total option volume. Date fixed effects accommodate market-wide volume dynamics. As before, we standardize all variables within stock.

[14] Barber et al. (2022) and Battalio, Jennings, Saglam, and Wu (2023) evaluate the BJZZ measure and suggest improvements to the measure.

Single-leg volume is positively associated with both call and put option trade volumes in our data, with all coefficients being statistically significant at least at the 10% level. For example, a one standard deviation (within stock) increase in weekly single-leg call volume is associated with a 0.17 standard deviation increase in retail call trade count in our data. The results hold at the monthly frequency for call volume but not for put volume. These results also validate 'single-leg' option volume as a measure of retail option trading.

Finally, retail traders are attracted to zero commissions. Therefore, as a broker switches to zero commissions, retail participation is expected to increase. We confirm this hypothesis in a difference-in-difference test. TD Ameritrade (TD) switched to zero commissions on October 3, 2019, while another popular broker in our data, TradeZero (TZ), already had zero commissions.[15] To better identify the effect of the zero-commission shock, we select a short window around the TD switch from September 1 to October 31, which includes 5,770 and 2,846 trades executed on TZ and TD, respectively. Note that this period is not part of the main sample because our data contain relatively few trades before 2020.

Table IA.1 in the Internet Appendix shows the results of a simple difference-in-difference regression in which daily trade volume executed at TD and TZ is regressed on indicator variables for the after period, TD, and their interaction. Daily trade volume is standardized to have a mean of one for both brokers prior to October 3, when TD switched to zero commissions. The table shows that average daily trade volume increases by 52.8% for TD after it switched to zero commissions relative to TZ trade volume, and this increase is statistically significant (a) 2.74 t-statistic). This result further validates the retail nature of our data.

6 Conclusion

In this paper, we examine the way active retail investors trade options using novel detailed data on their option and stock trades. We find that a typical option trade involves a retail investor buying a one-day S&P 500 call and closing the position within an hour. Apart from documenting an anatomy of modern retail option trading, our paper conveys three main messages. Firstly, options have rapidly grown in popularity and rival stocks as the primary instrument for short-

[15] https://www.businesswire.com/news/home/20191001006211/en/The-Best-Just-Got-Better-TD-Ameritrade-Introduces-0-Commissions-for-Online-Stock-ETF-and-Option-Trades

term speculation, with many investors switching to trading only options. Secondly, options play a unique role in retail trading and are not simply substitutes for stocks. For example, stock trades are concentrated in meme stocks, while option trades are concentrated in options linked to the S&P 500 index. Next, our findings alleviate the concerns that retail traders predominantly gamble with options and incur substantial losses as a result. We find that losses on option trades are relatively small, and the absence of positive realized leverage and skewness in trading profits suggests that gambling is not the main motive for option trading. Finally, investors are drawn to options as they offer an affordable means to trade high-priced stocks.

Overall, our results provide the first portrait of a new generation of retail investors who actively engage in trade options. We leave it for future research to explore how short-term speculative trading in options can be understood through the lenses of behavioral finance theories.

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Figure 1. Trends in retail option trading. This figure shows the fraction of option parent trades over all parent trades (stocks and options) in a given month (green), the fraction of accounts who trade options in a given month among all active accounts (blue), and the fraction of accounts who trade only options (and do not trade stocks) in a given month among all active accounts (orange).

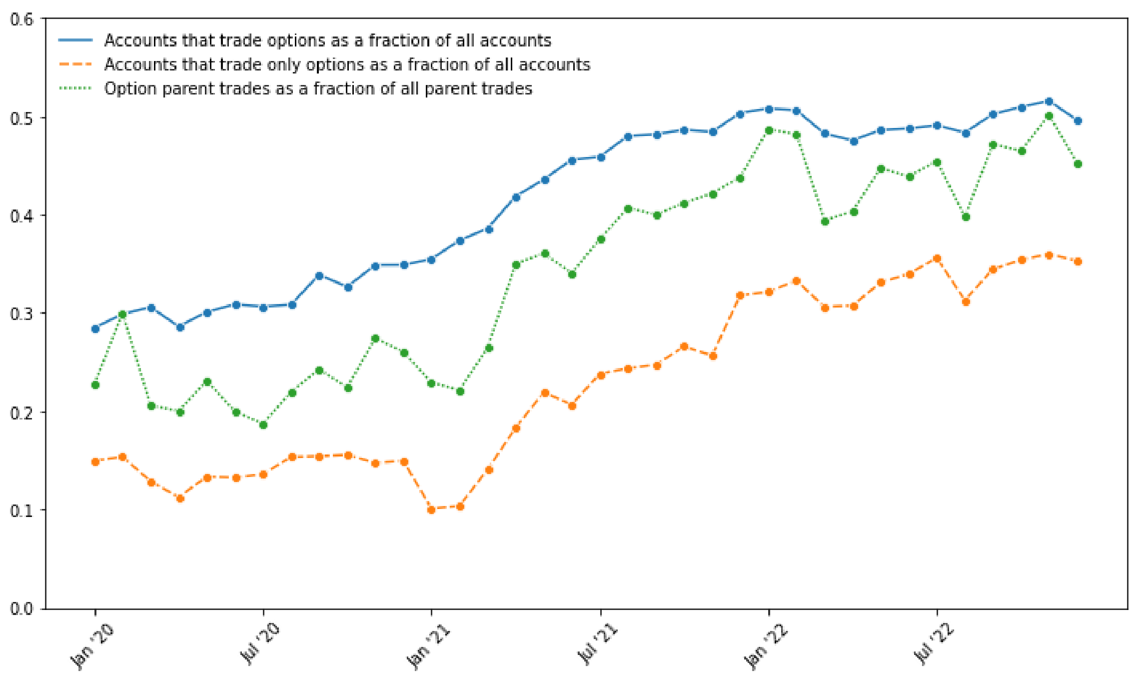

Figure 2. Top ten most active stocks and option underlyings as a fraction of all option trades (top plot) or stock trades (bottom plot). We report the share of non-top tickers at the bottom to highlight the difference in trade concentration between stocks and options.

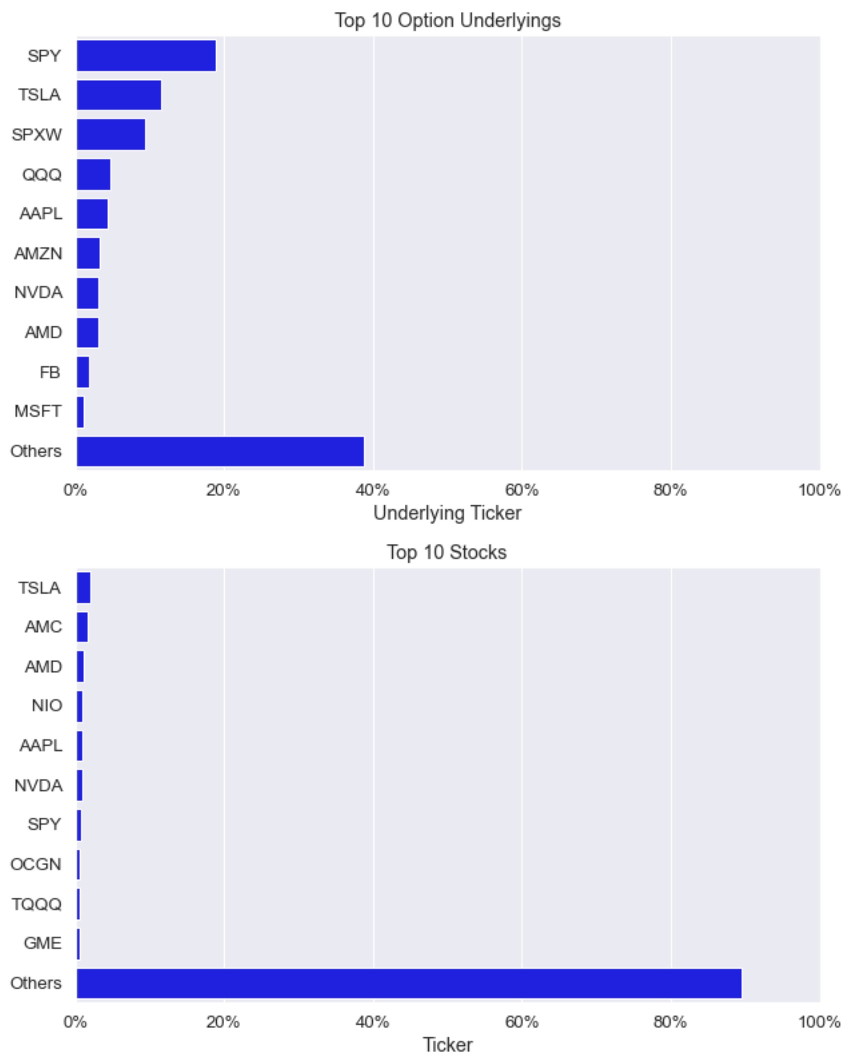

Table 1. Trader descriptive statistics. This table reports descriptive statistics for traders in our sample, which spans 1/2020 to 12/2022. For example, the number of stock round-trip trades is computed for each account (account-month), and descriptive statistics across accounts are reported in the first row of Panel (a) (Panel (b)). To be included in the sample, an account must have at least five trades. Average dollar trade size is computed from a random sample of about half of all accounts.

(a) Trader

	Mean	StDev	0.1	0.25	0.5	0.75	0.9	N
# Round-trip trades	466.1	488.0	26.0	87.0	296.0	757.8	998.0	5,182
# Stock round-trip trades	294.4	442.7	1.0	14.0	85.0	404.8	939.0	5,182
# Option round-trip trades	171.7	313.5	0.0	0.0	3.0	203.0	635.9	5,182
% Option trades	35.9	43.1	0.0	0.0	1.7	90.1	99.5	5,182
Unique stocks	98.4	118.8	5.0	15.0	52.0	143.0	270.0	4,783
Unique option underlyings	42.5	48.8	3.0	8.0	25.0	58.0	107.0	2,720
Average $ trade size (stock)	8,738	51,662	176	506	1,662	5,556	15,212	2,410
Average $ trade size (option)	1,857	9,128	109	219	463	1,138	2,568	1,213

(b) Trader-month

	Mean	StDev	0.1	0.25	0.5	0.75	0.9	N
# Round-trip trades	41.4	62.2	2.0	6.0	19.0	51.0	103.0	58,389
# Stock round-trip trades	26.1	56.2	0.0	0.0	5.0	25.0	74.0	58,389
# Option round-trip trades	15.2	35.3	0.0	0.0	0.0	14.0	49.0	58,389
% Option trades	37.4	45.8	0.0	0.0	0.0	100.0	100.0	58,389
Unique stocks	13.8	17.8	1.0	3.0	8.0	19.0	34.0	43,721
Unique option underlyings	9.2	11.1	1.0	2.0	5.0	12.0	22.0	25,889
Average $ trade size (stock)	7,778	58,003	147	445	1,470	4,767	13,447	20,862
Average $ trade size (option)	1,928	12,553	71	167	369	956	2,408	10,466

Table 2. Trade descriptive statistics. This table reports descriptive statistics for the trades in our sample, which spans 1/2020 to 12/2022. Long (Short) is an indicator variable for long (short) trades. Index denotes trades in which the underlying is the S&P 500 or an ETF. Day trade takes the value one if a trade is closed on the same day as it is opened, and zero otherwise. 0DTE takes the value one if an option trade is on the same day as the option's expiration. Option moneyness is computed using the closing stock price on the day of the trade. Moneyness is winsorized at the levels of 5% and 95%. The main sample includes 1,525,497 stock trades and 889,967 option trades. For a random subsample of about half of all accounts, we observe parent trade size, price, and holding period (655,229 stock trades and 299,017 option trades).

(a) Stock parent trade

	Mean	StDev	0.1	0.25	0.5	0.75	0.9	N
Long	0.63	0.48	0.00	0.00	1.00	1.00	1.00	1,525,497
Short	0.37	0.48	0.00	0.00	0.00	1.00	1.00	1,525,497
Index/Regular ETF	0.02	0.13	0.00	0.00	0.00	0.00	0.00	1,525,497
Day trade	0.88	0.32	0.00	1.00	1.00	1.00	1.00	1,525,497
Return	0.001	0.110	-0.053	-0.018	0.000	0.017	0.056	1,525,497
Stock price ($)	53.47	182.91	1.95	3.53	8.35	26.89	121.82	1,525,497
Trade size (shares)	747	4,324	10	50	150	500	1,376	655,229
Trade size ($)	8,798	87,076	177	486	1,620	5,244	16,920	655,229
Holding period (hours)	59.87	501.34	0.00	0.02	0.12	1.00	24.00	655,229

(b) Option parent trade

	Mean	StDev	0.1	0.25	0.5	0.75	0.9	N
Long	0.87	0.33	0.00	1.00	1.00	1.00	1.00	889,967
Short	0.13	0.33	0.00	0.00	0.00	0.00	1.00	889,967
Call (stock)	0.43	0.50	0.00	0.00	0.00	1.00	1.00	889,967
Put (stock)	0.22	0.42	0.00	0.00	0.00	0.00	1.00	889,967
Call (index)	0.16	0.37	0.00	0.00	0.00	0.00	1.00	889,967
Put (index)	0.18	0.39	0.00	0.00	0.00	0.00	1.00	889,967
Day trade	0.69	0.46	0.00	0.00	1.00	1.00	1.00	889,967
0DTE	0.24	0.42	0.00	0.00	0.00	0.00	1.00	889,967
Return	-0.009	0.947	-0.727	-0.213	0.010	0.165	0.611	889,967
Stock price, excl. SPX ($)	389.99	583.72	25.45	87.84	262.47	416.58	778.80	802,651
Call moneyness (stock)	0.96	0.06	0.85	0.93	0.97	1.00	1.02	386,290
Put moneyness (stock)	0.96	0.06	0.86	0.93	0.98	1.00	1.02	197,692
Call moneyness (index)	0.99	0.02	0.97	0.99	0.99	1.00	1.01	141,994
Put moneyness (index)	0.99	0.03	0.96	0.98	0.99	1.00	1.01	163,991
Trade size (contracts)	6	68	1	1	1	3	10	299,017
Trade size ($)	2,006	17,338	50	130	337	960	2,700	299,017
Holding period (hours)	85.12	362.21	0.02	0.07	0.48	24.00	168.00	299,017

Table 3. Return on option trades. This table regresses the return on option trades on a constant and indicator variables. We include indicators for short sales (naked option writing), call option, 0DTE, index or ETF, active trader (with 500 trades or more), backfilled trade, and TD Ameritrade broker (most popular broker in our sample). The backfilled trade indicator takes the value one for any trade that is completed before the account creation date. Standard errors are double-clustered by date and trader. Returns are winsorized at the levels of 0.01% and 99.99%. The sample period spans 1/2020 to 12/2022.

	Return (option trade)										
Constant	-0.0093***	-0.0395***	-0.0062	0.0019	0.0015	-0.0113***	-0.0131***	-0.0074**	-0.0310***	-0.0411***	-0.0440***
	(-3.57)	(-14.24)	(-1.56)	(0.65)	(0.45)	(-2.78)	(-4.15)	(-2.47)	(-6.04)	(-8.08)	(-8.82)
Short		0.2383***							0.2343***	0.2817***	0.2821***
		(15.66)							(15.25)	(14.43)	(14.43)
Call			-0.0051						-0.0005	-0.0009	-0.0004
			(-0.93)						(-0.08)	(-0.16)	(-0.07)
0DTE				-0.0471***					-0.0227***	-0.0266***	-0.0295***
				(-10.09)					(-4.65)	(-7.45)	(-8.08)
Index					-0.0312***				-0.0119***	0.0014	-0.0014
					(-7.56)				(-3.10)	(0.44)	(-0.46)
>500 trades						0.0027					
						(0.58)					
Backfill							0.0072*		0.0032	0.0046	0.0125***
							(1.84)		(0.88)	(1.34)	(3.32)
TD								-0.0046			
								(-0.98)			
Trader FE	No	No	No	No	No	No	No	No	No	Yes	Yes
Date FE	No	No	No	No	No	No	No	No	No	No	Yes
Adj. R^2	0.0000	0.0101	0.0000	0.0006	0.0004	0.0000	0.0000	0.0000	0.0104	0.0080	0.0081
Obs.	889,967	889,967	889,967	889,967	889,967	889,967	889,967	889,967	889,967	889,967	889,967

Table 4. Return on stock trades. This table regresses the return on stock trades on a constant and indicator variables. We include indicators for short sales, index ETF trade, active trader (with 500 trades or more), backfilled trade, and TD broker. The backfilled trade indicator takes the value one for any trade that is completed before the account creation date. Standard errors are double-clustered by date and trader. Returns are winsorized at the levels of 0.01% and 99.99%. The sample period spans 1/2020 to 12/2022.

	Return (stock trade)								
Constant	0.0011***	-0.0017***	0.0012***	0.0019**	-0.0002	0.0016***	-0.0036***	-0.0039***	-0.0025***
	(3.14)	(-3.22)	(3.20)	(2.32)	(-0.54)	(4.26)	(-5.85)	(-9.28)	(-6.95)
Short		0.0077***					0.0081***	0.0061***	0.0064***
		(10.03)					(10.48)	(11.55)	(12.16)
Index			-0.0023***				-0.0017***	0.0005	0.0002
			(-3.92)				(-2.95)	(0.71)	(0.25)
>500 trades				-0.0010					
				(-1.32)					
Backfill					0.0027***		0.0035***	0.0055***	0.0025***
					(5.21)		(6.84)	(9.93)	(3.85)
TD						-0.0023***			
						(-4.24)			
Trader FE	No	No	No	No	No	No	No	Yes	Yes
Date FE	No	No	No	No	No	No	No	No	Yes
Adj. R^2	0.0000	0.0015	0.0000	0.0000	0.0002	0.0001	0.0018	0.0008	0.0006
Obs.	1,525,497	1,525,497	1,525,497	1,525,497	1,525,497	1,525,497	1,525,497	1,525,497	1,525,497

Table 5. Difference in stock characteristics between option and stock trades. An indicator for option trade (one if an option trade, zero if a stock trade) is regressed on stock characteristics measured at the end of the previous month. Index/ETF trades are excluded. IdioVol (IdoSkew) is idiosyncratic volatility (skewness) of residuals relative to the Fama-French 3-factor model using the past-month of daily return data. MaxRet is the maximum of daily return over the previous month. Standard errors are clustered by day. t-statistics are reported in parentheses under regression coefficients.

	I(1 if option trade, 0 if stock trade)				
LogPrice	0.129***	0.048***	0.044***	0.019***	0.037***
	(37.77)	(23.65)	(15.81)	(13.74)	(9.52)
IdioVol			-0.372**	-0.209***	-0.047
			(-2.10)	(-3.68)	(-0.37)
IdioSkew			-0.006**	-0.002**	-0.003
			(-2.01)	(-2.29)	(-0.93)
MaxRet			0.047	0.031**	-0.007
			(1.16)	(2.21)	(-0.24)
Beta			-0.010***	-0.002**	-0.003
			(-4.06)	(-2.02)	(-0.59)
LogMktCap			0.051***	0.020***	0.002
			(20.25)	(20.48)	(0.34)
Month-Year FE	Yes	Yes	Yes	Yes	Yes
Trader FE	No	Yes	No	Yes	No
Stock FE	No	No	No	No	Yes
Adj. R^2	0.3800	0.0973	0.4128	0.1169	0.0035
Obs.	1,700,159	1,700,159	1,700,159	1,700,159	1,700,159

Table 6. Effect of stock splits on stock and option trading. This table consider stock splits over the sample period. For each split, we collect stock and option trades in the window that spans 60 days before and after the split, excluding the seven days immediately before and after the split. We restrict the sample to tickers that have at least 100 stock and option trades both before and after the split: AAPL, AMZN, GME, NVDA, TSLA, GOOG, SHOP, TQQQ. For each split ticker, we also construct a sample of two matched tickers by pre split price, number of option trades, and number of stock trades. In column (1), the sample includes only stock trades, and an indicator variable that takes the value one for treated (i.e., split) stock trades is regressed on split fixed effects and an indicator for post split trades. In column (2), the sample includes only option trades, and an indicator variable that takes the value one for treated option trades is regressed on split fixed effects and an indicator for post split trades. In column (3), the sample includes stock and option trades, and an indicator variable that takes the value one for option trades is regressed on split fixed effects and indicators for post split trades, treated trades, and the interaction of the two. Standard errors are clustered by split. t-statistics are reported in parentheses under regression coefficients.

	(1) Treated stock trade	(2) Treated option trade	(3) Option trade
Post split	0.117**	-0.064*	0.03
	(1.99)	(-1.69)	(1.22)
Treated			-0.043
			(-0.63)
Post split × Treated			-0.099***
			(-4.41)
Split FE	Yes	Yes	Yes
Matched stocks	Yes	Yes	Yes
Sample	Stock trades	Option trades	All trades
Adj. R^2	0.0164	0.0064	0.0153
Obs.	37,648	132,573	170,221

Table 7. Analysis of dollar profits. Panels (a)-(b) regresses the absolute profit and trade size on an indicator for option trades and fixed effects. Dollar gain and dollar trade size are winsorized at the levels of 0.5% and 99.5%. Standard errors are double-clustered by date and trader.

Panel (a): Regression

	|Net dollar gain|	|Net dollar gain|	$ trade size	$ trade size
Option	137.053***	119.631***	-5756.477***	-6177.536***
	(6.91)	(6.92)	(-12.03)	(-8.41)
Date FE	Yes	Yes	Yes	Yes
Trader FE	No	Yes	No	Yes
Adj. R^2	0.0104	0.0026	0.0301	0.0144
Obs.	954,246	954,246	954,246	954,246

Panel (b): Regression - buy trades only

	|Net dollar gain|	|Net dollar gain|	$ trade size	$ trade size
Option	134.945***	110.236***	-4615.429***	-4783.141***
	(8.54)	(7.79)	(-11.35)	(-9.66)
Date FE	Yes	Yes	Yes	Yes
Trader FE	No	Yes	No	Yes
Adj. R^2	0.0151	0.0037	0.0321	0.0166
Obs.	659153	659153	659153	659153

Table 8. Distribution of percentage return and dollar return. We consider four samples: all trades, purchases only, purchases excluding complex trades, and purchases excluding backfilled trades (e.g., covered calls). We report returns separately for stock and option trades. A trade is defined as backfilled if it is completed before the account creation date. To highlight returns in the tails of the distribution, we cover percentiles ranging from 0.5% to 99.5%.

	Distribution of net gain (percentile)									
	0.005	0.01	0.1	0.25	0.5	0.75	0.9	0.99	0.995	N
All trades										
% return (stock)	-0.38	-0.26	-0.05	-0.02	0.00	0.02	0.06	0.25	0.36	788,256
$ return (stock)	-3487	-1827	-123	-23	0	28	139	1807	3500	788,256
% return (option)	-2.10	-1.24	-0.72	-0.21	0.01	0.17	0.62	1.73	2.59	357,857
$ return (option)	-8531	-4200	-309	-61	1	60	287	3611	7403	357,857
Buy trades only										
% return (stock)	-0.43	-0.30	-0.06	-0.02	0.00	0.01	0.05	0.29	0.46	477,824
$ return (stock)	-3028	-1582	-109	-21	-0	17	91	1179	2350	477,824
% return (option)	-1.00	-1.00	-0.71	-0.22	0.00	0.11	0.35	1.87	2.85	309,471
$ return (option)	-6915	-3502	-296	-66	0	48	217	2523	5051	309,471
Buy trades only, excluding complex trades										
% return (stock)	-0.43	-0.30	-0.06	-0.02	-0.00	0.01	0.05	0.29	0.46	475,116
$ return (stock)	-2939	-1534	-108	-21	-0	17	90	1156	2292	475,116
% return (option)	-1.00	-1.00	-0.74	-0.25	0.01	0.14	0.39	1.91	2.81	205,477
$ return (option)	-5868	-3100	-282	-65	1	54	227	2357	4590	205,477
Buy trades only, excluding backfilled trades										
% return (stock)	-0.46	-0.31	-0.06	-0.02	-0.00	0.01	0.05	0.28	0.43	306,482
$ return (stock)	-3549	-1780	-113	-22	-0	17	90	1300	2671	306,482
% return (option)	-1.00	-1.00	-0.69	-0.22	0.00	0.11	0.34	1.84	2.78	202,783
$ return (option)	-7547	-3700	-309	-67	0	48	227	2661	5373	202,783

Table 9. Skewness of percentage return and dollar return (long trades). For each investor, we compute the realized skewness for option long trade return, excluding complex option trades, and the realized skewness for stock long trade returns. We then regress return skewness on an option trade indicator. Skewness is the adjusted Fisher–Pearson standardized moment coefficient. The sample spans January 2020 to December 2020.

	% return skewness		$ return skewness	
Constant	0.371***		-0.887***	
	(6.68)		(-10.44)	
Option	0.861***	0.967***	0.156	0.270**
	(9.11)	(10.87)	(1.19)	(2.17)
Trader FE	No	Yes	No	Yes
Adj. R^2	0.0209	0.0590	0.0001	0.0025
Obs.	3745	3745	3745	3745

Table 10. Results across traders' subsamples. This table examines multiple traders' subsamples: traders with a median trade duration lower or equal than one day ($\leq$ 1 day), traders with a median trade duration greater than one day ($>$ 1 day), traders with a median trade size less than \$200, traders with a median trade size greater than \$5,000, traders with a median number of trades per month lower than 10, traders with a median number of trades per month greater than 30, traders who trade both stocks and options (stock-option), and traders who only trade options (option-only). Within each trader sample, the table reports average price for stock trades, average underlying price for option trades, average fraction of trades in top 10 most traded stocks and options, median dollar return skewness for stock and option trades, and median of traders' average stock and option returns. For example, among traders with a trade horizon lower than one day, the median across traders' average return on option trades is -2.5%. The statistics for price, top 10 fraction, and average returns are computed for all traders in our data set, whereas the statistics for dollar skew require trade size and price that we observe for a subsample of all traders. Returns are winsorized at the levels of 0.01% and 99.99%.

	Trader subsample							
	Horizon		Trade size		Trades/month		Stock-option	Option-only
	$\leq$ 1 day	$>$ 1 day	$<$ \$200	$>$ \$5,000	$<$ 10	$>$ 30		
Price (stock)	\$49.32	\$97.28	\$25.82	\$85.46	\$58.83	\$52.44	\$76.22	-
Price (underlying)	\$419.02	\$307.23	\$268.67	\$497.78	\$325.51	\$427.22	\$380.67	\$458.03
Fraction top 10 (stock)	0.12	0.11	0.08	0.17	0.11	0.13	0.16	-
Fraction top 10 (option)	0.64	0.33	0.47	0.49	0.45	0.61	0.52	0.69
Skew (\$ stock return)	-1.38	-0.25	-0.54	-1.12	-0.45	-1.58	-0.93	-
Skew (\$ option return)	-1.19	-0.14	-0.40	-1.01	-0.44	-1.00	-0.57	-0.93
Average return (stock)	-0.001	0.000	-0.003	0.001	-0.001	-0.001	-0.001	-
Average return (option)	-0.024	-0.009	-0.034	-0.014	-0.026	-0.017	-0.021	-0.026
Unique traders (full sample)	3,878	1,304	507	332	1,494	1,982	2,321	399

Table 11. Prevalence of complex option strategies in the dataset. This table reports reports descriptive statistics on the fraction of complex option trades among all option trades for a given account. For example, among accounts that trade options, the median account has an estimated 10.2% of option trades that are part of a complex trade. We consider the following complex trades: call/put spread (long call/put and short call/put on the same underlying with the same expiration date on the same day), volatility spread (long/short call and long/short put on the same underlying with the same expiration date on the same day), covered call (long stock and short call on the same day), protective put (buy stock and buy put on the same day). Accounts that trade only stocks are excluded. N is the number of accounts.

	Complex trades as a fraction of option trades								
		Descriptive statistics across accounts							
	Mean	Mean	StDev	0.1	0.25	0.5	0.75	0.9	N
Fraction complex	0.160	0.134	0.127	0.000	0.034	0.102	0.196	0.315	2,720
Covered call	0.002	0.003	0.019	0.000	0.000	0.000	0.000	0.002	2,720
Protective put	0.001	0.005	0.049	0.000	0.000	0.000	0.000	0.003	2,720
Call spread	0.033	0.028	0.064	0.000	0.000	0.000	0.011	0.118	2,720
Put spread	0.033	0.027	0.065	0.000	0.000	0.000	0.006	0.109	2,720
Volatility spread	0.091	0.070	0.079	0.000	0.000	0.043	0.114	0.187	2,720

Table 12. Comparison with existing stock retail trading measures. Stock trade imbalance is equal to the number of buy parent orders minus the number of sell parent orders, aggregated over a week (left panel) or a month (right panel). Δ Robinhood users is the change in the number of RobinHood users holding a specific stock over a week or a month, which is computed using the RobinTrack data. TAQ retail trade imbalance is computed using the BJZZ algorithm. TAQ trade imbalance is computed using the Lee-Ready algorithm. All the variables are standardized within stock. The regression includes date fixed effects. The sample period is from 1/2020 to 8/2020. Standard errors are clustered by date. t-statistic are reported in parentheses, where *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Trade imbalance (weekly)				Trade imbalance (monthly)			
Δ Robinhood users	0.259***			0.188***	0.258***			0.179***
	(14.59)			(10.06)	(14.81)			(8.82)
TAQ retail trade imbalance		0.227***		0.104***		0.238***		0.139***
		(16.53)		(8.25)		(23.01)		(8.79)
TAQ trade imbalance			0.122***	0.014			0.122***	0.024
			(7.53)	(1.08)			(4.93)	(1.24)
Adj. R^2	0.0643	0.0499	0.0147	0.0712	0.0636	0.0546	0.0146	0.0787
Obs.	14,401	14,401	14,401	14,401	6,601	6,601	6,601	6,601

Table 13. Comparison with option trading volume. The dependent variable is total call or put option number of trades in the dataset, measured at the weekly or monthly level. Volume (auction) is single-leg auction option volume (Bryzgalova et al. (2022)). Volume (total) is total option volume. All the variables are standardized within stock. The sample period is from January 2020 to December 2022. The regression includes date fixed effects. Standard errors are clustered by date. t-statistic are reported in parentheses, where *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Number of trades (weekly)		Number of trades (monthly)	
	Call	Put	Call	Put
Call volume (auction)	0.165***		0.073	
	(10.43)		(1.57)	
Call volume (total)	0.330***		0.401***	
	(15.58)		(8.33)	
Put volume (auction)		0.117***		0.075***
		(8.80)		(2.62)
Put volume (total)		0.231***		0.272***
		(15.10)		(9.62)
Adj. R^2	0.2423	0.1294	0.2096	0.1201
Obs.	26,229	25,349	11,527	10,851

Internet Appendix to "An Anatomy of Retail Option Trading"

Table IA.1. Number of trades and switch to zero commission. TD Ameritrade (TD) introduced zero commission on October 3, 2019. We regress daily trade volume executed at TD and TradeZero (TZ) over 9/1/2019 to 10/31/2019 on a constant and indicator variables. Daily trade volume is scaled to have a mean of one for both TD and TZ prior to October 3. ≥Oct3 is an indicator variable for trades executed on or after October 3. The underlying sample includes 8,616 trades (5,770 executed at TZ and 2,846 executed at TD).

	Number of trades
Const	1.000***
	(26.92)
≥Oct3	0.280**
	(2.45)
≥Oct3*TD	0.528***
	(2.74)
Adj. R^2	0.3195
Obs.	86

Table IA.2. Return on option trades (excluding complex trades). Option trades that are classified as complex are excluded from the analysis. This table regresses the return on option trades on a constant and indicator variables. We include indicators for short sales (naked option writing), call option, 0DTE, index or ETF, active trader (with 500 trades or more), backfilled trade, and TD Ameritrade broker (most popular broker in our sample). The backfilled trade indicator takes the value one for any trade that is completed before the account creation date. Standard errors are double-clustered by date and trader. Returns are winsorized at the levels of 0.01% and 99.99%. The sample period spans 1/2020 to 12/2022.

	Return (option trade)										
Constant	-0.0062*	-0.0374***	0.0009	0.0073*	0.0062	-0.0056	-0.0117***	-0.0043	-0.0185***	-0.0364***	-0.0383***
	(-1.81)	(-12.00)	(0.17)	(1.89)	(1.48)	(-1.31)	(-2.72)	(-1.05)	(-3.06)	(-5.92)	(-6.04)
Short		0.3125***							0.3115***	0.3654***	0.3659***
		(15.80)							(15.83)	(14.26)	(14.24)
Call			-0.0111						-0.0054	-0.0017	-0.0014
			(-1.59)						(-0.75)	(-0.25)	(-0.20)
0DTE				-0.0574***					-0.0350***	-0.0329***	-0.0374***
				(-9.25)					(-5.38)	(-7.45)	(-8.13)
Index					-0.0404***				-0.0311***	-0.0042	-0.0063
					(-7.16)				(-5.52)	(-0.98)	(-1.48)
>500 trades						-0.0011					
						(-0.19)					
Backfill							0.0102**		0.0045	0.0070*	0.0132***
							(1.98)		(0.99)	(1.69)	(2.75)
TD								-0.0045			
								(-0.74)			
Trader FE	No	No	No	No	No	No	No	No	No	Yes	Yes
Date FE	No	No	No	No	No	No	No	No	No	No	Yes
Adj. R^2	0.0000	0.0156	0.0000	0.0011	0.0006	-0.0000	0.0000	0.0000	0.0167	0.0102	0.0103
Obs.	596,561	596,561	596,561	596,561	596,561	596,561	596,561	596,561	596,561	596,561	596,561

Table IA.3. 0DTE and other options. This table reports average characteristics of 0DTE trades and non-0DTE option trades. The sample period 1/2020 to 12/2022 and includes 794,692 option trades. Long is an indicator for a long trade. Call is an indicator for a call option trade. Returns are winsorized at the levels of 0.01% and 99.99%.

	0DTE	not 0DTE
Long	0.933	0.854
Call	0.509	0.620
Call moneyness	0.991	0.959
Put moneyness	0.993	0.963
Underlying price (excl. index)	$563.271	$360.325
Fraction S&P 500/SPY options	0.620	0.183
Average return	-0.046	0.001
Average return (no backfill)	-0.047	-0.001
Trade size	$1068.646	$2268.093
Number of trades	210,494	679,473

Table IA.4. Fractional share trading and underlying stock price of option trades. This table reports descriptive statistics for stock trades price and option trades underlying stock price for brokers that do not allow fractional share trading and for brokers that allow fractional share trading. The sample is restricted to trades for which we observe the broker.

	Mean	StDev	0.1	0.25	0.5	0.75	0.9	N
Brokers that do not allow fractional share trading								
Stock price ($)	49.76	180.07	1.98	3.55	8.13	23.41	107.59	1,030,363
Underlying stock price ($)	386.58	590.98	24.89	82.75	252.06	417.52	735.72	436,863
Brokers that allow fractional share trading								
Stock price ($)	94.21	244.45	2.18	4.78	16.11	73.04	222.03	115,127
Underlying stock price ($)	575.77	784.59	29.91	118.28	326.76	736.27	1084.59	96,145