# An Anatomy of Retail Option Trading

Vincent Bogousslavsky and Dmitriy Muravyev*

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*Bogousslavsky is with Boston College, Carroll School of Management, and Muravyev is with University of Illinois Urbana-Champaign, Gies College of Business. We greatly appreciate comments from Cindy Alexander, Svetlana Bryzgalova, Chukwuma Dim, Hitesh Doshi, Gregory Eaton, Mobeen Iqbal, Russell Jame, Marc Lipson, Scott Mixon, Esen Onur, Chay Ornthanalai, Michaela Pagel, Anna Pavlova, Neil Pearson, Andriy Shkilko, Davide Tomio, Matteo Vacca, Yanbin Wu, and seminar and conference participants at Boston College, University of Virginia (Darden), City University of Hong Kong, Fidelity Investments, U.S. Securities and Exchange Commission, Commodity Futures Trading Commission, FSU Truist Beach Conference, 6th Future of Financial Information Conference, CDI Derivatives Conference, NFA Annual Meeting, the Microstructure Exchange, HKU, CUHK, and 2024 FMA Conference on Derivatives and Volatility. We thank Mark Dugan and Matthew Hagerty for outstanding research assistance. Correspondence: Vincent Bogousslavsky: bogoussl@bc.edu; Dmitriy Muravyev, dmuravy2@illiois.edu.

# An Anatomy of Retail Option Trading

**Abstract**

The recent surge in retail option trading sparked concerns about trading motives and large losses. We offer the first trader-level analysis of modern retail option trading using novel data of $15 billion in retail stock and option trades. Option trades constitute one-third of all trades, concentrate in few underlyings, and are dominated by short-term purchases. They incur modest losses compared to wide bid-ask spreads. Retail investors use options to participate in high-priced underlyings, with little leverage or skewness-seeking in realized trade returns. Our investors are relatively sophisticated but exhibit remarkable heterogeneity, with main results holding across investor styles.

# 1 Introduction

Retail traders account for a large portion of trading volume, attracting public and regulatory attention. While retail stock trading has been extensively studied (Barber and Odean (2013)), much less is known about retail option trading despite its large increase since the COVID-19 pandemic. The Options Clearing Corp reports a 35% increase in option trading volume between 2020 and 2021, largely attributed to growth in retail trading.[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 raised concerns about reckless trading, potentially resulting in large losses (e.g., de Silva, Smith, and So (2023)).[2] Indeed, wide bid-ask spreads in options can lead to large losses for active traders (e.g., Muravyev and Pearson (2020)). These concerns prompted calls for stricter regulation of retail option trading (e.g., FINRA Regulatory Notice 22-08).

Motivated by these concerns, we provide the first study of modern retail investors' *individual* behavior in the options market, using detailed trader-level data on both option and stock trades. Our data allow us to quantify investor behavior, profitability, and trading motives, thus extending the growing literature on U.S. retail option trading that relies on proxies of *aggregate* retail behavior.[3]

We obtain our data from a trading journal provider. Trading journals offer advanced performance tracking and analytics tools. Users link their brokerage accounts for automatic and verified trade import. To maintain verified trade status, users cannot selectively import trades. The journal supports only retail brokers, such as TD Ameritrade. We observe 5,182 traders who made 2.4 million parent trades—including 0.9 million option trades—worth about $15 billion between 2020 and 2022. The average trade sizes ($8,798 for stocks, $2,006 for options) and frequency (41 trades per investor-month) suggest these are investors' primary trading accounts. Each parent trade consists of child trades that open and then close a position, or an occasional option expiration record. Thus,

[1] For example, WSJ on 9/26/2021, https://www.wsj.com/articles/individuals-embrace-options-trading-turbocharging-stock-markets-11632661201

[2] "Buying some options or going for a high-risk stock – it's still better than a lottery ticket." Daniel Moravec, a retail trader, WSJ on 6/8/2024, https://www.wsj.com/finance/stocks/degen-stock-crypto-trading-market-trend-69d12a56

[3] Bryzgalova et al. (2022) identify retail trading using option trades submitted to single-leg price improvement auctions (SLAN), while Eaton, Green, Roseman, and Wu (2023) and de Silva et al. (2023) rely on the "customer" category from the Options Open-Close Volume Summary data set. However, both proxies include institutional trades alongside retail trades and capture retail trading activity at an aggregate level rather than track individual traders.

we observe detailed data on retail trading of stocks, options, or both.

Our sample provides a novel perspective on retail trading. Prior work often focuses on less sophisticated retail traders like Robinhood users.[4] We study a complementary group of retail investors who are, on average, more sophisticated given their journal use and larger, more frequent trades. Importantly, remarkable heterogeneity across our traders allows us to validate key findings across different levels of trade size, trading frequency, holding period, and brokers.

We document several stylized facts about retail option trading. First, we confirm the growing popularity of options among retail investors (e.g., Bryzgalova et al. (2022)). 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 early 2020 to 49% in late 2022. Thus, despite the spotlight on retail stock trading, retail option trading is gaining comparable importance. Strikingly, 8% of our investors trade only options, a novel "option-only" trading style.

Second, our retail investors 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. Moreover, option trading is becoming more concentrated over time. In contrast, stock trades are more dispersed, and the top ten stocks represent only 9% of all stock trades. A trader-level analysis shows that investors tend to trade different stocks but the same option underlyings. Since retail option trading is concentrated in only a few stocks, traditional per-stock analyses across two-thousand optionable stocks could present a skewed perspective.

Third, our analysis of trade characteristics reveals that retail investors in our data use options for short-term speculation rather than hedging. A typical retail option trade involves a purchase of a short-term call or put option linked to the S&P 500 index held for only a few hours. 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,

[4] Prior work on modern retail trading often relies on Robintrack data, which tracks the number of Robinhood users holding a stock over time (e.g., Barber et al. (2022); Eaton et al. (2022); Lipson, Tomio, and Zhang (2023)).

the holding period is highly skewed, with a 3.5 days average but only a half-hour median, making accurate holding period measurement crucial when assessing trade profitability.

Motivated by concerns about large retail losses, we estimate per-trade and per-trader profitability. Stock trades earn close to zero return, consistent with small bid-ask spreads and unpredictable stock returns. Option trades earn a −0.9% average return. This loss is smaller than the typical quoted bid-ask spread of 3.7% in our sample and slightly exceeds trading fees (included in the return). Thus, retail traders likely use limit orders to avoid paying the spread. Option trade returns vary from −4.5% to −0.5% across subsamples. Factors like index options, option type, and journal sign-up timing show inconsistent or weak effect on profitability. 0DTE trades earn 3% lower returns. Naked option sales, though rare, earn 20% on average robustly across specifications.[5] For trader-month profitability, option trading losses exceed stock trading losses by $157 ($t$-statistic of −0.86) within a trader. In contrast, option-only traders lose $547 per month. Overall, while retail losses in our sample are non-negligible, especially for option-only traders, concerns about severe retail option losses may be overstated.

Why do retail investors trade options over stocks? Retail traders favor options over stocks for high-priced stocks, even within the same trader or stock, controlling for size, volatility, and other characteristics. Indeed, the median stock trade price of $8 contrasts with a $262 median underlying price for option trades (excluding S&P 500 trades). Stock splits provide causal evidence that traders seek affordable alternatives to high-price stocks. As a stock becomes more affordable to trade post split, the propensity to trade the stock relative to the stock's options increases by about 10% in our data. The one-share trade size constraint can potentially bind for high-priced stocks, encouraging traders to switch to options. But most traders in our sample can afford multiple shares of high-priced stocks, and for such traders the stock price remains the main predictor of option versus stock trades. The pattern also persists among brokers offering fractional shares. One possibility is that options on high-priced stocks are more liquid, which may attract additional retail volume.

Embedded leverage is often considered a primary reason for option trading (e.g., Frazzini and Pedersen (2022)) as a long call or put can generate higher profits than the same dollar investment in the underlying, given favorable price movements. We examine *realized* leverage by comparing absolute dollar profits between option and stock trades by the same investor—a comparison not

[5] Bryzgalova et al. (2022) also find that option sales are more profitable than purchases.

possible without trader-level data. Surprisingly, retail investors achieve modest realized leverage from option trading because the smaller option trade size partially offsets the embedded leverage. Specifically, option trades in our sample yield 14.5-to-1 average leverage per dollar relative to stock trades controlling for stock and investor fixed effects. But retail option trades are about six times smaller, resulting in a 2.5-to-1 realized dollar leverage. This is only slightly more leverage than can be obtained from margin stock trading.[6] Notably, while we observe realized leverage, traders' intentions remain inherently unobservable.

Investors may buy options for their lottery-like characteristics and positive skewness potential (e.g., Boyer and Vorkink (2014)). Our evidence suggests that this is not the primary motivation. In theory, options held to expiration generate highly skewed payoffs with large potential gains and limited losses. Yet, we find little evidence of *realized* positive skewness in our sample. Dollar profits for option trades display nearly symmetric distribution with slight negative skewness. For option purchases, 10th and 90th percentiles are -$296 and $217, with similar results in the distribution tails.[7] Both option and stock trades yield negative dollar return skewness within a trader. Two factors contribute to this divergence from theoretical option payoffs: traders' short holding periods and their tendency to realize gains earlier than losses on option purchases. Although traders may target positive skewness, their actual returns show otherwise.

We leverage the trader-level nature of our data to show that *stock-option* combinations are rare despite university courses and retail brokers promoting such strategies. Covered calls and protective puts account each for just 0.2% of our option trades. Furthermore, Li, Musto, and Pearson (2023)) find that vertical spreads—buying and selling calls (or puts) with different strikes but same expiry—are the most popular "complex" option strategy, comprising 10% of all option trades. In our retail sample, however, these spreads represent at most 8% of parent option trades. Thus, retail investors seem to use complex strategies less frequently than others. These results, together with short holding periods, suggest that retail traders use options primarily for speculation rather than hedging. All previous results remain robust when complex trades are excluded.

Our retail data help validate widely-used retail proxies and vice versa. Stock trading imbalance

[6] While traders could deploy unused capital into multiple option positions, the results hold when the sample is restricted to single daily option trades.

[7] Even percentage returns, instead of dollar profits, are slightly negatively skewed until $-100\%$ becomes binding for option purchases at the 1st percentile.

in our data is strongly positively correlated with established measures of retail imbalance, such as the change in the number of Robinhood traders holding a stock (Barber et al. (2022), Eaton et al. (2022)) and the Boehmer et al. (2021) retail order imbalance, controlling for the Lee and Ready (1991) imbalance. Option volume in our data is positively related to the retail option trading measure of Bryzgalova et al. (2022), controlling for total option volume.

Retail investors in our sample are highly heterogeneous, with holding periods ranging from sub-hour to weeks and trading activity ranging from under seven to over 50 trades per month. Thus, a representative retail investor is inherently hard to define, highlighting the importance of studying distinct segments of the retail population. Our main findings remain stable across trader subsamples based on trade frequency and size, holding horizon, broker, and stock-option usage. The largest variation appears in option trade losses across levels of investor sophistication as proxied by trade size. Traders with small average trade size (<$200) lose 3.4% versus 1.4% for those with larger average trade size (>$5,000). Thus, unsophisticated investors incur higher losses. Importantly, while the results appear robust, they should be extrapolated with caution because we only observe a subset of the retail population.

**Related Literature.** A growing literature studies retail trading in options using aggregate proxies for retail trading. Retail option trading exploded in popularity recently (Bryzgalova et al. (2022)) and can affect implied volatility (Eaton et al. (2023)) and underlying stock volatility (Lipson et al. (2023)). Hendershott, Khan, and Riordan (2022) and Ernst and Spatt (2022) study retail execution in option auctions. Lakonishok et al. (2007) find that the least sophisticated investors were chasing dot-com bubble by buying calls on growth stocks. Leveraging trader-level data, we present the first detailed analysis of retail investors' joint option and stock trading, examining profitability, trading motives, and investor heterogeneity.

Bryzgalova et al. (2022), Beckmeyer et al. (2023), and de Silva et al. (2023) raise concerns about large retail option losses: "the aggregate portfolio of retail investors lost $2.1 billion from November 2019 to June 2021," "retail investors lost $184,000 on the average day" in 0DTE S&P 500 options, and "retail losses of 5-to-9% on average." While the first two papers focus on aggregate retail losses, which naturally grew with retail participation, we quantify per-investor and per-trade losses. Unlike de Silva et al. (2023) who study earnings announcements across all optionable stocks, we find that retail option trading concentrates in few liquid underlyings, with earnings events comprising a small share of total retail activity. Furthermore, prior studies face data constraints that affect profit calculations. The "single-leg auction" proxy by Bryzgalova et al. (2022) includes only market orders that cross the spread, while the "open-close" proxy by de Silva et al. (2023) lacks trade prices, and both proxies assume a fixed holding period (e.g., one day). We measure profits precisely but for a small share of the retail population. Finally, we find smaller losses for the modern U.S. sample than trader-level international studies. For example, Bauer, Cosemans, and Eichholtz (2009) show that clients of a Dutch online broker from 2000 to 2006 incurred substantial option losses.[8]

To our knowledge, we are the first to directly study how retail trading in stocks and options interact, contributing to the literature on retail trading across asset classes.[9] Kogan et al. (2023) show that retail investors trade crypto differently than stocks. Similarly, we find that they trade options differently than stocks—a much closer asset class. Retail option trading is concentrated in a few tickers (indices and high-price technology stocks) but stock trades are spread across many tickers (mostly low-price stocks). Moreover, retail traders rarely combine same-ticker option and stock positions. Thus, profitability and other analyses can be done independently on stock and option trades. We also find that stock trades break even on average, with symmetrically distributed profits. Even if traders seek positive skewness, they do not achieve it, consistent with Fedyk (2022).

## 2 A Novel Data Set

We introduce a novel data set of retail stock and option trading obtained from a trading journal provider. Trading journals help investors track and analyze their trades.[10] Third-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 analyze 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.

[8] See also Han, Lee, and Liu (2009); Hu, Kirilova, Park, and Ryu (2023); Pitkäjärvi and Vacca (2024).

[9] This literature on retail stock trading 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); Gargano and Rossi (2018); Barber et al. (2022); Eaton et al. (2022); Ozik, Sadka, and Shen (2021); Chapkovski, Khapko, and Zoican (2021); Dyhrberg, Shkilko, and Werner (2022)) focus on the behavior of the new generation of retail investors. Ferko, Mixon, and Onur (2024) study retail trading in the futures market.

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

Traders cannot selectively import trades to the journal we study.

The trading journal that we use makes customer trades public by default, which the overwhelming majority of users did not change (and might not have noticed). Thus, anyone can observe their trading journals. We extract users' profile and trade history for 5,182 investors. A typical profile includes basic user information such as an id number, nickname, self-reported location, and account-creation date. Users can also list their social media profiles or follow each other but few do so. 76% of our accounts do not follow any account, and 87% do not have any follower. This suggests that a large majority of traders do not use these social features.

A user profile includes by default verified data on up to 1,000 consecutive round-trip "parent" trades made by a trader in her brokerage account. Each parent trade involves opening and closing a position in a stock or option. To illustrate a parent trade, an investor might acquire GameStop shares in two 100-share purchases, then exit the complete 200-share position in a single sale. 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). While we observe trades, we do not observe cash balances or aggregate account sizes.

This default data set does not include trade size and price. To address this limitation, we separately collect additional information for a random sample of about 50% (2,577) of all traders. This additional data set contains parent order size as well as information on the underlying child trades. 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, entry 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.[11]

We focus on trades executed between 2020 and 2022. Some of the collected trades occur before the 2020-2022 sample period, but there are few of them. We also collect data for 2022 trades that were closed in 2023 to avoid potential biases due to missing uncompleted trades at the end

[11] When we collect the child trade information, the number of trades per account is not subject to the 1,000 parent trades cap, which allows us to expand the original data set.

of the sample. We require all of our trades to be matched to CRSP by ticker and date except for index option trades, which are matched separately to the underlying index. We are able to match about 94% of trades. Many 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 did not facilitate crypto trading during our sample period. Thus, almost all investors in our data trade only U.S. stocks and options.

We compare reported returns on stock parent trades to stocks' CRSP return over the holding period. This comparison flags accounts with abnormal reported returns. We also manually review all accounts with extreme reported returns. This leads us to exclude several accounts for which option trades are mistakenly reported as stock trades. We also exclude accounts with less than five reported trades as we do not want (very) small accounts to unduly influence within-account analyses. After applying these filters, we end up with a sample of 5,182 investors.

Trade history often predates journal creation, and about 48% of trades are made after account creation. Even after a user stops logging into the journal, trades continue to be automatically loaded. Later, we use post sign-up trades to compare trade performance pre and post account creation.

## 2.1 Descriptive Statistics

In total, the data set includes 1,525,356 stock parent trades and 889,967 option parent trades, including 655,087 and 299,017 trades with complete price and size information. The 1.5 million parent stock trades are worth about 13.4 billion dollars (counting only the entry side of each parent trade) and the 0.9 million option parent trades are worth about 1.8 billion dollars in option premiums.

Table 1 reports characteristics of stock and option trades 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, 4,781 trade at least some stocks and 2,720 trade at least some options. About 48% of all investors do not trade options, but about 8% of all investors trade options exclusively. About a quarter of trader-month feature only option trades.

An average investor trades 98 unique stocks and 42 unique option underlyings over her tenure in our data (Panel (a)). In the average trader-month, 14 stocks and 9 underlyings are traded

(Panel (b)). The pattern is similar but less dramatic for the median investor. Thus, option trading is more concentrated than stock trading, which we explore in Section 3.

We observe substantial heterogeneity in the number of trades across investors. The average trader-month features 26.1 stock trades and 15.2 option trades. However, a quarter of trader-month have six or fewer trades, while another quarter have more than 50 trades. The median trader-month features 19 trades per month, countering the view that our sample *primarily* consists of "semi-professional" investors.

Most of our analyses are at the trade level. To facilitate them, Table 2 reports descriptive statistics for stock trades in Panel (a) and option trades in Panel (b). Table 2 shows that trade size is substantial, even though we winsorize it at 0.01% and 99.9% to avoid potential reporting mistakes. Stock trades have an average (median) trade size of $8,800 ($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, a $11,205 average stock purchase in the Barber and Odean (2000) data set is about twice as large as in our data after adjusting for inflation. For a major U.S. broker, Gargano and Rossi (2018) report an average trade size of $16,000 for 11,000 accounts randomly chosen over 2013 to 2014. In contrast, the eToro investors studied by Kogan et al. (2023) have an average trade size of $311 and account balance of $987.

Thus, our sample contains many regular active retail investors rather than buy-and-hold investors or investors who put a few hundred dollars in a 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.[12] We also confirm in the Internet Appendix that TD Ameritrade's trading volume in our data increases substantially after TD introduced zero commissions on October 3, 2019, relative to another already commission-free broker.

The large dollar trade size suggests that the journal features investors' primary trading accounts. Our investors could own other investment accounts, such as retirement accounts. However, this limitation should not affect our analysis. These other accounts are unlikely to feature options, and we focus on investors' active trading decisions.

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

## 2.2 Scope and Selection

The data set provides the first direct look into how modern retail U.S. investors trade stocks and especially options. This allows us to benchmark option trades to stock trades within and across investors and estimate trading performance accounting for true trading costs and holding periods. The main limitation is that we only observe traders who sign up for the journal. These traders may be more active and sophisticated than other retail investors because they are interested in advanced tools to monitor their performance. They could also differ from other retail investors along other characteristics. Thus, our results may not speak about the "representative" retail investor.

The concept of a representative retail trader is challenged by the substantial heterogeneity among retail investors, analogous to the diversity among institutional investors. Our sample captures this variation through traders from diverse professional backgrounds and locations—from a practicing pharmacist in Houston to a retired software engineer in Omaha to an aspiring trading guru in New York.[13] This heterogeneity manifests itself quantitatively: 75% of traders (3,878) have median holding horizons under one day while 25% (1,304) hold for longer; trade sizes range from under \$200 (507 traders) to over \$5,000 (332 traders); and trading frequency varies from fewer than 10 trades per month (1,494 traders) to more than 30 (1,982 traders). We examine the robustness of our findings across trader style subsamples in Section 5.1. Investor heterogeneity highlights the importance of studying different segments of the retail population. Therefore, our study complements prior work that focuses on presumably less sophisticated investors such as Robinhood users.

Furthermore, due to brokers' reluctance to share client data, previous studies on retail trading in options rely on indirect identification through public data. Most notably, Bryzgalova et al. (2022) identify retail trades using OPRA's SLAN flag. Though of great value for researchers, this proxy has limitations: some SLAN trades are institutional, and the retail component captures only part of all market orders and excludes limit orders. Consequently, SLAN-identified retail trades likely over-represent less sophisticated (i.e., cost-insensitive) retail investors. We compare stock and option order flow and volume in our data to aggregate retail trading measures in Section 6.

Our data set offers three distinct advantages: (1) we observe retail trades directly without contamination by institutional trading activity and capture all order types including limit orders;

[13] A few users shared links to their public social media profiles, which allows us to identify them.

(2) we track detailed investor-level data enabling analysis of trading patterns such as position lifecycles and stock-option interactions within a trader; and (3) we cover eight brokers serving distinct clienteles, expanding beyond single-broker studies like Barber and Odean (2000).

# 3 Retail Trading and Profitability

In this section, we document and compare stylized facts about the trading style and profitability of retail investors in options versus stocks.

## 3.1 Stylized Facts

First, we confirm the increasing popularity of options among retail investors. While previous studies have documented the rise in retail option trading (e.g., Bryzgalova et al. (2022)), we show that the proportion of option trading by retail investors has increased relative to stock trading both in aggregate and within individual investors in our data. Figure 1 shows that the proportion of option trades relative to all trades in a month increased from 23% to 45% between 2020 and 2022. By the end of our sample period, retail investors in our sample trade options nearly as frequently as stocks. On the extensive margin, the proportion of accounts trading options increased from 29% to 50%. Figure 1 also documents an increase from 15% to 36% in the proportion of investors in a given month trading only options (and not stocks) from 2020 to 2022. This "options-only" trend suggests that many retail investors have become sufficiently comfortable with option trading to deviate from "traditional" stock trading.

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 data. Option trades are notably concentrated. The ten most traded option underlyings account for as much as 60% of all option trades. This concentration has increased over time. The top ten underlyings' share increased from 47% in 2020 to 74% in 2022. ETF and index options dominate retail option trading activity. SPY and SPX options alone constitute 26% of all retail option trades. The remaining top option underlyings are QQQ and major technology stocks. In contrast, stock trades are more dispersed. The ten most popular stocks account 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 includes esoteric high-risk investments such as triple-leveraged version of QQQ (TQQQ), GameStop (GME), and a Chinese electric vehicle maker (NIO). This dichotomy in trading patterns suggests that retail investors approach options and stocks with distinct strategies and preferences.

Retail option trading's concentration in a few underlyings affects the interpretation of traditional *per-stock* analyses across thousands of optionable stocks. First, many analyses exclude ETFs such as SPY, which are popular with retail according to our data. Second, equal-weighted analyses give highly-traded stocks like TSLA and AAPL the same weight as stocks with minimal retail option activity. The resulting averages thus underweight the economic importance of stocks where retail traders are most active, which happen to have narrower bid-ask spreads and more active options.

Figure 2 indicates that investors trade different stocks but the same option underlyings. This fact is not explained by having few investors trading the same options and many investors trading different stocks (see Section 5.1). Furthermore, Table 1 shows that a median investor trades eight distinct stocks and five distinct underlyings in a month but 52 stocks and only 25 option underlyings over her tenure. Thus, investors are more likely to try new stocks than new option underlyings. Investors adjust the set of stocks they trade each month. Since earlier research such as Barber and Odean (2000) documents that retail investors mostly trade familiar stocks, this finding suggests that retail trading patterns have changed. The widespread adoption of online trading platforms and increased information flow through social media may have expanded investors' awareness of and access to diverse investment opportunities.

Third, Table 2 shows that purchases (i.e., trades that open new long position) constitute 87% of option trades, while sales represent only 13%, resulting in a 7-to-1 buy-sell ratio. Thus, naked option selling is rare. This is not surprising since many brokers either prohibit or require special permission for naked option selling. Consequently, option purchases mainly open new positions while option sales mainly close existing ones. Though the majority of stock trades establish long positions, short sales constitute 37% of stock trades in our data. This suggests that retail short selling is more prevalent than in the prior period studied by Kelley and Tetlock (2017).

Fourth, retail investors in our data tend to bet on short-term price swings. The average option trade maturity is two weeks. The median option trade maturity decreases from four days in 2020 to one day in 2022. 0DTE constitute 24% of all option trades and become increasingly popular over the sample period. This result is in line with the shift in option trading volume towards 0DTE options observed at the aggregate level (e.g., Beckmeyer et al. (2023)). We discuss 0DTE trades in more detail in Section 5.2. Furthermore, 69% of option trades are day trades (i.e., closed on the same day as opened) whereas 88% of stock trades are day trades. For the subset of trades with detailed timestamps, the median holding period is 0.12 hours for stocks and 0.48 hours for options. These short holding periods suggest that investors in our data are unlikely to trade options for hedging purposes.

Table 2 also describes option type and moneyness. Call trades outnumber put trades for single stocks, but the reverse is true for index/ETF trades. In Table IA.1 in the Internet Appendix, we show that long call trades outnumber long put trades by more than 2-to-1 for single stock options. However, this ratio is less than 1-to-1 for index and ETF options. This suggests that retail investors differentiate between equity and index options. Finally, most trades occur in at-the-money (ATM) or slightly out-of-the-money (OTM) options.

### 3.2 Profitability

In this section, we assess the profitability of retail option trades.

Table 2 shows that our 889,967 parent option trades yield an average return of $-0.9\%$, while stock trades in our sample earn an average return near zero. The moderately negative average return on option trades includes broker commissions, exchange fees, and any costs of crossing the bid-ask spread. In fact, this average loss only slightly exceeds typical option trading fees. For example, TD Ameritrade charges $0.65 per option contract, paid both on entry and exit. For an average trade size of six contracts and $2,006, this fee translates to about 0.4% of trade value. Notably, the observed average loss on retail option trades is much smaller than typical quoted bid-ask spreads, which is 3.7% for the option child orders that we are able to uniquely match with OPRA. Possibly, retail traders use limit orders to avoid paying the spread.

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 outliers on sample averages. However, the results are similar for unwinsorized returns. We regress option trade returns on a constant and indicators for short-sale trades, call option trades, 0DTE option trades, index/ETF option trades, and pre sign-up trades. The pre sign-up trade indicator equals one for trades completed before the account creation date. Standard errors are double-clustered by trader and date.

Column (1) of Table 3 sets the baseline: an average option trade earns a $-0.93\%$ return with a $-3.57$ $t$-statistic. We document several trade categories for which profits deviate from the average using univariate indicator regressions. Most striking, in Column (2), naked option sales (only 13% of all option trades) are profitable, earning a 20% return while option purchases lose 3.95% on average. Bryzgalova et al. (2022) also find that option sales are more profitable than option purchases. 0DTE option trades lose 4.71% relative to other option trades ($t$-statistic of $-10.09$), while non 0DTE trades earn 0.19%, which is statistically insignificant. 0DTE options have lower prices and thus larger relative bid-ask spreads, which can lead to larger losses. Index/ETF option trades earn an average $-3\%$ return versus a 0.15% return for single-stock option. We find no statistically significant differences in returns 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 highlight within-trader variation in profitability. The last three columns of Table 3 report results that are generally consistent with the univariate analyses and are robust across fixed effect specifications. For example, naked option sales earn a 28% incremental return with controls and fixed effects, which is similar to the 24% unconditional incremental return. Thus, differences in trader skill between option buyers and sellers do not explain the outperformance of option shorts. One possible contributing factor is that option shorts tend to have lower moneyness than option purchases (Table IA.1). The profitability results for 0DTE and index option trades become less dramatic after adding controls. With all controls and without (with) fixed effects, 0DTE trades lose 2.27% (2.95%) more than other trades. Finally, index option trades perform similarly to stock option trades within a trader.

One 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 journal creation akin to a "backfill bias." Fortunately, we observe the journal's account creation dates, and almost half of the trades are from the pre-journal period. In a univariate regression in Column (6) of Table 3, pre sign-up option trades lose on average $-0.59\%$ versus $-1.31\%$ for post sign-up trades, and the difference is not statistically significant at the level of 5%. With controls and fixed effects, the difference increases to 1.25% with a $t$-statistic of 3.32. Though a potential backfill bias appears small in our sample, we confirm our main results in the sample of post sign-up trades.

In Section 5.1, we evaluate how our main results vary across trader groups, categorized by trading style, size, activity level, and broker. Across all groups, stock trades tend to earn near-zero return, while option trades tend to lose $-1\%$ to $-3\%$. Hence, the profitability results hold beyond the "average" investor in our sample.

Comparing option and stock trade returns is challenging due to options' embedded leverage and smaller trade size reported in Table 2. To provide an alternative perspective on retail profitability, we supplement the analysis of per-trade returns with trader-month dollar profits. This dollar-based analysis accounts for trade size differences and captures how frequent trading can compound even small percentage losses into substantial dollar losses given short holding periods.

In Table 4, we estimate trader-month dollar losses for all trades in Panel (a) and for post sign-up trades in Panel (b). We also compare stock-only, option-only, and joint stock-option traders in the last three columns the table. For each trader-month, we compute the dollar profit from trading options and stocks. Without any filters, trader-month dollar performance is \$552 lower for option trades than for stock trades ($t$-statistic of $-4.58$). For post sign-up trades and including trader and day fixed effects, average option trading losses exceed stock trading losses by \$157 ($t$-statistic of $-0.86$). For post sign-up trades, stock-only traders earn a statistically insignificant profit of \$62.46 per trader-month on average ($t$-statistic of 0.44). Joint stock-option traders lose \$276.17 more on option trades than stock trades, which is statistically significant at the 10% level. In stark contrast, option-only traders lose \$547.49 per trader-month. Thus, options appear detrimental to investors' performance from this perspective.

Overall, the above results provide specific estimates to evaluate profitability concerns aired in the popular press and the literature, which generally assumes that retail investors pay most of the bid-ask spread. While option trading losses are sizable relative to stock trading losses in our sample, and especially so in dollar terms, they do not validate concerns about "catastrophic" option trading losses. These estimates might represent a lower bound on retail losses since our sample likely captures relatively sophisticated investors compared to the retail population. In Section 5.1, we explore how these estimates vary across subsamples within our data.

# 4 Why Do Investors Trade Options?

In this section, we explore potential motives for retail option trading. We consider several explanations. Retail investors could be attracted to options instead of stocks because of their low price, high embedded leverage, lottery-like payoffs, and associated multi-leg strategies. The strength of our setup is that we can compare option trading to stock trading within a trader.

## 4.1 Stock Price and Option Affordability

Table 2 shows a striking difference: the median stock trade has a stock price of about $8, while the underlying price of the median option trade is much higher, reaching about $262 (excluding S&P 500 option trades). This large price difference persists within individual traders. A natural explanation is that options serve as a low-cost substitute for expensive stocks. Options typically trade much lower than the underlying's share price, and investors can readily find options with premiums that fit their budget constraints by going for short-maturity or out-of-the-money options.

We examine differences in characteristics associated with option and stock trades. An indicator variable is set to one for option trades and zero for stock trades. We regress this indicator on stock characteristics measured at the prior month end, using data from the Chen and Zimmermann (2021) library. The characteristics include log stock price, idiosyncratic volatility and skewness (from the Fama-French 3-factor model estimated on past month's daily data), maximum daily return over the prior month, CAPM beta, and log market capitalization. Month fixed effects capture market trends. We also estimate specifications with trader fixed effects to analyze how individuals choose between stocks and options, and with stock fixed effects to account for time-invariant stock characteristics. The analysis excludes ETF and index-linked trades.

Table 5 confirms that option trades have on average a much higher underlying stock price than stock trades. Option trades concentrate in large cap stocks, which is expected because many small-cap stocks have few and illiquid options. Stock price remains, however, statistically significant even after controlling for market capitalization and other characteristics. Notably, characteristics motivated by theories of investor attention and skewness preference—including volatility, skewness, maximum return, and beta—show weak or counterintuitive relationships with the choice between options and stocks. Once we include stock fixed effects in Column (4), stock price is the only characteristic that remains statistically significant to explain trading an option over the underlying stock. In Column (5), we show that the results holds when the sample is restricted to optionable stocks. Thus, retail traders favor options over stocks for high-priced stocks, even within the same trader or stock, and controlling for stock characteristics.

Figure 2 shows that option trading is concentrated in big-name technology stocks, which tend to have high prices. Investors may discuss these "hot" stocks on social media. A rise in bullish sentiment, often following price increases, may increase investors' propensity to trade options in these stocks. To control for this social-media effect, we use the sentiment measure in Dim (2024), which is an average of Seeking Alpha authors' belief about the stock's future prospects.[14] Column (6) of Table 5 reports that the price effect remains strong in the restricted sample with available sentiment measure.

Stock splits allow us 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.[15]

To test this hypothesis, we analyze trading activity in the 60 days before and after stock splits, excluding the seven days around the split to mitigate the potential impact of short-term attention-driven trading. The results are robust to including these days. We start with all stock splits and then restrict the sample to split events with sufficient trading activity; i.e., at least 100 stock and option trades in our data both before and after the split, which results in 11 split events.[16] 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-difference 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.

The first two columns of Table 6 report the post-split change in retail activity in stocks and options separately. For the stock trade sample, Column (1) regresses an indicator variable for

[14]The measure ranges from −1 (bearish) to 1 (bullish). We use the last available value of the measure at the end of the current month for each ticker. Using the previous-month value yields similar results. We thank Chukwuma Dim for sharing this measure.

[15]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.

[16]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.

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, with a 2.00 $t$-statistic. This result is consistent with lower post-split prices attracting retail stock traders. Similarly, Column (2) applies an analogous specification to option trades, showing that split stocks experience 6.4% fewer option trades post-split compared to matched stocks with a $t$-statistic of 1.69. Thus, stock splits simultaneously increase retail activity in the underlying stock while reducing option trading.

We study the substitution between stock and option trading following splits in Column (3). We regress an option trade indicator that takes the value one for options and zero for stocks on post-split and treated trade indicators, their interaction, and event fixed effects. The pre-split difference in option trading propensity between treated and matched stocks is statistically insignificant. However, the interaction between post-split and treated indicators reveals a decline of 9.9% with a $t$-statistic of $-4.41$. As splits make stocks more affordable to trade directly, investors shift their trading activity from options to the underlying stocks, supporting an affordability channel.

Does a binding one-share constraint in high-priced stocks explain why retail investors switch from stock to options trading? The one-share constraint seems relevant for brokers targeting small retail accounts, such as Robinhood. Indeed, many of these brokers introduced fractional share trading to help investors access markets.[17] Summary statistics in Table 2 suggest, however, that most traders in our sample possess sufficient capital for trading high-priced stocks. Furthermore, most brokers in our sample do not offer fractional trading. For the brokers that do offer fractional shares and thus for which the one-share constraint should be irrelevant, we continue to observe the same strong relationship between stock prices and the preference for options over stocks, as shown in Table IA.2 in the Internet Appendix.

An alternative explanation may lie in market structure. Options on high-priced stocks typically enjoy greater liquidity and tighter bid-ask spreads (e.g., Christoffersen et al. (2018)). This enhanced liquidity could attract retail traders seeking better execution and more flexible trading strategies. These options may also benefit from greater liquidity in the first place because price-constrained investors trade them actively.

[17] *"We have so many investors that just want to dip their feet into the market and put ten dollars in," Robinhood CEO Vlad Tenev told CNBC in a phone interview. "We think this will empower even more people to invest."* Source: `https://www.cnbc.com/2019/12/12/robinhood-joins-a-wave-of-fractional-stock-trading-offers.html`

## 4.2 Embedded Leverage

High embedded leverage is often considered a primary reason for trading options (e.g., Frazzini and Pedersen (2022)). A long option provides embedded leverage, potentially yielding larger profits than the same dollar investment in the underlying stock given a favorable price movement.

Table 7 reports the distribution of percentage returns and dollar returns for three samples of trades in our data: all trades, purchases, and purchases excluding pre sign-up trades. As expected, options purchases offer more extreme percentage returns than stock purchases. For example, the 90th percentile are 35% and 7% for options and stocks, respectively, which implies a leverage of about 7-to-1 for the same dollar investment. This ratio is similar at the 99th and 99.5th percentiles.

Retail investors in our data, however, do not fully utilize this embedded leverage. An average option trade is 4.4 times smaller than an average stock trade: $2,006 vs. $8,800 as shown in Table 2. This smaller trade size partially offsets the embedded leverage. Panel (b) of Table 7 shows that the *dollar* return of stock purchases at the 90th percentile is only 2.4 (217/91) times larger than the corresponding dollar return of option purchases. If we restrict the sample to call option purchases, the leverage of option-to-stock purchases percentage and dollars returns at the 90th percentile are 7.6-to-1 and 2.5-to-1, respectively. This realized option leverage of 2.5-to-1 is comparable to traditional margin trading in stocks, which offers 2-to-1 leverage.

To better compare stock and option trades, we regress the log of absolute percentage gain, trade size, and absolute dollar gain on an indicator for option trades, controlling for stock and trader fixed effects. This log specification lets us focus on relative magnitudes, which are easier to interpret than absolute magnitudes. The percentage gain highlights the per-dollar leverage embedded in options (compared to stock trades), while the dollar gain highlights the total dollar realized leverage that retail investors achieved. The trade size connects per-dollar and realized leverage.

Table 8 reports the results. The bottom row of Panel (a) reports the implied leverage of option trades relative to stock trades estimated from the option indicator coefficient. Without fixed effects, the percentage return leverage of options relative to stocks is about 9 (Column (1)). However, option trade size is only about 0.31 as large as stock trade size (Column (2)). Since dollar return equals percentage return times trade size. The implied dollar return leverage of options relative to stocks is only 2.82 ($= 9.17 \times 0.31$), which explains the difference in percentage returns and dollar returns in Table 7. Panel (b) of Table 8 adds stock and trader fixed effects. The implied percentage return leverage of options relative to stocks is 14.69, which is higher than in Panel (a). However, this is counterbalanced by a lower option trade size. Ultimately, implied dollar return leverage with underlying and trader fixed effects is 2.82 (= $14.69 \times 0.17$), which is close to the estimate in Panel (a). These realized leverage estimates are only slightly higher than the 2-to-1 leverage that can be achieved by margin stock trading.

We also regress absolute dollar profit and trade size on an indicator for option trades and fixed effects and report the results in Table IA.3 in the Internet Appendix. Controlling for trader and date fixed effects, option trades generate absolute dollar gains that are \$110 to \$121 higher than stock trades. While this difference is statistically significant, it represents only about 1.3% of the average stock trade size. Option purchases are on average \$4,801 smaller than stock purchases when controlling for trader and date fixed effects.

A potential concern with the previous analysis is the assumption that traders leave the capital saved from smaller-sized option trades uninvested. If traders instead execute multiple option trades at once rather than a single larger stock trade, our previous results could be misleading. In Table IA.3 in the Internet Appendix, we exclude same-day multiple option trades by any trader, which also excludes multi-leg strategies. The results are similar to our baseline estimates. Finally, since stock trades typically have shorter duration than option trades, our findings cannot be explained by a mechanical effect from longer stock holding periods.

In summary, our retail investors do not appear to fully utilize options' leverage potential. Despite large difference in absolute percentage gains, absolute dollar gains are only marginally higher on option trades than on stock trades. Though the results are consistent with the use of options to get leverage, the realized dollar leverage ratio is on average about the same as what can be achieved with margin stock trading. This suggests that retail traders adjust their position sizes based on the perceived risks of the financial instrument.

### 4.3 Preference for Positive Skewness

Retail investors may buy options to seek positive skewness since long option positions offer lottery-like payoffs with limited downside and large potential gains. While we cannot directly observe trading motives, skewness-seeking behavior should manifest itself in positively skewed realized dollar profits. However, we report two tests showing that option trades do not exhibit such positive profit skewness.

Our first test examines the asymmetry in the distribution of dollar trade profit in Table 7. Stock trades provide a useful benchmark, showing nearly symmetric profit distribution. For example, stock purchases have 10th and 90th percentiles of −\$109 and \$91, respectively. This symmetry remains robust across extreme percentiles and various trade subsamples, including when pre sign-up or multi-leg trades are excluded.

Perhaps surprisingly, 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 distribution leans slightly to the left. This trend continues as we examine further 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 in the sample of non-backfilled trades, as reported in the last panel of the table. Importantly, the negative realized skewness persists even among investors with holding periods longer than one day (Section 5.1). In a study of Taiwanese day traders, Barber et al. (2020) also find that stock trading profits are not particularly skewed. We find a similar result for option trading profits.

While dollar profits provide the most direct test for realized skewness achieved by retail investors, we also investigate the skewness in option relative profits or returns. Table 7 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 negative skewness, which does not support skewness preferences. However, option returns cannot fall below −100% for option purchases, which binds for more extreme percentiles and results 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, a large option trade held for an hour would not result in strong positive skewness.

In the second test, we use regression analysis to test for differences in the skewness of stock and option trades. We compute realized skewness per trader separately for option and stock purchases as the adjusted Fisher–Pearson standardized third moment coefficient. Thus, we get two skewness values per investor if the investor trades both stocks and options or one value if the investor trades only stocks or options. In Table IA.4 in the Internet Appendix, we regress return skewness on an option trade indicator and fixed effects. Percentage return skewness is higher for option trades than for stock trades. However, dollar return skewness of option and stock trades are not statistically different, and the difference is economically small. With trader fixed effects, the difference is statistically significant with a $t$-statistic of 2.17 but remains small in economic terms.

Overall, we do not find strong evidence of skewness in realized dollar profits of option trades.

### 4.4 Multi-Leg Strategies

Options are commonly viewed by academics and practitioners as building blocks to construct customizable payoffs. For example, a call spread creates limited-risk directional exposure by pairing a long call with higher strike to a short call with lower strike on the same underlying, or a covered call "generates yield" by combining a long stock with a short call. These multi-leg "complex" strategies allow investors to build positions with custom risk-reward profiles that simple directional trades cannot achieve.

While Li et al. (2023) find that about one-third of all option trades are flagged as complex in OPRA during our sample period, with vertical spreads being the most prevalent, this estimate likely understates their true prevalence. The multi-leg flag in OPRA is only triggered if a trade involving multiple options is simultaneously executed in the special complex order book, but such positions can also be established through separate trades rather than simultaneous complex orders. Furthermore, OPRA only covers option trades and its complex trade flags exclude stock-option combinations such as covered calls.

Our data offer unique insights into retail investors' use of multi-leg strategies since we observe all trades by an investor, whether executed simultaneously or not. Moreover, by tracking both stock and option trades for each investor, we provide the first direct analysis of covered calls and protective puts. We focus on four widely-recognized complex strategies featured in textbooks and broker tutorials: call spreads, put spreads, covered calls, and protective puts. We classify trades as complex based on same-day position combinations. A call spread is identified when an investor buys a call and sells a different-strike call. Covered calls and protective puts are identified when stock positions are established alongside their respective option trades on the same day.

We provide an upper bound on the fraction of option-only strategies. For instance, we misclassify a trade as complex if an investor buys a call in the morning, sells it by mid-day, and then shorts a call in the afternoon.[18] Similarly, an iron condor—a combination of call spread and put spread—counts as two complex trades instead of one. We could underestimate the fraction of covered calls if the investor already owns the stock. However, establishing positions on different days is unlikely in our sample due to short holding periods.

Table 9 reports the frequency of complex strategies that we study across traders. Strikingly, *stock-option* combinations are rare despite university courses and retail brokers promoting such strategies. Covered calls and protective puts account each for just 0.2% of our option trades. Even at the 90th percentile across all traders, they jointly account for about 0.3% of trades. This scarcity of stock-option combinations suggests that stock and option trading can be analyzed independently—a notable finding for retail trading studies that typically observe only one market.

Li et al. (2023)) find that vertical spreads—buying and selling calls (or puts) with different strikes but same expiry—are the most popular complex option strategy, comprising 10% of all option trades. In our retail sample, however, these spreads represent at most 8% of parent option trades. Thus, retail investors seem to use complex strategies less frequently than others. However, there is substantial heterogeneity across traders, and some of our traders appear to heavily rely on trading option spreads.

Overall, while educational resources advertise complex strategies as an essential part of the option trading toolbox, our retail investors prefer simple strategies that involve trading one option at a time. These results, together with short holding periods, also suggest that retail traders use options primarily for speculation rather than hedging.

# 5 Trader Heterogeneity

In this section, we document trader heterogeneity in our data and evaluate how our main results vary across trader subsamples. We also discuss an important subsample of trades: 0DTE trades.

[18] Complex trades are classified using the trade entry date, which is available for all parent trades. Intraday timestamps are available only for a subset of the trades.

### 5.1 Trader Subsamples

We examine how our main results vary across ten trader subsamples categorized by trading horizon, trade size, trading activity level, broker, and option-stock choice. We classify day traders versus longer-horizon traders based on whether their median trade duration exceeds one day. Large versus small traders are distinguished using median trade sizes of $5,000 and $200, respectively. Active traders execute more than 30 trades monthly, while less active traders execute fewer than 10. We compare traders across two major brokers in our sample: TD Ameritrade and Interactive Brokers. Lastly, we contrast traders who trade only options with those who trade both stocks and options. The above thresholds are chosen to ensure adequate sample sizes in each category while showcasing the substantial heterogeneity across traders in our data.

Within each trader sample, we compute key statistics characterizing our main results. These 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 sample under consideration), measures of per-dollar and total dollar leverage, median dollar return skewness for stock and option trades, and median of traders' average stock and option returns. For example, we compute the average return on option trades for each trader and then take the median across all traders in a subsample.

Table 10 shows that the main results are broadly robust across these trader subsamples. First, for all subsamples, option trading is concentrated in few underlying symbols, while stock trading is much more dispersed. Top ten symbols typically account for 50 to 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%).

Second, all subsamples are close to breaking even on their stock trades and lose on average $-0.9\%$ to $-3.4\%$ on their option trades. Small-stake traders, who are presumably less sophisticated, lose the most per option trade ($-3.4\%$) and stock trade ($-0.3\%$).

Third, retail traders use options as an affordable way to trade high-priced stocks. Within all trader subsamples, the 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.

Fourth, per-dollar invested option returns show high leverage, especially for the large trader sample. However, the realized total dollar leverage only ranges between 1.29 and 2.53, consistent with our finding that retail investors do not fully utilize option-embedded leverage, instead downsizing their option trades.

Finally, realized dollar return skewness is consistent across all traders' samples. The dollar return distribution is slightly negatively skewed with similar magnitude for stock and option trades. For example, dollar return skewness for multi-day traders is $-0.24$ for stock trades and $-0.14$ for option trades.

Trader heterogeneity is crucial, as highlighted in studies on specific retail investor groups like Robinhood users (Welch (2022); Fedyk (2022)). Despite variations in magnitudes, our main results are consistent across investor groups within our data set.

### 5.2 0DTE Trades

There are growing concerns that the surge in zero days to expiration (0DTE) option trading could potentially trigger market instability (e.g., Brogaard, Han, and Won (2023); Dim, Eraker, and Vilkov (2024); Adams, Fontaine, and Ornthanalai (2024)). We do not directly address these policy concerns but instead contrast 0DTE trades to non-0DTE trades with the aim to provide stylized facts about 0DTE retail option trading in our data.

0DTE options have seen a dramatic rise in popularity, now representing nearly half of all SPX option trades (e.g., Beckmeyer et al. (2023)). Our retail trading data confirms this trend: 0DTE trades comprise 23.7% of all option trades in our sample, with their share nearly tripling from 11.7% in 2020 to 32.8% in 2022.

In Table IA.7, we compare the properties of 0DTE and non-0DTE option trades for equity and index options separately. 0DTE index trades account for 70.8% of 0DTE trades, whereas non-0DTE index trades account for 23.1% of non-0DTE trades. A vast majority of 0DTE trades start with an option purchase. The difference is large for non-index trades: 97.1% 0DTE versus 84.5%. The underlying price for 0DTE trades is higher ($641 vs. $365, excluding index trades), consistent with retail investors preferring shorter-term options on high-priced stocks.

In Table 3, 0DTE trades underperform other option trades by 3%. Similarly, Table IA.7 shows that the average return of 0DTE trades is about $-4.6\%$ with little difference between index and non-index trades. Among non-index trades, retail losses are concentrated in 0DTE options. As suggested by option pricing theory, short-term options exhibit higher embedded leverage and have lower prices. Consequently, the average trade size for 0DTE trades is much smaller, at $1,077 for index trades and $1,044 for non-index trades. This compares to $2,927 non-0DTE index trades and $2,053.4 for non-0DTE other trades. The smaller trade size of 0DTE trades translates into dollar losses per trade that are fairly close to non-0DTE trades for index trades: −$44.8 versus −$32.0.

## 6 Validating Aggregate Retail Measures

In this section, we use our retail data to help validate widely-used retail proxies of stock and option trading. These proxies, in turn, help validate the reliability of our retail data set.

We first show that stock trade imbalance in our data is positively correlated with aggregate measures of retail stock trading. We compute 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 and compute the imbalance at the weekly and monthly frequencies. We benchmark our imbalance measure against two well-known 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)).[19] Availability of RobinTrack data limits the sample period for this test to January 2020 until 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 IA.5 in the Internet Appendix reports regressions of the stock trade imbalance in our data set on the Robinhood users 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 univariate regressions, each of these imbalance measures is 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 0.21 standard deviation increase in our monthly trade imbalance, even though our data does not include Robinhood trades.

[19] Barber et al. (2022) and Battalio et al. (2023) evaluate the BJZZ measure and suggest improvements to the measure.

Interestingly, once all three proxies are included in the joint regression, the Lee-Ready imbalance becomes statistically insignificant while the BJZZ imbalance and Robinhood users change remain strongly statistically 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.

Second, we examine the proxy for retail option volume proposed by Bryzgalova et al. (2022). They classify option trades flagged SLAN in OPRA as retail and share. We use SLAN volume aggregated each day by underlying and option type.[20] In order to isolate retail volume and mitigate the influence of non-retail activity, we control for total option volume obtained from OPRA. Due to sparsity in our data, we aggregate volume measures at the weekly and monthly frequencies.

Table 11 reports panel regressions of retail option trade count on single-leg auction volume, controlling for total option volume. Date fixed effects control for market-wide volume dynamics. As before, we standardize all variables within stock. Single-leg auction volume is positively associated with both call and put option trade volumes in our data at both weekly and monthly frequencies with all coefficients being statistically significant at the 1% level. For example, a one standard deviation (within stock) increase in weekly SLAN call volume is associated with a 0.09 standard deviation increase in retail call trade count in our data, controlling for total option volume. The results provide support for the use of SLAN option volume as a measure of retail option trading.

# 7 Conclusion

In this paper, we leverage novel trader-level data to provide the first detailed analysis of how modern U.S. retail investors trade options and stocks.

Our analysis reveals several key findings in our data. First, options have evolved from a supplementary instrument to rivaling stocks as retail investors' primary vehicle for short-term speculation. Second, a typical option trade involves buying a short-term option on a high-priced stock or the S&P 500 and closing the position within hours. Third, options serve a distinct role in retail portfolios rather than act as substitutes for stocks. While stock trades are dispersed across many tickers, option trading is concentrated in few underlyings. Fourth, trading losses are non-negligible but

[20]We thank Taisiya Sikorskaya for providing the data through her website.

relatively small compared to typical bid-ask spreads. Concerning trading motives, we find limited evidence of leverage or skewness seeking in realized total dollar option profits. Option trades are smaller than stock trades, partially mitigating embedded leverage, and their realized dollar returns show no positive skewness despite their lottery-like payoffs. Instead, retail investors appear drawn to options as an affordable mean to trade high-priced stocks, which is supported by causal evidence from stock splits. Retail option trading is dominated by short-term speculation rather than hedging, with almost no covered calls and protective puts.

Retail investors in our data show remarkable trading heterogeneity, which challenges the notion of a "typical" retail trader and emphasizes why studying different segments of the retail population is crucial. While our sample consists of (presumably) more sophisticated investors, our main findings hold across different types of traders, whether we segment them by their trading frequency, position sizes, holding periods, or choice of broker. Though this consistency across different trader groups suggests that our findings may apply more broadly, we acknowledge the need for caution since our data captures only one slice of the retail trading landscape.

Our findings raise several questions for future research. Understanding how behavioral factors shape short-term option trading strategies and how retail traders navigate wide bid-ask spreads deserves particular attention. Moreover, while our analyses suggest measured rather than reckless risk-taking, examining this finding across other retail samples would be valuable. These research avenues grow more important as retail traders increasingly shape options markets.

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

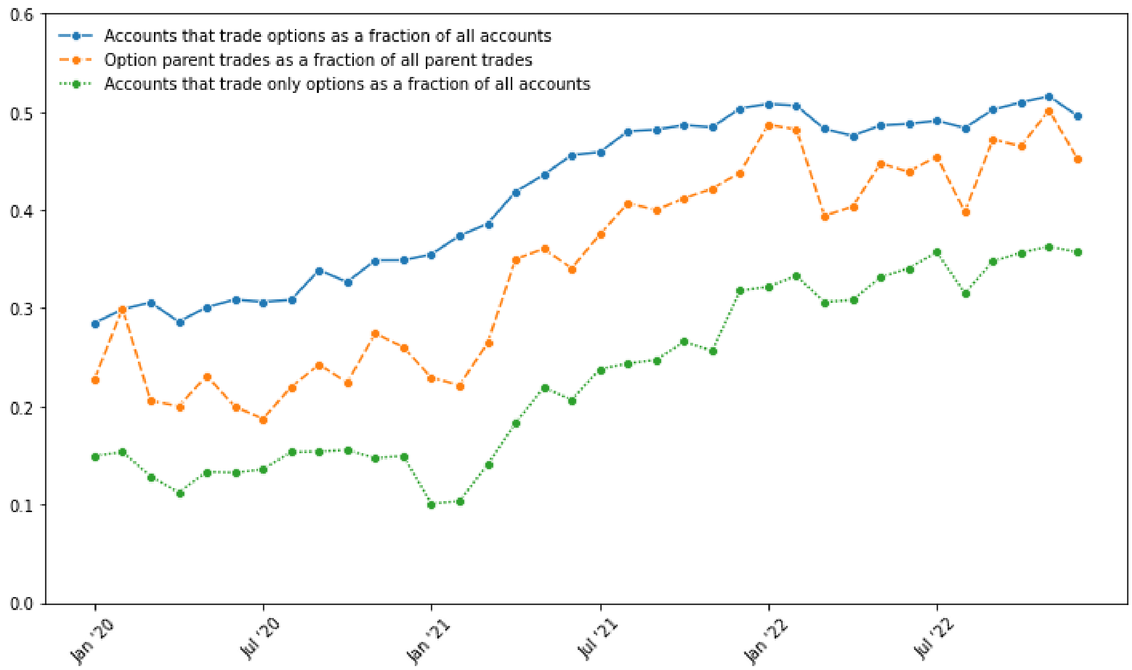

**Figure 2.** Top ten most active stocks and option underlyings as a fraction of all option trades (top plot) or stock trades (bottom plot). We report the share of non-top tickers at the bottom to highlight the difference in trade concentration between stocks and options.

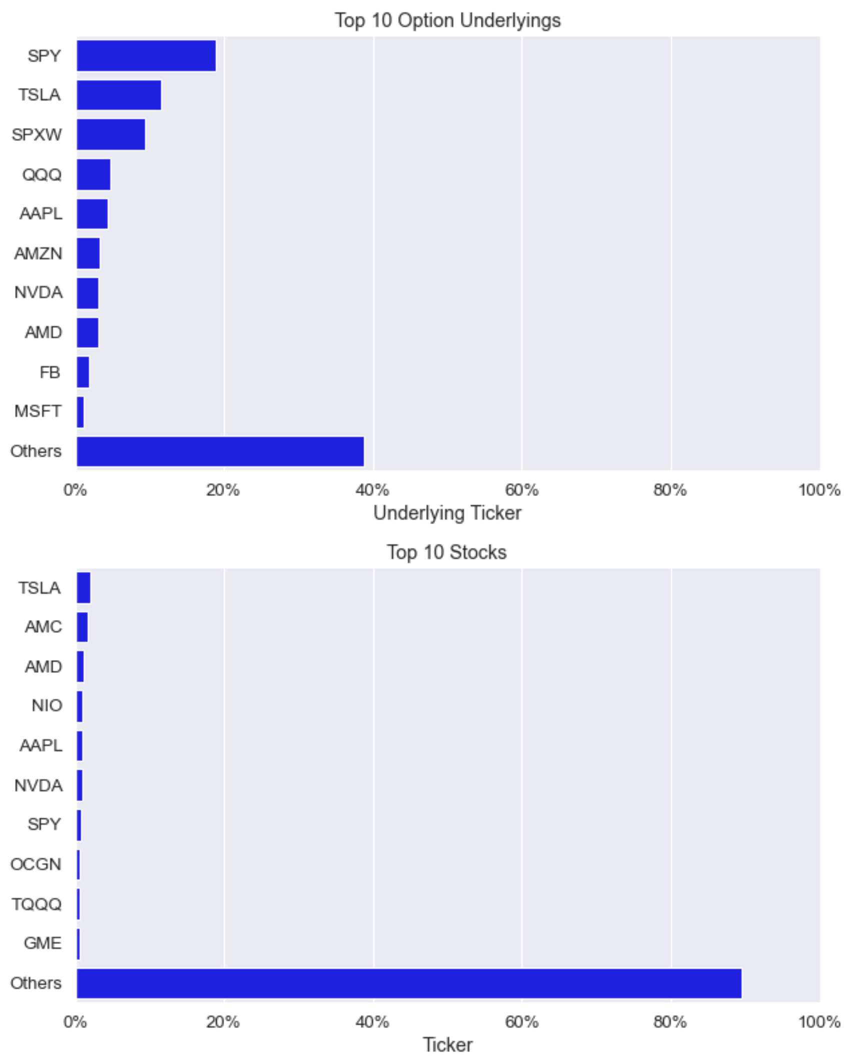

**Table 1.** Trader descriptive statistics. This table reports descriptive statistics for traders in our sample, which spans 1/2020 to 12/2022. For example, the number of stock round-trip trades is computed for each account (account-month), and descriptive statistics across accounts are reported in the 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 | 487.9 | 26.0 | 87.0 | 296.0 | 757.8 | 998.0 | 5,182 |
| # Stock round-trip trades | 294.4 | 442.6 | 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 | 90.2 | 99.5 | 5,182 |
| Unique stocks | 98.4 | 118.8 | 5.0 | 15.0 | 52.0 | 143.0 | 270.0 | 4,781 |
| Unique option underlyings | 42.5 | 48.8 | 3.0 | 8.0 | 25.0 | 58.0 | 107.0 | 2,720 |
| Average $ trade size (stock) | 8,777 | 51,737 | 182 | 513 | 1,676 | 5,573 | 15,325 | 2,403 |
| 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 | 56.3 | 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 | 43,685 |
| Unique option underlyings | 9.2 | 11.1 | 1.0 | 2.0 | 5.0 | 12.0 | 22.0 | 25,889 |
| Average $ trade size (stock) | 7,793 | 58,053 | 149 | 449 | 1,477 | 4,778 | 13,482 | 20,826 |
| 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%. Index stock (option) trades are trades in the following securities (underlyings): SPX, SPXW, SPY, XSP, QQQ, XND, NDX, TQQQ, IWM. 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), as well as time to expiration (264,054 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 | 1,525,356 |
| Short | 0.37 | 0.48 | 0.00 | 0.00 | 0.00 | 1.00 | 1.00 | 1,525,356 |
| Index/Regular ETF | 0.02 | 0.13 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1,525,356 |
| Day trade | 0.88 | 0.32 | 0.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1,525,356 |
| Return | 0.00 | 0.11 | −0.05 | −0.02 | 0.00 | 0.02 | 0.06 | 1,525,356 |
| Stock price ($) | 53.11 | 179.06 | 1.95 | 3.53 | 8.35 | 26.88 | 121.68 | 1,525,356 |
| Trade size (shares) | 747 | 4,324 | 10 | 50 | 150 | 500 | 1,380 | 655,087 |
| Trade size ($) | 8,800 | 87,085 | 177 | 486 | 1,620 | 5,246 | 16,924 | 655,087 |
| Holding period (hours) | 59.88 | 501.39 | 0.00 | 0.02 | 0.12 | 1.00 | 24.00 | 655,087 |

(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 |
| Call moneyness | 0.97 | 0.05 | 0.88 | 0.95 | 0.98 | 1.00 | 1.01 | 528,284 |
| Put moneyness | 0.97 | 0.05 | 0.90 | 0.96 | 0.99 | 1.00 | 1.01 | 361,683 |
| 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 ($) | 389.99 | 583.72 | 25.45 | 87.84 | 262.47 | 416.58 | 778.80 | 802,651 |
| Trade size (contracts) | 6 | 68 | 1 | 1 | 1 | 3 | 10 | 299,017 |
| Trade size ($) | 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 |
| Hours to expiration | 326.32 | 1116.50 | 4.58 | 24.78 | 72.43 | 198.32 | 744.02 | 264,054 |

**Table 3.** Return on option trades. This table regresses option trade returns on a constant and indicator variables. We include indicators for short sales (naked option writing), call option, 0DTE trade, index or ETF underlying, pre sign-up trade. The pre sign-up trade indicator takes the value one for any trade that is completed before the journal 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. Standard errors are double-clustered by trader and date, and the associated $t$-statistic are reported in parentheses, where *, **, and *** denote significance at the 10%, 5%, and 1% level.

| | Return (option trade) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Constant | -0.0093*** | -0.0395*** | -0.0062 | 0.0019 | 0.0015 | -0.0131*** | -0.0310*** | -0.0411*** | -0.0440*** |
| | (-3.57) | (-14.24) | (-1.56) | (0.65) | (0.45) | (-4.15) | (-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) |
| Pre sign-up | | | | | | 0.0072* | 0.0032 | 0.0046 | 0.0125*** |
| | | | | | | (1.84) | (0.88) | (1.34) | (3.32) |
| 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 | 0.0101 | 0.0000 | 0.0006 | 0.0004 | 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 |

**Table 4.** Dollar profits per trader-month. Each month, profits on stock and option trades are summed for each trader. Trader-month profits are regressed on an indicator for option trades and fixed effects. In some specifications, the sample is restricted to stock-only traders, option-only traders, and joint (stock-option) traders. Post sign-up trades refer to trades that are executed after the journal account creation date. Dollar gain is winsorized at the levels of 0.5% and 99.5%. Standard errors are double-clustered by trader and date, and the associated $t$-statistic are reported in parentheses, where *, **, and *** denote significance at the 10%, 5%, and 1% level.

| | (a) Net dollar gain per trader-month (all trades) | | | | | |
|---|---|---|---|---|---|---|
| | All | All | All | Stock-only | Option-only | Joint |
| Constant | 82.85 | 68.61 | | 221.52* | −549.03*** | −114.85 |
| | (0.90) | (1.04) | | (1.81) | (−3.63) | (−1.13) |
| Option | −551.58*** | −508.91*** | −209.18 | | | −344.27*** |
| | (−4.58) | (−4.12) | (−1.56) | | | (−2.96) |
| Date FE | No | Yes | Yes | No | No | No |
| Trader FE | No | No | Yes | No | No | No |
| Adj. $R^2$ | 0.0024 | 0.0020 | 0.0002 | 0.0000 | -0.0000 | 0.0011 |
| Obs. | 36,188 | 36,188 | 36,188 | 14,174 | 1,291 | 20,723 |

| | (b) Net dollar gain per trader-month (post sign-up trades) | | | | | |
|---|---|---|---|---|---|---|
| | All | All | All | Stock-only | Option-only | Joint |
| Constant | −39.65 | −58.14 | | 62.46 | −547.49*** | −199.67* |
| | (−0.38) | (−0.74) | | (0.44) | (−3.78) | (−1.69) |
| Option | −444.01*** | −387.70*** | −157.23 | | | −276.17* |
| | (−3.20) | (−2.64) | (−0.86) | | | (−1.96) |
| Date FE | No | Yes | Yes | No | No | No |
| Trader FE | No | No | Yes | No | No | No |
| Adj. $R^2$ | 0.0014 | 0.0010 | 0.0001 | 0.0000 | 0.0000 | 0.0006 |
| Obs. | 24,916 | 24,916 | 24,916 | 10,217 | 893 | 13,806 |

**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. IdioVol (IdioSkew) 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. SentimentSA is investor sentiment measured with SeekingAlpha authors' belief about the stock's future prospects. In Column (5), the sample is restricted to optionable stocks only. Index/ETF trades are excluded. Standard errors are clustered by date, and the associated $t$-statistic are reported in parentheses, where *, **, and *** denote significance at the 10%, 5%, and 1% level.

| | I(1 if option trade, 0 if stock trade) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| LogPrice | 0.129*** | 0.044*** | 0.019*** | 0.037*** | 0.044*** | 0.093*** |
| | (37.77) | (15.81) | (13.74) | (9.52) | (9.04) | (3.84) |
| IdioVol | | -0.372** | -0.209*** | -0.047 | -0.021 | 0.255 |
| | | (-2.10) | (-3.68) | (-0.37) | (-0.12) | (0.98) |
| IdioSkew | | -0.006** | -0.002** | -0.003 | -0.004 | -0.002 |
| | | (-2.01) | (-2.29) | (-0.93) | (-1.30) | (-0.27) |
| MaxRet | | 0.047 | 0.031** | -0.007 | -0.018 | -0.035 |
| | | (1.16) | (2.21) | (-0.24) | (-0.47) | (-0.65) |
| Beta | | -0.010*** | -0.002** | -0.003 | -0.004 | -0.028*** |
| | | (-4.06) | (-2.02) | (-0.59) | (-0.73) | (-4.30) |
| LogMktCap | | 0.051*** | 0.020*** | 0.002 | 0.006 | -0.066** |
| | | (20.25) | (20.48) | (0.34) | (0.86) | (-2.31) |
| SentimentSA | | | | | | 0.004 |
| | | | | | | (0.60) |
| Month-Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Trader FE | No | No | Yes | No | No | No |
| Stock FE | No | No | No | Yes | Yes | Yes |
| Stocks | All | All | All | All | Opt. only | All |
| Adj. $R^2$ | 0.3800 | 0.4128 | 0.1169 | 0.0035 | 0.0046 | 0.0053 |
| Obs. | 1,700,159 | 1,700,159 | 1,700,159 | 1,700,159 | 1,356,317 | 194,759 |

**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, and the associated $t$-statistic are reported in parentheses, where *, **, and *** denote significance at the 10%, 5%, and 1% level.

| | (1)<br>Treated stock trade | (2)<br>Treated option trade | (3)<br>Option trade |
|---|---|---|---|
| Post split | 0.117** | −0.064* | 0.034 |
| | (2.00) | (−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. $R^2$ | 0.0165 | 0.0064 | 0.0154 |
| Obs. | 37,598 | 132,573 | 170,171 |

**Table 7.** Distribution of percentage return and dollar return. We consider four samples: all trades, purchases only, and purchases excluding pre sign-up trades (e.g., covered calls). We report returns separately for stock and option trades. A trade is defined as pre sign-up 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 |
| *(a) All trades* | | | | | | | | | | |
| % return (stock) | −0.37 | −0.26 | −0.05 | −0.02 | 0.00 | 0.02 | 0.06 | 0.25 | 0.36 | 788,114 |
| % return (option) | −2.10 | −1.24 | −0.72 | −0.21 | 0.01 | 0.17 | 0.62 | 1.73 | 2.59 | 357,857 |
| $ return (stock) | −3488 | −1827 | −123 | −23 | 0 | 28 | 139 | 1808 | 3500 | 788,114 |
| $ return (option) | −8531 | −4200 | −309 | −61 | 1 | 60 | 287 | 3611 | 7403 | 357,857 |
| *(b) Buy trades only* | | | | | | | | | | |
| % return (stock) | −0.42 | −0.29 | −0.06 | −0.02 | 0.00 | 0.01 | 0.05 | 0.29 | 0.46 | 477,707 |
| % return (option) | −1.00 | −1.00 | −0.71 | −0.22 | 0.00 | 0.11 | 0.35 | 1.87 | 2.85 | 309,471 |
| $ return (stock) | −3029 | −1583 | −109 | −21 | −0 | 17 | 91 | 1179 | 2351 | 477,707 |
| $ return (option) | −6915 | −3502 | −296 | −66 | 0 | 48 | 217 | 2523 | 5051 | 309,471 |
| *(c) Buy trades only, post sign-up trades* | | | | | | | | | | |
| % return (stock) | −0.45 | −0.31 | −0.06 | −0.02 | −0.00 | 0.01 | 0.05 | 0.28 | 0.43 | 306,365 |
| % return (option) | −1.00 | −1.00 | −0.69 | −0.22 | 0.00 | 0.11 | 0.34 | 1.84 | 2.78 | 202,783 |
| $ return (stock) | −3550 | −1781 | −113 | −22 | −0 | 17 | 90 | 1300 | 2672 | 306,365 |
| $ return (option) | −7547 | −3700 | −309 | −67 | 0 | 48 | 227 | 2661 | 5373 | 202,783 |

**Table 8.** Leverage. In this table, we regress the log of absolute percentage gain, trade size, and absolute dollar gain on an indicator for option trades (Panel (a)) and fixed effects (Panel (b)). The row "Leverage" indicates the implied of option trades relative to stock trades from the regression and is computed as $e^b$, where $b$ is the estimate coefficient on the option trade indicator variable. The sample is restricted to *buy trades*. Dollar gain and dollar trade size are winsorized at the levels of 0.5% and 99.5%. Standard errors are clustered by underlying, and the associated $t$-statistic are reported in parentheses, where *, **, and *** denote significance at the 10%, 5%, and 1% level.

| Panel (a): Regression | | | |
|---|---|---|---|
| | (1) log \|net % gain\| | (2) log $ trade size | (3) log \|net $ gain\| |
| Option | 2.216*** | -1.180*** | 1.038*** |
| | (37.28) | (-10.36) | (8.06) |
| Constant | -4.190*** | 7.104*** | 2.945*** |
| | (-78.91) | (123.10) | (180.20) |
| Adj. $R^2$ | 0.3031 | 0.0955 | 0.0625 |
| Obs. | 659,036 | 659,036 | 659,036 |
| Leverage | 9.17 | 0.31 | 2.82 |

| Panel (b): Regression with fixed effects | | | |
|---|---|---|---|
| | (1) log \|net % gain\| | (2) log $ trade size | (3) log \|net $ gain\| |
| Option | 2.687*** | -1.795*** | 0.919*** |
| | (34.98) | (-32.91) | (31.43) |
| Underlying FE | Yes | Yes | Yes |
| Trader FE | Yes | Yes | Yes |
| Adj. $R^2$ | 0.1330 | 0.1005 | 0.0148 |
| Obs. | 659,036 | 659,036 | 659,036 |
| Leverage | 14.69 | 0.17 | 2.51 |

**Table 9.** Prevalence of multi-leg option and option-stock strategies. This table reports reports descriptive statistics on the fraction of specific complex option trades among all option trades. The first "Mean" column reports the mean across all trades. The other columns reports descriptive statistics across accounts. 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), 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 | $N$ |
| Covered call | 0.002 | 0.004 | 0.020 | 0.000 | 0.000 | 0.000 | 0.000 | 0.002 | 2,720 |
| Protective put | 0.002 | 0.005 | 0.050 | 0.000 | 0.000 | 0.000 | 0.000 | 0.003 | 2,720 |
| Call spread | 0.039 | 0.042 | 0.106 | 0.000 | 0.000 | 0.000 | 0.012 | 0.158 | 2,720 |
| Put spread | 0.039 | 0.041 | 0.109 | 0.000 | 0.000 | 0.000 | 0.007 | 0.146 | 2,720 |

**Table 10.** Results across traders' subsamples. This table examines multiple traders' subsamples: traders with a median trade duration lower or equal than one day (≤ 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 whose broker is TD Ameritrade (TD), traders whose broker is Interactive Brokers (IB), 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, median of traders' average stock and option returns, and median of traders' ratio of average absolute option return to average absolute stock return. 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 and leverage (option-to-stock absolute return) 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%. Dollar gain is winsorized at the levels of 0.5% and 99.5%.

| | Trader subsample | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Horizon | | Trade size | | Trades/month | | Broker | | Stock-option | Option-only |
| | ≤ 1 day | > 1 day | < \$200 | > \$5,000 | < 10 | > 30 | TD | IB | | |
| Top 10 (stock) | 0.12 | 0.11 | 0.08 | 0.17 | 0.11 | 0.13 | 0.15 | 0.18 | 0.16 | - |
| Top 10 (option) | 0.64 | 0.33 | 0.47 | 0.49 | 0.45 | 0.61 | 0.56 | 0.54 | 0.52 | 0.69 |
| Return (stock) | −0.001 | 0.000 | −0.003 | 0.001 | −0.001 | −0.001 | −0.001 | −0.002 | −0.001 | - |
| Return (option) | −0.024 | −0.009 | −0.034 | −0.014 | −0.026 | −0.017 | −0.025 | −0.011 | −0.021 | −0.026 |
| Price (stock) | \$49.32 | \$97.28 | \$25.82 | \$85.46 | \$58.83 | \$52.44 | \$83.56 | \$103.39 | \$76.22 | - |
| Price (underlying) | \$419.02 | \$307.23 | \$268.67 | \$497.78 | \$325.51 | \$427.22 | \$398.05 | \$569.73 | \$380.43 | \$457.98 |
| Option-to-stock \|%ret\| | 5.93 | 5.89 | 4.89 | 14.99 | 4.53 | 7.20 | 5.03 | 7.93 | 5.91 | - |
| Option-to-stock \|\$ret\| | 1.84 | 1.72 | 2.53 | 1.29 | 1.53 | 1.87 | 2.03 | 1.39 | 1.81 | - |
| Skew \$ (stock) | −1.38 | −0.24 | −0.54 | −1.12 | −0.45 | −1.58 | −0.89 | −0.38 | −0.93 | - |
| Skew \$ (option) | −1.19 | −0.14 | −0.40 | −1.01 | −0.44 | −1.00 | −1.20 | −0.48 | −0.56 | −0.93 |
| Unique traders | 3,878 | 1,304 | 507 | 332 | 1,494 | 1,982 | 1,017 | 390 | 2,319 | 401 |

**Table 11.** 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 (OPRA). All the variables are standardized within stock. The sample period is from January 2020 to December 2022. Standard errors are clustered by date, and the associated $t$-statistic are reported in parentheses, where *, **, and *** denote significance at the 10%, 5%, and 1% level. $t$-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) | 0.094*** | | 0.074*** | |
| | (6.84) | | (5.45) | |
| Call volume (total) | 0.211*** | | 0.290*** | |
| | (12.78) | | (16.09) | |
| Put volume (auction) | | 0.090*** | | 0.084*** |
| | | (7.80) | | (3.71) |
| Put volume (total) | | 0.170*** | | 0.224*** |
| | | (16.33) | | (10.28) |
| Date FE | Yes | Yes | Yes | Yes |
| Adj. $R^2$ | 0.1774 | 0.1210 | 0.1764 | 0.1228 |
| Obs. | 22,160 | 21,654 | 9,850 | 9,428 |

# Internet Appendix to "An Anatomy of Retail Option Trading"

This Internet Appendix reports additional results and tables to supplement the main text.

## IA.A Additional Results

### IA.A.1 Switch to Zero Commission

Retail traders are attracted to zero commissions. The introduction of zero-commission policies should therefore increase retail participation, which helps validate our data. We examine this through a difference-in-difference analysis around TD Ameritrade's (TD) switch to zero commissions on October 3, 2019.[1] We compare TD's trading volume to TradeZero (TZ), a broker that already offered commission-free trading.

To isolate the effect of TD's commission change, we analyze a two-month window from September 1 to October 31, capturing 5,770 TZ trades and 2,846 TD trades. While this period precedes our main sample, it provides a clean identification of the zero-commission effect. Our difference-in-difference regression compares standardized daily trading volumes between TD and TZ, using indicator variables for the post-change period, TD trades, and their interaction. The results, presented in Internet Appendix Table IA.6, show TD's trading volume increased by 52.8% relative to TZ after eliminating commissions, with a statistically significant $t$-statistic of 2.74. Thus, retail investors' response to TD Ameritrade's zero-commission policy is as expected.

## IA.B Additional Tables

[1]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

**Table IA.1.** Trade descriptive statistics with additional stock/index and long/short splits. This table reports additional descriptive statistics for the trades in our sample to complement Table 2. 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. 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%. Index stock (option) trades are trades in the following securities (underlyings): SPX, SPXW, SPY, XSP, QQQ, XND, NDX, TQQQ, IWM.

| | Option parent trade | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Mean | StDev | 0.1 | 0.25 | 0.5 | 0.75 | 0.9 | N |
| Long call (stock) | 0.38 | 0.49 | 0.00 | 0.00 | 0.00 | 1.00 | 1.00 | 889,967 |
| Short call (stock) | 0.05 | 0.22 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 889,967 |
| Long put (stock) | 0.18 | 0.38 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 889,967 |
| Short put (stock) | 0.04 | 0.20 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 889,967 |
| Long call (index) | 0.14 | 0.35 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 889,967 |
| Short call (index) | 0.01 | 0.12 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 889,967 |
| Long put (index) | 0.17 | 0.37 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 889,967 |
| Short put (index) | 0.02 | 0.14 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 889,967 |
| 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 |
| Long moneyness | 0.97 | 0.05 | 0.90 | 0.96 | 0.99 | 1.00 | 1.01 | 776,968 |
| Short moneyness | 0.94 | 0.07 | 0.82 | 0.90 | 0.96 | 0.99 | 1.01 | 112,999 |

**Table IA.2.** 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 and excludes index option trades.

| | Mean | StDev | 0.1 | 0.25 | 0.5 | 0.75 | 0.9 | N |
|---|---|---|---|---|---|---|---|---|
| Brokers that do not allow fractional share trading | | | | | | | | |
| Stock price ($) | 49.26 | 174.60 | 1.98 | 3.55 | 8.13 | 23.40 | 107.46 | 1,030,231 |
| Underlying stock price ($) | 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 |

**Table IA.3.** Absolute dollar profit. In this table, we regress the absolute dollar profit and trade size on an indicator for option trades and fixed effects. Panel (a) considers all trades. Panel (b) restricts the sample to buy trades. Panel (c) excludes multiple option trades in the same day for any trader. Dollar gain and dollar trade size are winsorized at the levels of 0.5% and 99.5%. Standard errors are double-clustered by trader and date, and the associated $t$-statistic are reported in parentheses, where *, **, and *** denote significance at the 10%, 5%, and 1% level.

| Panel (a): Regression | | | | |
|---|---|---|---|---|
| | \|Net dollar gain\| | \|Net dollar gain\| | $ trade size | $ trade size |
| Option | 137.024*** | 119.185*** | −5758.962*** | −6199.278*** |
| | (6.91) | (6.87) | (−12.03) | (−8.42) |
| Date FE | Yes | Yes | Yes | Yes |
| Trader FE | No | Yes | No | Yes |
| Adj. $R^2$ | 0.0104 | 0.0026 | 0.0301 | 0.0145 |
| Obs. | 954,104 | 954,104 | 954,104 | 954,104 |

| Panel (b): Regression - buy trades only | | | | |
|---|---|---|---|---|
| | \|Net dollar gain\| | \|Net dollar gain\| | $ trade size | $ trade size |
| Option | 134.916*** | 109.758*** | −4618.304*** | −4801.265*** |
| | (8.54) | (7.73) | (−11.35) | (−9.67) |
| Date FE | Yes | Yes | Yes | Yes |
| Trader FE | No | Yes | No | Yes |
| Adj. $R^2$ | 0.0151 | 0.0036 | 0.0322 | 0.0166 |
| Obs. | 659,036 | 659,036 | 659,036 | 659,036 |

| Panel (c): Regression - one option trade per trader-day only | | | | |
|---|---|---|---|---|
| | \|Net dollar gain\| | \|Net dollar gain\| | $ trade size | $ trade size |
| Option | 136.921*** | 120.980*** | −6152.400*** | −5848.964*** |
| | (7.59) | (6.82) | (−13.46) | (−8.86) |
| Date FE | Yes | Yes | Yes | Yes |
| Trader FE | No | Yes | No | Yes |
| Adj. $R^2$ | 0.0027 | 0.0014 | 0.0058 | 0.0044 |
| Obs. | 686,273 | 686,273 | 686,273 | 686,273 |

**Table IA.4.** Skewness of percentage return and dollar return. 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 | 0.377*** | | -0.887*** | |
| | (6.79) | | (-10.41) | |
| Option | 0.855*** | 0.937*** | 0.155 | 0.277** |
| | (9.04) | (10.52) | (1.18) | (2.22) |
| Trader FE | No | Yes | No | Yes |
| Adj. $R^2$ | 0.0207 | 0.0558 | 0.0001 | 0.0026 |
| Obs. | 3,739 | 3,739 | 3,739 | 3,739 |

**Table IA.5.** 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, and the associated $t$-statistic are reported in parentheses, where *, **, and *** denote significance at the 10%, 5%, and 1% level. $t$-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 | 0.153*** | | | 0.110*** | 0.209*** | | | 0.144*** |
| | (14.20) | | | (9.52) | (14.47) | | | (8.81) |
| TAQ retail trade imbalance | | 0.144*** | | 0.065*** | | 0.197*** | | 0.113*** |
| | | (14.64) | | (6.78) | | (23.14) | | (9.01) |
| TAQ trade imbalance | | | 0.078*** | 0.010 | | | 0.103*** | 0.027 |
| | | | (6.68) | (1.03) | | | (4.60) | (1.44) |
| Date FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Adj. $R^2$ | 0.0511 | 0.0407 | 0.0111 | 0.0565 | 0.0551 | 0.0478 | 0.0134 | 0.0683 |
| Obs. | 14,042 | 14,042 | 14,042 | 14,042 | 6,604 | 6,604 | 6,604 | 6,604 |

**Table IA.6.** Number of trades and switch to zero commissions. 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.7.** 0DTE trades. This table reports average characteristics of 0DTE trades and non-0DTE option trades. Long is an indicator for a long trade. Call is an indicator for a call option trade. Index trades are trades in the following underlyings: SPX, SPXW, SPY, XSP, QQQ, XND, NDX, TQQQ, IWM. Returns are winsorized at the levels of 0.01% and 99.99%.

| | 0DTE | | Not 0DTE | |
|---|---|---|---|---|
| | Index | Others | Index | Others |
| Long | 0.918 | 0.971 | 0.887 | 0.845 |
| Call | 0.471 | 0.602 | 0.458 | 0.668 |
| Call moneyness | 0.994 | 0.985 | 0.986 | 0.953 |
| Put moneyness | 0.994 | 0.988 | 0.980 | 0.954 |
| Underlying price (excl. index) | - | 640.11 | - | 365.23 |
| Fraction S&P 500/SPY options | 0.876 | 0.000 | 0.793 | 0.000 |
| Average return | -0.046 | −0.045 | −0.015 | 0.006 |
| Trade size | 1077.3 | 1044.8 | 2927.8 | 2053.4 |
| Average return (dollar) | −44.8 | −41.1 | −32.0 | −17.6 |
| Number of trades | 149,024 | 61,470 | 156,961 | 522,512 |