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Retail Trading in Options and the Rise of the Big Three Wholesalers

SVETLANA BRYZGALOVA, ANNA PAVLOVA, and TAISIYA SIKORSKAYA*

ABSTRACT

We document a rapid increase in retail trading in options in the United States. Facilitated by payment for order flow (PFOF) from wholesalers executing retail orders, retail trading recently reached over 60% of total market volume. Nearly 90% of PFOF comes from three wholesalers. Exploiting new flags in transaction-level data, we isolate wholesaler trades and build a novel measure of retail options trading. Our measure comoves with equity-based retail activity proxies and drops significantly during U.S. brokerage platform outages and trading restrictions. Retail investors prefer cheaper, weekly options with average bid-ask spread of 12.6%, and lose money on average.

THE ADVENT OF ZERO-COMMISSION TRADING in stocks and options has revolutionized retail brokerage services in the United States. Since their

*Svetlana Bryzgalova and Anna Pavlova are at London Business School and CEPR. Taisiya Sikorskaya is at London Business School. Any errors or omissions are the responsibility of the authors. For helpful comments and discussions, we thank Brad Barber; Robert Battalio; James Choi; Thomas Ernst; Francisco Gomes; Ahmed Guecioueur; Björn Hagströmer; Rawley Heimer; Su Li; Camelia Kuhnen; Dmitriy Muravyev; Cameron Peng; Neil Pearson; Veronika Pool; Alessandro Previtero; Mirela Sandulescu; Chester Spatt; Davide Tomio; Dimitri Vayanos; Ivo Welch; Ingrid Werner; conference participants at the 2022 CDI Annual Conference on Derivatives, the 2022 NBER Asset Pricing meeting, the 2022 NBER Behavioral Finance meeting, the 2022 NFA meeting, 12th Annual Miami Behavioral Finance Conference, the 11th TAU Finance Conference, the 2023 AFA meeting, and Cambridge Centre for Alternative Finance; and seminar participants at Chicago Fed, Florida International University, Indiana University, London Business School, London Quant Group, Queen Mary University of London, Stockholm Business School, TMX Group, the University of Central Florida, the University of Notre Dame, and the University of Hong Kong for their thoughtful comments. We thank Brad Barber for providing data on Robinhood investor frenzies and Miguel Chumbo for outstanding research assistance. We have also benefited from conversations with Ed Monrad and Shyam Chandramouli of Optiver and Parker Lim of XTX Markets, in addition to the generous support of the AQR Asset Management Institute at London Business School. We are grateful to NASDAQ Global Data Products for generously sharing the data used in this paper. We have read *The Journal of Finance*'s disclosure policy and have no conflicts of interest to disclose.

Correspondence: Anna Pavlova, London Business School and CEPR;
e-mail: apavlova@london.edu.

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market entry in 2015, the smartphone investing app Robinhood and other commission-free brokerages have attracted an unprecedented inflow of retail customers. At the peak of its popularity in late 2021, Robinhood alone had amassed 21.3 million monthly active users, as reported in the company's quarterly statements. The new generation of retail investors are young and tech-savvy yet amateur investors. A survey by Financial Industry Regulatory Authority (FINRA (2021a)) reports that 38% of investors who opened a (taxable) brokerage account in 2020 did so for the first time. Of these new investors, 22% were between ages 18 and 29 and 66% were under 45 years old. Moreover, a third of first-time investors had account balances of less than $500.

One concern frequently brought up in the context of the recent retail trading boom is related to the controversial practice of payment for order flow (PFOF). Retail brokerages route clients' orders to financial intermediaries (known as wholesalers) for execution and receive PFOF in return. In equities, wholesalers cross this order flow on their private trading platforms, away from national exchanges, and other market makers cannot compete for these orders. This is known as *internalization*. PFOF is a divisive practice because such order flow fragmentation may lead to wider bid-ask spreads on exchanges and because it may incentivize investors to trade more (see SEC (2022)). In June 2022, Gary Gensler, chair of the U.S. Securities and Exchange Commission (SEC), publicly criticized PFOF and order execution quality for retail investors.[1] However, the SEC's attention has focused almost exclusively on equities; in fact, Gensler gave the options market as an example of superior retail order execution. Unlike equities, all options in the United States trade on exchanges, which should mechanically expose option orders to direct competition from other market makers. It is therefore thought that internalization is specific to equities.

In this paper, we argue that much of the retail order flow in options is also effectively internalized. We identify a friction that may hinder competition from other market makers on options exchanges. Specifically, wholesalers frequently execute retail orders through so-called *price improvement mechanisms*, which, as we show, often amounts to internalization. This allows us to isolate wholesaler trades and build a proxy for retail trading in options by exploiting a recently introduced flag for price improvement mechanisms in transaction-level data. We find that our measure of retail trading grew 101% from January 2020 to July 2021, in line with the growth in PFOF for options.[2] Retail traders prefer cheaper, weekly options—the average quoted bid-ask spread for which is as high as 12.6%—and lose money on average. A large fraction of retail order flow is serviced by very few wholesalers: The share in PFOF of the top three has grown to nearly 90% as of the second quarter of 2021.

[1] See https://www.bloomberg.com/news/articles/2022-06-08/sec-chief-takes-aim-at-payment-for-order-flow-in-sweeping-plans

[2] We consider the combined PFOF from the largest U.S. retail brokerages reports under SEC Rule 606 (routing of orders). See Section I.A for the list of brokerages in our sample.

We start by documenting the stylized fact that, although only a fraction of investors trade options, most of the PFOF received by retail brokerages comes from options, not equities. For example, in 2021, U.S. brokerages received $2.4 billion in PFOF for options and only $1.3 billion for equities. The lion's share of PFOF for options came from only three wholesalers: Citadel, Susquehanna, and Wolverine.

Retail brokers in the United States are required to provide the best execution to their clients, so they have an agreement with a wholesaler to provide price improvement relative to the best available bid and ask prices.[3] To do so, they often use an options exchange process known as a price improvement auction or mechanism. Exploiting a flag for price improvement mechanisms, introduced by the Options Price Reporting Authority (OPRA) in November 2019 for transaction-level data, we are able to identify wholesaler trades and build a novel measure of retail trading in options. In our data, these are trades executed through a single-leg price improvement mechanism, which we abbreviate as SLIM.[4] The monthly dollar trading volume in SLIM transactions grew by 101% from January 2020 to July 2021, alongside the PFOF in options (158%).

We show that our measure picks up recent retail investor frenzies in GameStop and other "meme" stocks, as captured by mentions on `WallStreetBets`, an investing forum popular with new retail investors. Furthermore, it is strongly correlated with an alternative retail investor trading measure—small trades in options (up to 10 contracts)—commonly used in the media and industry,[5] as well as with Robinhood user popularity provided by Robintrack and the retail frenzies measure of Barber et al. (2022). We also construct a novel retail popularity measure based on the internalized volume in the underlying stock or exchange-traded fund (ETF) using public data and show that it comoves with SLIM trades in the corresponding options.

We provide several more tests to argue that our measure does indeed capture retail trades. First, SLIM trading in options on tickers popular with retail investors drops significantly during outages on large U.S. retail brokerage platforms. For example, when comparing SLIM trading in the options on the same ticker during the times when these popular trading platforms experience an outage versus normal operation, we find that SLIM trading in options on popular stocks and ETFs declines significantly. Broker platform outages are plausibly exogenous to retail trading in options on a particular ticker. Second, we run a similar test on tickers subject to trading restrictions

[3] Most of the order flow in options received by retail brokerages in our sample is routed to wholesalers. The fraction of orders routed directly to exchanges is small; see Table IA.I in the Internet Appendix. The Internet Appendix is available in the online version of the article on *The Journal of Finance* website.

[4] Specifically, we use OPRA type "SLAN," which stands for single-leg non-ISO price improvement mechanisms. See Section I.B of the Internet Appendix for a description.

[5] For instance, Bloomberg relies on small trades to proxy retail participation in options; see https://www.bloomberg.com/professional/blog/gamestop-highlights-importance-of-option-related-equity-flows/.

imposed by the same retail brokerages in 2021. We find that SLIM trading in those tickers drops significantly, by almost 30%, when all large brokers restrict trading at the same time. Finally, we present more evidence supporting SLIM as a measure of retail trading in options based on expiration-day rules of retail brokerages, stock splits, and call option exercise patterns.

The new generation of retail investors is more tech-savvy and participates in investment forums, but they are still financial novices. It is quite striking that they are so active in options markets, despite much higher bid-ask spreads on options relative to stocks.[6] Notably, 50% of retail trades in our sample are in ultra short-term options, that is, options with less than a week to expiration, with an average quoted bid-ask spread of 12.6%. However, the true trading costs for options may be obfuscated by the zero commissions; an opportunity to trade options is displayed prominently on gamified investing apps used by the new generation of investors.[7] Moreover, on some investing platforms, including Robinhood, weekly options are presented as a default choice to an options trader. In addition, retail investors may be attracted to the cheap way of achieving leverage that these options provide: Embedded leverage in weekly options is very high, often exceeding 50 (see Table IA.IV in the Internet Appendix).

What can our measure tell us about retail investor preferences in options? Retail investors in our sample strongly prefer call options to puts: The volume share in calls is 69%. They further trade mostly at-the-money (72% of trades) or slightly out-of-the-money (23% of trades) options. The latter involve especially high trading costs, with an average quoted bid-ask spread of 29%. In terms of size, 42% of retail trades have a "micro" size of up to $250, and their average quoted bid-ask spread is 23.5%. We document that retail investors prefer options on larger companies, with lower share prices and higher recent trading volume (e.g., attention-grabbing stocks). This result is consistent with the literature on retail participation in equities. We view these cross-sectional relationships as suggestive evidence of speculative rather than hedging motives behind retail trades. Finally, we document significant increases in both call and put net purchases during retail investor frenzies, especially in trades of a smaller size.

Are retail option trades profitable? To answer this question, we analyze the performance of SLIM trades at the one-, two-, five-, and 10-day horizons, as well as that of SLIM trades held until expiration. On aggregate, these trades lose money for all horizons considered. For example, assuming a holding horizon of 10 days, we estimate that the aggregate portfolio of retail investors lost

[6] Muravyev and Pearson (2020) report that the average quoted bid-ask spread of options on stocks in the S&P 500 is as high as 17.2%. In comparison, for S&P 500 stocks, this number is 3.55 basis points (bps) (as reported in Hagströmer (2021)). Higher aggregate PFOF for options relative to that for stocks (see Table IA.III in the Internet Appendix) indicates that executing order flow in options is a lucrative business for wholesalers.

[7] Chapkovski, Khapko, and Zoican (2021) show that gamification induces risk-taking among novice traders, while Kalda et al. (2021) find that trading on smartphones induces investors to purchase riskier and lottery-type assets.

$2.1 billion from November 2019 to June 2021. The bulk of the losses comes from the indirect costs of trading. The aggregate trading costs, measured as the distance from an actual trade price to midquote for all SLIM trades in our sample, amount to a staggering $6.4 billion. This number is much higher than direct trading costs (about $900 million), computed using commissions of retail brokerages in our sample.[8]

We next examine the types of options contracts that retail investors lose money on. Regardless of the performance measure (i.e., dollar performance, per-dollar profitability, or delta-hedged performance), the aggregate net losses are concentrated in trades in short-term contracts. Further decomposition by trade direction suggests that there are two types of retail investors in our data: those who buy short-term options and lose money, and those who sell these contracts and make significant profits, even after transaction costs.

We also find that retail trading in options, in particular, high volume imbalances in calls and puts, tends to predict returns on the underlying stocks over the next trading day. This could be consistent with the informed trading hypothesis. However, given the short-term nature of predictability and our other findings on SLIM behavior and performance, these results seem to be more in line with the price pressure caused by the hedging demand of the intermediaries servicing retail order flow.

How big is retail participation in the options market, and what fraction of their trading does our measure capture? We perform a back-of-the-envelope calculation to assess how SLIM trading volume compares to the retail trading volume that can be inferred from the recently revised SEC Rule 606 forms filed by brokerages in the United States. First, we estimate that retail investors constitute 62% of the total trading volume in options. This magnitude is striking, given that this market has traditionally been thought to be populated largely by institutional and/or sophisticated investors. Second, we find that SLIM reflects 70% of inferred trading volume from market and marketable limit orders and 30% of the total inferred retail trading volume (or 18% of total market volume). To make up for the remaining retail trading and to alleviate concerns related to order selection into SLIM, we propose three alternative measures of retail trading that are noisier but capture a larger fraction of the overall retail trading volume in options. Specifically, we first consider another way in which wholesalers can internalize transactions of up to five contracts and use the new OPRA trade flags to isolate such trades. We then add to those trades a refined subset of small trades (of up to 10 contracts), again using OPRA flags to define the subset, and finally also include small dollar-value trades (up to $5,000). We show that these measures are similar to SLIM in terms of observables, for example, preference for short-term options and call contracts. Like SLIM, these measures comove positively with proxies for retail investor popularity and drop significantly during outages experienced by large U.S. retail brokerages and during trading restrictions imposed by these brokerages. Additionally, they are not statistically different from SLIM in terms of their

[8] Robinhood does not charge commissions for options trades, but many other brokerages still do.

net profitability. We thus conclude that while the SLIM methodology does not capture the entire retail volume, SLIM trades are comparable to our broader measures of retail trading.

Finally, we argue that our retail trading measure is less noisy than the popular industry alternative of small trades. Using the new OPRA trade flags, we identify many institutional transactions that are broken down into multiple small trades. The naive small trades measure may therefore contain many false positives, contaminating empirical analysis.

Our paper is related to the emerging literature exploring retail investor trading in the age of Robinhood. Focusing on retail investor equity holdings and trading, Welch (2022), Barber et al. (2022), Boehmer et al. (2021), Eaton et al. (2022b), and Fedyk (2021) argue that the new generation of investors differs from retail investors previously examined in the literature (most notably by Barber and Odean (2001)) along several important dimensions. Although the counts of retail investor equity positions are available from Robintrack, data on their trading in options are not available to researchers. To our knowledge, we are the first to document retail investor preferences and market participation in options, which we infer from transaction-level data using newly introduced OPRA trade types.

We are aware of the following papers on retail trading in options. Using account-level data from a brokerage, Bauer, Cosemans, and Eichholtz (2009) document that retail investors' motives for trading appear to be gambling and entertainment and that they incur substantial losses on their options investments. Lakonishok et al. (2007) argue that speculation is the key driver of retail investors' trading in options and that during the dot-com bubble, they favored options on growth stocks. Our paper documents that this phenomenon is even more widespread than initially thought, given that retail trading in options accounts for over 60% of the total market volume. Furthermore, our findings indicate that most of this trading is likely related to gambling as opposed to hedging motives. In contemporaneous work, Eaton et al. (2022a) use retail brokerage outages to document that options on stocks popular with retail investors experience demand pressures that affect their implied volatilities, and de Silva, Smith, and So (2022) document that retail investors lose on their trades around earnings announcements. These papers mainly exploit data from Nasdaq options trade outlines. Our paper uses transaction-level data for the entire U.S. options market to document the trading patterns of the new generation of retail investors. We confirm the findings of Lakonishok et al. (2007) that retail investors have a strong preference for call options and that on average they write more options than they buy. We additionally document that they choose ultra short-term (weekly) options (consistent with preferences for skewness discussed in Barberis and Huang (2008) and Boyer and Vorkink (2014)), participate in trading frenzies, and incur large trading costs (possibly masked by zero-commission offers). The literature also documents poor retail investor performance during the bubble episode in the Chinese warrant market, attributing poor performance to feedback trading, herding, and buying out-of-the-money warrants too close to expiration (Xiong and Yu (2011), Cai et al. (2021), Li, Subrahmanyam, and Yang (2021), and Pearson, Yang, and Zhang (2021)).

Finally, also related to our work are papers on options market structure and liquidity, for example, Battalio, Griffith, and Van Ness (2021), Ramachandran and Tayal (2021), Muravyev and Pearson (2020), Christoffersen et al. (2018), Battalio, Shkilko, and Van Ness (2016), Muravyev (2016), and Mayhew (2002). None of these papers, however, constructs measures of retail investor trading or, more generally, examines retail investors. In independent contemporaneous work, Ernst and Spatt (2022) and Hendershott, Khan, and Riordan (2022) propose the same method as ours to identify wholesaler trades in the options market. Their main focus is on the price improvement (relative to the best prevailing quotes) achieved by wholesalers. Our focus is on the behavior of retail investors in the options market and on their performance during the recent retail trading boom.

I. PFOF and Rise of Retail Trading in Options Market

In this section, we document novel facts about retail trading in the U.S. options market. Leveraging several granular data sets and regulatory filings, we describe the market for PFOF in stocks and options. We propose a new measure of retail activity in the options market based on transaction-level data, describe its composition, and show how it relates to existing stock-level retail activity measures and other characteristics of the underlying. We validate our measure using plausibly exogenous trading restrictions and show that it is representative of broader measures of retail trading in options.

A. Data

We use option transaction–level data from OPRA LiveVol provided by CBOE. Those data cover all trades on 16 U.S. exchanges in index, ETF, and equity options. In our analysis, we focus on ETF and equity options and exclude index options.[9] Our sample covers the period November 4, 2019, to June 30, 2021.

Following the literature, we remove canceled trades, trades with nonpositive size or price, and trades with a negative spread (difference between best ask and best bid), and we keep only those trades for which trade price is above the best bid minus spread and below the best ask plus spread. We aggregate trades of the same contract with the same quote time, exchange ID, trade price, and trade condition ID into one line. We do not exclude open or close trades from our analysis, but we confirm that excluding trades before 9:45 a.m. and after 3:50 p.m. does not change our results. We winsorize trade prices, sizes, and spreads at the 99.5$^{\text{th}}$ percentile daily. To compute trade imbalances, we follow the method described in Muravyev (2016)—trades with prices above (below) the midpoint are classified as "buy" ("sell") trades and trades at the midpoint

[9] Our sample also includes some American Depositary Receipts (ADRs). For brevity, we refer to underlying assets as "stocks and ETFs" in the text that follows.

are classified according to the quote rule on the exchange in which the trade took place.[10]

We use daily option price, volume, and open interest (OI) data from OptionMetrics. These data are available at the contract level for the period January 4, 1996, and June 30, 2021. We lag OI for all data after November 28, 2000, to obtain a series of consistent OI as of the end of day.[11] We exclude contracts with a nonstandard settlement.

We also use data from Nasdaq Options Trade Outline (NOTO) and the PHLX Options Trade Outline (PHOTO) End-of-Day files with order classification by the originating counterparty (customers, professional customers, market makers, firms, or broker/dealers). This sample covers the period November 4, 2019, to June 30, 2021.

All standard stock- and ETF-level data come from the Center for Research in Security Prices (CRSP). These data include dividend history, stock prices and returns, and outstanding shares. To link with OptionMetrics, we rely on the SecId-PERMNO crosswalk provided by WRDS.

Our data on retail investor popularity are as follows. To construct a measure of ticker mentions on `WallStreetBets` and its popularity, we use information on both posts and comments available from the Pushshift Reddit Dataset, the largest publicly available Reddit data set, that includes all posts and comments on the platform and is continuously updated in real time. In particular, we use monthly dump files for the period November 2019 to June 2021 to collect both original submissions (posts) and comments in the Daily Discussion and Unpinned Daily Discussion threads of the `WallStreetBets` forum. To count ticker mentions in the downloaded posts and comments, we start from the list of unique historical tickers from CRSP. We then search for the historical tickers in all comments and sum by date. Note that we exclude tickers that might coincide with popular words used on the forum ("USA," "YOLO," "IPO," "MOON," etc.) We further search only for capitalized tickers, which the Reddit audience typically use. Since we exclude some tickers, omit any lower case mentions, and do not cover other threads of the forum (such as occasional megathreads), our measure provides a lower bound for ticker popularity. We provide a full description of the data set and our filters on ticker exclusion in Section III.D of the Internet Appendix.

For Robinhood breadth of ownership, we use Robintrack data, which are provided in intraday snapshots and cover the period May 5, 2018, to August 13, 2020. We use the number of users holding a stock as of the last intraday snapshot.

[10] We have also confirmed that our results hold if we use two alternative methods: a so-called quote rule, which excludes midpoint trades and is shown to have strong performance for options data by Savickas and Wilson (2003), and the Lee and Ready (1991) algorithm, which applies the tick rule to classify trades at midpoint instead of excluding them. The resulting ticker-level imbalances have a correlation of over 99% between the quote and Lee-Ready (1991) methods, while the correlation of each with the Muravyev (2016) method is 94%.

[11] The lag is due to the change in the reporting format of OptionMetrics. This implies that end-of-day OI is measured after option exercises.

In addition, we rely on FINRA Over-the-Counter (OTC) Transparency data for stock trading volumes executed away from lit exchanges, that is, automated trading system (ATS), typically referred to as "dark pool," and non-ATS OTC trades. Pursuant to FINRA's Regulatory Notice 15-48, these are available as of April 2016 by security and venue.[12]

Recently revised Rule 606[13] requires broker-dealers to report aggregate data on PFOF in stocks and options, as well as their composition across a number of categories. We download these forms for the largest brokers in the United States directly from their websites. We consider all the leading retail brokerages that rely on wholesalers for PFOF in servicing retail flow. A list of brokers, largest venues, and brokers' corresponding payments for order flow is reported in Table IA.III in the Internet Appendix. We consider PFOF and PFOF-implied volume for each reporting broker. Note that our sample does not include Interactive Brokers, because they do not rely on the PFOF model and send retail orders directly to exchanges. In tests with broker platform outages and trading restrictions, we merge TD Ameritrade and Charles Schwab from October 2020 because that is when Charles Schwab completed its acquisition of TD Ameritrade. Details on our samples of outages and restrictions are reported in Sections IV.A and IV.B of the Internet Appendix, respectively.

B. Zero Commissions, PFOF, and Market Structure

The global retail brokerage industry has changed drastically in recent years. More platforms are offering zero-commission trading in equities, and commissions in other asset classes have been reduced as well. Elimination of commissions has fueled a retail participation boom in financial markets, an increase in day trading, and gamification of investing.[14] The success of the zero-commission business model relies on PFOF received from intermediaries in exchange for routing retail orders to them for execution. In response to the changing industry landscape and to promote transparency, the SEC introduced new reporting requirements for brokers. In this section, we use the forms filed in compliance with the new rule (Rule 606 reports) to describe the market for PFOF.

Figure 1 plots monthly PFOF received by U.S. retail brokerages in our sample since the more detailed reporting of PFOF was made compulsory by the SEC. Although only a fraction of retail investors trade options, the amount of PFOF from options exceeds that from stocks by about 100% in each month in our sample. In 2021, the annual PFOF from options was \$2.4 billion, compared to \$1.3 billion from equities. Our results below help shed light on why PFOF in options is so large.

[12] Details are on the website of FINRA: https://otctransparency.finra.org/otctransparency/AtsIssueData. For details on the rule, see: https://www.finra.org/rules-guidance/notices/15-48.

[13] For details, see https://www.sec.gov/rules/final/2018/34-84528.pdf

[14] See, for example, the interview with the SEC chair: https://www.cnbc.com/amp/2022/01/19/secs-gensler-warns-investors-about-frequent-trades-on-brokerage-apps.html.

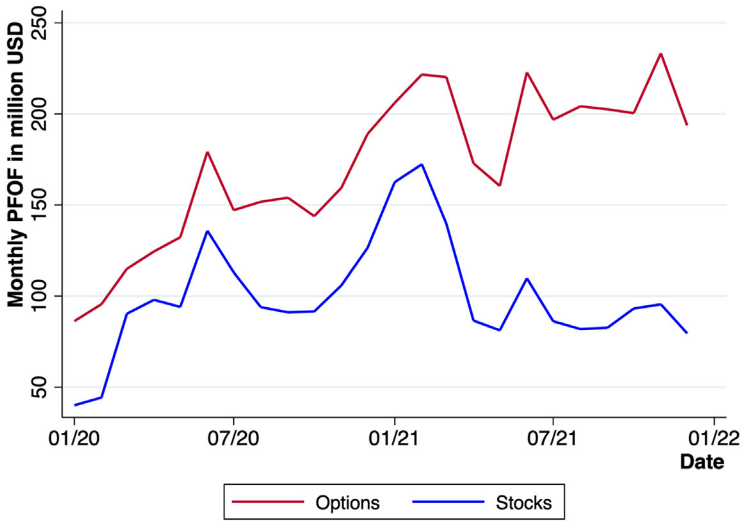

Figure 1. Payment for order flow: Options versus stocks. This figure plots aggregate monthly payments for order flow received by U.S. retail brokerages.

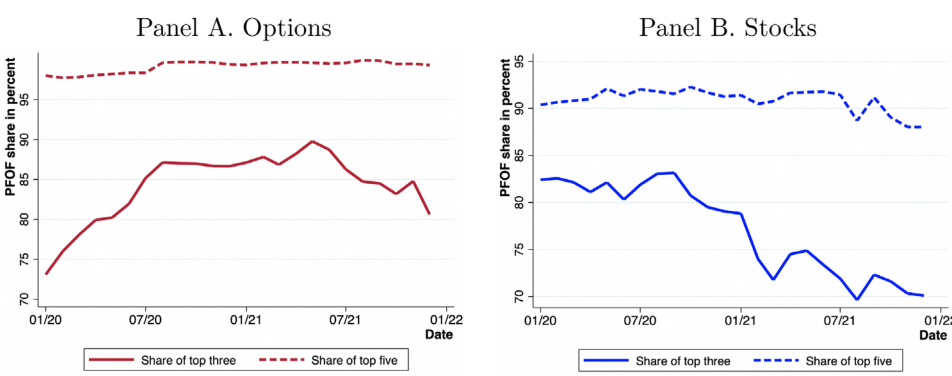

Figure 2. Market concentration in PFOF: Options versus stocks. This figure plots the share of PFOF received by U.S. retail brokerages from the top three and top five wholesalers. The top three wholesalers in options are Citadel, Susquehanna, and Wolverine, while the top three wholesalers in stocks are Citadel, Virtu, and Susquehanna.

Despite recent growth in retail trading and the commercial success of the zero-commission model, the wholesaler market remains quite concentrated, with the top five PFOF providers accounting for over 95% of the total PFOF received by U.S. brokerages (see Figure 2). Also apparent from Figure 2 is the high concentration of PFOF providers in options, with the share of the top three providers—Citadel, Susquehanna, and Wolverine—increasing from 73% at the beginning of our sample, and reaching an average value of about 85%, to peaking at nearly 90% in the second quarter of 2021. Below, we refer to Citadel, Susquehanna, and Wolverine as the *Big Three wholesalers* in options.

C. SLIM: A Measure of Retail Trading in Options

In this section, we propose a new measure of retail trading in options. Our methodology relies on detecting wholesaler-intermediated trades in transaction-level options data.

A highly publicized advantage for investors to have their orders routed to a wholesaler by a retail brokerage in exchange for PFOF is that the wholesaler promises a price improvement to customers, that is, an execution price that is at least as good as or better than the best quoted price, known as National Best Bid and Offer, or NBBO. To meet this commitment, wholesalers frequently execute retail orders through price improvement auctions/mechanisms, offered by most options exchanges in the United States (see Section I.E of the Internet Appendix).

This is how it works. A retail investor sends an order, which the broker routes to a wholesaler in exchange for PFOF and price improvement. Unlike a stock order, which can be internalized by a wholesaler on its own private trading platform, all options orders in the United States must be executed on exchanges. The wholesaler therefore engages its affiliated market maker to bring a paired order (with the affiliated market maker taking the other side) to a price improvement auction on an exchange. Market participants ("responders") have a window of time to respond (by sending a "contra" offer) with a better price (hence the name "price improvement mechanism"), which could lead to the wholesaler losing the trade. In practice, the fees set by exchanges are stacked against responders, and it is prohibitively expensive to break up many of these paired trades.[15] These responder fees are so high because exchanges also compete for the order flow and incentivize wholesalers to bring orders to them.[16]

Our novel measure of retail trading activity in options is based on trades that went through price improvement auctions. To construct it, we use a data set from OPRA that includes all options transactions in the United States. We take advantage of a unique feature of our data set, namely, the new trade-type flags introduced by OPRA on November 4, 2019. This classification is

[15] On most exchanges, order execution by a wholesaler-affiliated market maker is charged the fee of just \$0.05 per contract. In contrast, it would cost another market maker \$0.50 to break up/respond to one of these already paired orders during an auction. In the latter case, the wholesaler receives a net rebate of \$0.30 per contract simply for bringing the order to the exchange. Section I.E of the Internet Appendix contains a detailed description of the fee structure pertaining to price improvement mechanisms on U.S. options exchanges and highlights the fee advantages enjoyed by affiliated market makers.

[16] To some extent, this is natural, since markets benefit from the presence of largely uninformed retail flow and wholesalers are therefore compensated for delivering these orders. However, the structure and size of the fees associated with servicing retail order flow that would lead to the optimal level of competition among market makers and efficient order execution remains an open question.

significantly more detailed than its predecessors, and hence we construct our measure starting from November 4, 2019. Specifically, we use the OPRA transaction code SLAN, which stands for "single-leg price improvement mechanism"; we use the acronym SLIM to refer to these trades (see Section I.B of the Internet Appendix for a description). In our analysis below, we focus primarily on *SLIM Share*, which could be computed as a frequency share and as a trading volume share. We adopt the latter definition, as it is more relevant for assessing the economic importance of retail traders. We compute it daily and aggregate it to a ticker level using total options trading volumes. We discuss other measures constructed using SLIM trades, for example, SLIM imbalances, later in this section.

Price improvement auctions were first introduced to improve trade execution for institutional investors, but a specific type of them that we use, single-leg non-ISO price improvement auctions (OPRA trade type "SLAN"), are now used by wholesalers for executing retail orders. ISO stands for "intermarket sweep orders," a type of market orders developed for large institutional trades that take all available liquidity at the best price, then all liquidity at the next best price, and so on, until the order is filled. Trades that are executed in ISO price improvement auctions have a very different profile than SLIM trades—these are large institutional trades. There are also multileg price improvement auctions and stock options auctions, among others (see Section I.B of the Internet Appendix for more details), which may have some retail investor transactions, but they are a much noisier measure of retail trading and hence we restrict our measure to single-leg non-ISO price improvement auctions.

For comparison, we also report a measure of retail trading in options often used in the media and industry: *Small Share*, the volume share of trades of up to 10 contracts, and the corresponding trading volume in small trades.[17] The frequency share of small trades is 89% in our sample, which overestimates retail investor activity in options. This measure is noisier than SLIM because in addition to retail trades, it contains transactions of proprietary trading firms (e.g., Simplex Trading) or ISO orders of large institutional investors, which were broken into smaller trades by order execution algorithms. For example, ISO transactions are reported by OPRA as a collection of separate small transactions for the same contract but at different prices and different exchanges. In our sample, the small trades measure picks up 27.2% of ISO trades. Using the OPRA flag for ISOs, we can approximately reconstruct the original order by bunching together trades in the same contract at virtually the same time on multiple exchanges. Table IA.VI in the Internet Appendix contrasts ISO trades as reported by OPRA and bunched ISO trades. In the original

[17] Another popular measure of retail trading in options is based on the "customer" order classification provided by some exchanges. Bryzgalova, Pavlova, and Sikorskaya (2022) highlight false positives of this order classification using OPRA codes for transactions executing a specific sophisticated arbitrage trading strategy—dividend play.

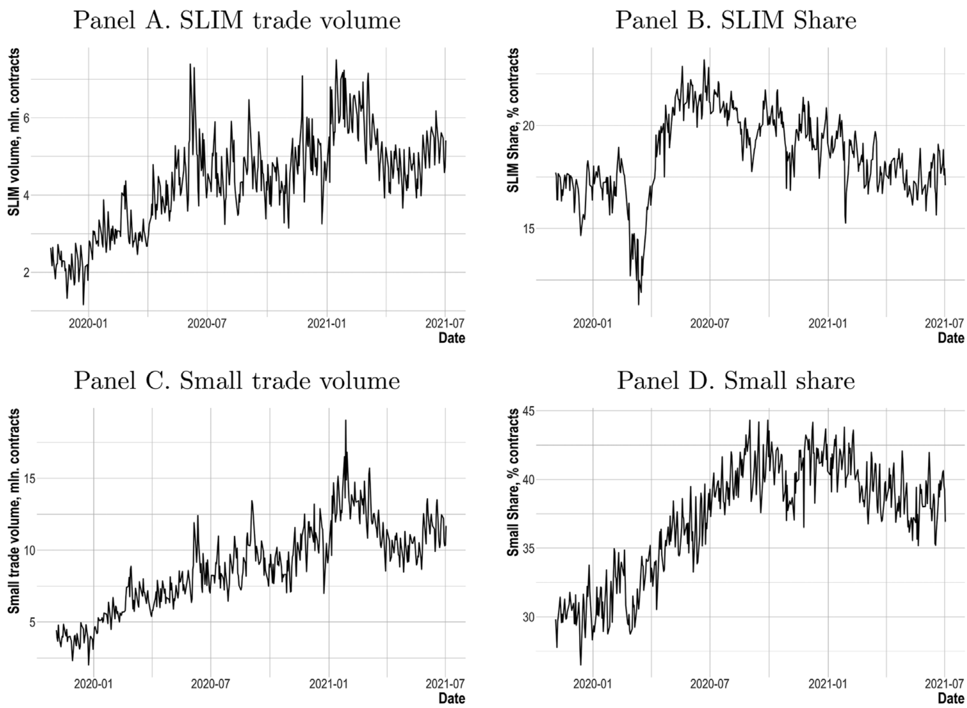

Figure 3. Retail investor trading in options. This figure characterizes retail investor trading in the U.S. options market between November 2019 and June 2021. Panels A and C plot total daily trading volumes in SLIM and small trades, respectively. Panels B and D plot daily *SLIM Share* and *Small Share*, respectively, averaged across all stocks and ETFs in our sample.

transactions data, the volume share of trades above $20,000 is only 9.6%, while in the bunched sample this share reaches 20.1%. In Section I.E below, we propose a refinement of the small trades measure based on the new OPRA trade flags, which is a more accurate measure of retail trading than all small trades.

In Figure 3, we plot our retail trading measure in options, *SLIM Share*, alongside *Small Share*. We also plot the total volume of SLIM and small trades. Panels A and C reveal significant growth of and comovement between SLIM and small trading volumes: Retail investor trading shows a marked increase in our sample. For example, the dollar trading volume in SLIM and small transactions grew by 101% and 135%, respectively, from January 2020 to July 2021. This is in line with the growth of PFOF for options, which is 158% over the same period, based on monthly data. The growth in retail trading is especially high from January 2020 to March 2021. This period includes several well-publicized retail investor frenzies in equities and a meteoric rise in the number of Robinhood's active users. This increased participation is also reflected in higher average shares, especially in summer 2020, when the average *SLIM Share* was over 20%.

Table I presents various features of SLIM trades and compares them to non-SLIM trades in the options market. To formally test the differences between them, we compute the average daily characteristics for SLIM and non-SLIM trades across each of the dimensions reported in Table I. Values with asterisks correspond to the features of the SLIM trades that are statistically different from those of non-SLIM trades at the 1% level at a daily frequency. We report the daily averages and test their differences relative to those of non-SLIM trades in Tables IA.VII and IA.VIII in the Internet Appendix, respectively.

One striking fact is that retail investors prefer to trade options with the shortest maturities: 49.9% of SLIM trades (in terms of their volume share) are in weekly options, compared with 41.5% for the non-SLIM trades. This difference is highly significant, both statistically and economically. The average bid-ask spread in options with less than a week to expiration is a whopping 12.6%. The effective spread is lower, 6.6%, indicating that these orders did indeed receive price improvement. However, the effective spread is still orders of magnitude higher than that in equities.

Why do retail investors opt for ultra short-term options? One possible explanation is that options with the shortest maturity are listed as the default on trading apps (e.g., they are a default choice on Robinhood).[18] Another explanation is investor preferences for lotteries or gambling. This explanation is consistent with preferences for skewness, as discussed in Barberis and Huang (2008) and Boyer and Vorkink (2014), and with a number of other behavioral biases (e.g., overconfidence, sensation-seeking, and preferences for gambling), summarized in table 1 of Liu et al. (2022).[19] Finally, retail investors may simply be cash-constrained.[20] Indeed, weekly options have the lowest prices relative to otherwise identical contracts with longer maturities, so retail investors could select the cheapest alternative. At a 12.6% quoted bid-ask spread, however, the cheapest alternative is by no means cheap to trade. Lured by recent low- or zero-commission offers, retail investors possibly underestimate the indirect trading costs in the options market.[21]

Table I also reveals that retail investors strongly prefer calls to puts: The volume share in calls is 71.5%. We further find that written options are slightly more popular with retail investors than purchased options. Retail brokerages

[18] Default options often have a significant impact on financial decision making; see Madrian and Shea (2001), Choi et al. (2004), Beshears et al. (2009), and Beshears et al. (2021), among others.

[19] Weekly at-the-money options, favored by retail investors, often have an implied leverage of 58 to 72. Table IA.IV in the Internet Appendix reports implied leverage for various option groups.

[20] For evidence that the new generation of retail traders in options is cash-constrained, see FINRA (2021a). Additionally, in Section VII.C of the Internet Appendix, we examine stock splits and present evidence suggestive of cash constraints.

[21] The PFOF model and its implications for execution quality and cost transparency have been under regulatory scrutiny for years. See, for example, the 2021 U.S. Congressional hearing on Robinhood entitled "Game Stopped? Who Wins and Loses When Short Sellers, Social Media, and Retail Investors Collide," https://www.nytimes.com/2021/02/19/business/dealbook/robinhood-hearing-congress.html.

Table I

Composition of SLIM and Non-SLIM Trades

This table reports characteristics of trades by category. Our sample is from November 2019 to June 2021. (Implied) *Trade direction* is based on whether the trade price is above (buy), below (sell), or at the midpoint. *Quoted spread* is the spread between the best bid and best ask on the contract (across all exchanges) relative to the midpoint price at the time of the trade. *Effective spread* is the absolute percentage deviation of the trade price from the midpoint price at the time of the trade, multiplied by two. For both spreads, we report frequency-weighted averages. *Moneyness* for calls is measured as $(MidpointPrice - Strike)/Strike$, with the opposite sign for puts. The last row reports the frequency-weighted average for the full sample. Here, we report the full-sample aggregates. SLIM values are flagged with * when they are statistically different from the respective values for non-SLIM trades with a p-value below 1% at a daily frequency (using Newey-West standard errors with the optimal number of lags, which is, on average, 15 days; see Tables IA.VII and IA.VIII in the Internet Appendix for more details).

		SLIM trades				Non-SLIM trades			
Characteristic	Category	Frequency Share, %	Volume Share, %	Quoted Spread, %	Effective Spread, %	Frequency Share, %	Volume Share, %	Quoted Spread, %	Effective Spread, %
Type	Call	71.5*	69.4*	13.5*	6.6*	64.2	61.7	11.0	8.4
	Put	28.5*	30.6*	14.0*	6.9*	35.8	38.3	12.7	8.7
Trade size (contracts)	1	46.2*	6.6*	13.9*	6.4*	48.9	8.1	11.1	8.1
	2-5	30.9*	13.9*	12.7*	6.2*	30.4	15.5	11.5	8.4
	6-10	11.6*	14.9*	14.2*	7.3*	10.3	14.5	12.8	9.4
	11-100	10.7*	54.7*	15.1*	8.4*	9.8	48.6	13.2	10.1
	Above 100	0.5*	9.9*	15.2*	11.9*	0.6	13.2	14.4	11.3
Trade size (dollars)	Below 250	41.6*	14.9*	23.5*	11.6*	39.7	15.6	19.8	14.5
	250–500	15.5*	9.2*	8.7*	3.8*	15.3	8.8	8.1	5.3
	500–1,000	13.7*	11.6*	7.4*	3.1*	14.2	11.1	6.9	4.4
	1,000–2,500	13.7*	17.5*	6.2*	2.6*	14.7	16.9	5.9	3.7
	2,500–5,000	6.9*	13.5*	5.2*	2.1*	7.4	13.1	4.9	3.1
	5,000–10,000	4.5	12.9*	4.5*	1.9*	4.4	11.3	4.3	2.7
	10,000–20,000	2.4	9.8*	3.9*	3.1*	2.4	8.9	3.7	5.9
	20,000–50,000	1.4*	7.6*	3.5*	6.7*	1.5	8.4	3.3	13.9
	Above 50,000	0.4*	3.2*	3.2	11.9*	0.6	5.9	3.1	20.7
Trade direction	Sell	49.6*	49.3*	13.9*	7.2*	49.0	48.4	10.5	8.0
	Buy	46.6*	47.5*	13.0*	6.6*	47.6	48.3	12.6	9.7
	Midpoint	3.8*	3.1*	19.0*	0.0*	3.3	3.3	14.8	0.0

(*Continued*)

Table I—*Continued*

		SLIM trades				Non-SLIM trades			
Characteristic	Category	Frequency Share, %	Volume Share, %	Quoted Spread, %	Effective Spread, %	Frequency Share, %	Volume Share, %	Quoted Spread, %	Effective Spread, %
Time to expiry	Less than a week	48.2*	49.9*	12.6	6.6*	42.3	41.5	13.3	10.1
	1–2 weeks	13.9*	13.0*	12.4*	6.0*	14.6	13.3	10.0	7.2
	2–4 weeks	15.9*	15.2*	15.2*	7.1*	17.1	16.9	11.2	7.5
	1–3 months	13.3*	13.5*	14.0*	6.2*	15.5	16.5	9.8	6.6
	3–12 months	7.3*	7.2*	18.5*	7.8	8.5	9.7	10.2	7.9
	Over a year	1.4*	1.3*	17.7*	9.3*	2.0	2.1	12.7	11.8
Moneyness	Below −2	0.3	0.2*	54.1	28.4*	0.3	0.4	47.6	32.2
	−2 to −1	0.3	0.4*	50.8*	25.5*	0.4	0.5	44.2	27.4
	−1 to −0.1	23.4*	24.0*	28.7*	13.9*	24.1	25.2	21.3	15.0
	At the money	71.7*	71.6*	8.7*	4.2*	70.0	69.0	8.4	6.2
	0.1 to 1	4.0*	3.6*	8.6*	4.8*	5.0	4.6	5.9	7.0
	1 to 2	0.2*	0.1*	9.0*	7.6*	0.2	0.2	6.6	15.1
	Above 2	0.1*	0.1*	16.8*	11.5*	0.1	0.1	12.1	26.9
Trade direction and type	Sell - Call	35.2*	34.0*	13.6*	7.0*	31.4	29.7	9.8	7.9
	Sell - Put	14.4*	15.3*	14.6*	7.6*	17.6	18.7	11.6	8.2
	Buy - Call	33.6*	33.3*	13.0*	6.6*	30.8	30.0	12.1	9.5
	Buy - Put	13.0*	14.3*	13.1	6.7*	16.9	18.3	13.6	10.0
	Midpoint - Call	2.6*	2.1	19.7*	0.0*	2.0	2.0	14.0	0.0
	Midpoint - Put	1.1*	1.0*	17.4*	0.0*	1.3	1.3	16.1	0.0
ETF	No	81.4	73.0*	14.9*	7.2*	81.5	71.4	12.2	9.0
	Yes	18.6	27.0*	8.4*	4.4*	18.5	28.6	8.9	6.7
Total		100	100	13.7	6.7	100	100	11.6	8.6

in our sample place various restrictions on naked options positions, as detailed in FINRA (2021b). Therefore, while written puts may simply be covered with cash, written calls (that do not simply close a preexisting long position in the same contract) are most likely part of a covered call strategy. We also use the Nasdaq NOTO and PHOTO end-of-day files for our sample period and provide trade classification by the originating counterparty. Following de Silva, Smith, and So (2022), we use the "customer" classification to generate a proxy for daily retail trader position and find the negative imbalance there as well. All of these findings confirm the results of Lakonishok et al. (2007), who use account-level data to document the same behavior for customers of a discount brokerage and a full-service brokerage. Muravyev and Pearson (2020) document a 3.4% sell imbalance in OPRA data for options on S&P 500 stocks. One could argue, however, that the new generation of retail investors is cash-constrained and does not have sufficient collateral for writing options. The buy-sell imbalance in SLIM trades could then be due to the fact that our measure contains some institutional transactions, which are sell-imbalanced, while genuinely retail transactions include more buys than sells.

From Table I, we observe that retail investors trade mostly at-the-money (72% of trades) or slightly out-of-the-money (23%) options. The latter involves higher trading costs, with average quoted bid-ask spread of 28.7%. Furthermore, 41.6% of retail trades have a "micro" size of up to $250, compared to 39.7% for non-SLIM trades, and their average quoted bid-ask spread is 23.5%. Descriptive statistics in Table I are similar for dollar volume shares, reported in Table IA.IX in the Internet Appendix. These observations suggest that retail investors are entering the options market with an intent to speculate rather than hedge—a point also made in Lakonishok et al. (2007) and Bauer, Cosemans, and Eichholtz (2009). All of these results are similar if we use the quote rule to classify trades and exclude open and close trades, as shown in Table IA.X in the Internet Appendix.

In Table I, 10.8% of SLIM trades volume (or 1.8% based on the frequency share) are above $20,000. The literature on retail trading in equities typically considers such large trades to be institutional (starting from Lee and Radhakrishna (2000)). In our sample, these trades are indeed likely to be institutional. They are also large enough to have a price impact: Table I shows that effective spreads exceed quoted spreads for these trades. We acknowledge the presence of false positives in our baseline measure, and throughout the Internet Appendix we show the robustness of our subsequent results to using SLIM trades below $20,000 as an alternative proxy for retail trades. For example, Table IA.XI in the Internet Appendix shows the descriptive statistics of trades below $20,000, which are very similar to those without the size filter. We further discuss potential limitations of our measure of retail trading in options in Sections I.E and III.E below.

We next explore how our measure of retail activity in the options market relates to the characteristics of options contracts and their underlying. To do so, we first run the following panel regression, separately for call and put options:[22]

$$SLIM\ Trading_{i,t} = \boldsymbol{\gamma}' X_{i,t} + \boldsymbol{\delta}' C_{i,t} + \alpha_i + \mu_t + \varepsilon_{i,t}. \tag{1}$$

For call or put contracts of each ticker i on date t, we consider two measures for $SLIM\ Trading_{i,t}$. The first is $SLIM\ Share_{i,t}$, the volume share of SLIM trades among all the options transactions in ticker i on date t, which reflects the general presence of retail investors. The second measure is $SLIM\ Imbalance_{i,t}$, in both calls and puts, which is the volume difference in buy and sell SLIM trades scaled by the total volume of SLIM trades, corresponding to a buy or sell tilt in retail investor trades.

Our vector of characteristics $X_{i,t}$ includes the following ticker-level variables: log dollar trading volume in options on $t-1$, log price on $t-1$, log total trading volume (lit, ATS, and non-ATS OTC) in the underlying stock or ETF over the previous week, relative spread in the underlying averaged over the previous week, volatility of the underlying returns over the previous week, and log market capitalization as of $t-1$. Our vector of contract characteristics $C_{i,t}$, equal-weighted at the ticker i level, includes quoted spread, options moneyness, their time to expiration in months, and leverage.[23] We include ticker and date fixed effects, α_i and μ_t. Finally, we report descriptive statistics for all these variables in Table IA.XII in the Internet Appendix.

Table II presents the results of estimating equation (1). A notable feature of SLIM trades is that retail investor share and order imbalance are higher in the options on the underlying with a larger market capitalization and a higher trading volume in the previous week. The latter is consistent with higher retail participation in attention-grabbing securities. Furthermore, retail investors tend to prefer tickers with lower underlying price (and hence cheaper options as well). In addition, retail trading is more prevalent in the options on more liquid stocks and ETFs. Earlier studies document similar relationships for the stock-level imbalances (see Boehmer et al. (2021) and Welch (2022)).[24]

Notably, we see that *SLIM Imbalance* in calls is likely to be higher in smaller stocks. However, we also see that our chosen set of characteristics has smaller overall explanatory power for imbalances. It suggests that most of the potential price pressure originated from retail investors in the options market seems to be unrelated to fundamentals. This is consistent with the retail flow being fairly balanced and, hence, attractive to market makers.

[22] Splitting the contracts allows us to document differential relationship with the past return on the underlying stock or ETF. All the other results remain similar if we pool both types of contracts together.

[23] Results are not sensitive to whether we use equal- or volume-weighting for contract characteristics at the ticker level. Furthermore, our results are robust to including implied volatility, trade size, delta, and other option Greeks, such as theta, vega, and gamma, among the contract-level controls.

[24] Both *SLIM Share* and *SLIM Imbalance* are also correlated with a quasi-Robinhood portfolio, designed to reflect retail-popular tickers. Portfolio weights are based on the previous total trading volume, following the general procedure of Welch (2022). See Table IA.XIII in the Internet Appendix.

Table II

Retail Trading in Options and Underlying Characteristics

This table reports results of estimating (1) on daily data from November 2019 to June 2021. *SLIM Share* is the ticker-level volume share of SLIM trades. *SLIM Imbalance* is the ticker-level volume imbalance for SLIM trades. *Underlying price* (log) is as of the day before. *Underlying return* is the total return over the last week. *Underlying spread* is averaged over the previous week. *Underlying volatility* is return volatility over the previous week. *Option spread* is the contract quoted relative spread. *Option time to expiration* (in months), moneyness, spread, and leverage are equal-weighted across trades at the ticker level. All regressions include date and ticker fixed effects. All variables are standardized within the contract type (call or put). t-statistics are based on standard errors clustered by ticker and date (in parentheses). $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.1$.

	SLIM Share		SLIM Imbalance	
	Call (1)	Put (2)	Call (3)	Put (4)
Option volume, lagged log	−0.002	−0.036***	0.038***	0.028***
	(−0.76)	(−13.88)	(12.08)	(9.04)
Underlying price, log	−0.269***	−0.212***	−0.044***	−0.063***
	(−15.83)	(−14.11)	(−3.82)	(−5.91)
Underlying return, past week	−0.005***	0.013***	−0.005***	0.005***
	(−3.79)	(9.96)	(−3.28)	(3.34)
Total volume in underlying, past week log	0.060***	0.048***	0.009*	0.032***
	(10.00)	(9.07)	(1.82)	(5.97)
Underlying spread	−0.030***	−0.011***	−0.016***	−0.013***
	(−7.64)	(−3.07)	(−4.54)	(−3.46)
Underlying volatility, past week	0.001	0.000	−0.005**	−0.004*
	(0.32)	(0.12)	(−2.17)	(−1.75)
Market cap, lagged log	0.069***	0.043**	−0.071***	−0.004
	(2.81)	(2.08)	(−4.39)	(−0.30)
Option time to expiry	−0.010***	−0.014***	0.003*	−0.002
	(−7.17)	(−11.15)	(1.85)	(−1.10)
Option moneyness	−0.018***	−0.016***	−0.003*	0.001
	(−9.68)	(−8.60)	(−1.85)	(0.36)
Option spread	−0.024***	−0.025***	−0.009***	−0.008***
	(−11.70)	(−13.11)	(−3.59)	(−3.28)
Option leverage	0.007***	0.002	−0.000	0.000
	(3.27)	(1.15)	(−0.07)	(0.14)
Observations	1,334,444	1,107,614	1,077,136	801,723
Adjusted R^2	0.116	0.088	0.021	0.023

A natural question to ask is how *SLIM Share* and *SLIM Imbalance* relate to other measures of retail activity. For options, we use small trades as another proxy for retail activity, a measure popular in the industry despite its caveats discussed above. We also consider a number of retail trading measures in equities, proposed in recent literature. These stock-level measures include retail trading imbalances (Boehmer et al. (2021)), breadth of Robinhood user ownership (Welch (2022) and Eaton et al. (2022b)), and counts of `WallStreetBets` ticker mentions (also Eaton et al. (2022b)). Due to data availability, we focus on the latter two.

We add one more measure of retail equity trading to the list: internalized volume, which is the share of non-ATS OTC weekly trading volume in total volume (i.e., the aggregate of lit, ATS, and non-ATS OTC volumes), at the stock level, based on FINRA and CRSP data.[25] FINRA makes public the identities of the largest market makers executing non-ATS OTC transactions. Internalized trades for stocks are executed off lit exchanges, yet not in "dark pools" (which are classified as ATS transactions). The non-ATS OTC transactions consist primarily of internalized order flow from retail and institutional customers of wholesalers. Table IA.XIV in the Internet Appendix ranks market makers by their non-ATS OTC volume share. This ranking closely resembles the one in which we sort wholesalers by their share in PFOF. To the best of our knowledge, this measure has not been used in the extant literature to date. For more details, see Section III.B of the Internet Appendix.

To understand the relationship between *SLIM Share*/*SLIM Imbalance* and other measures of retail activity, we run a panel regression similar to that in equation (1), but we now also consider other measures of retail activity, one at a time:

$$SLIM\ Trading_{i,t} = \beta Retail_{i,t} + \boldsymbol{\gamma}' X_{i,t} + \boldsymbol{\delta}' C_{i,t} + \alpha_i + \mu_t + \varepsilon_{i,t}, \tag{2}$$

where $Retail_{i,t}$ is one of the following measures of retail activity at the ticker level: $share^{small}$, the volume share of trades up to 10 contracts for ticker i on date t (within call and put options); *Internalized volume in underlying*$_{i,t}$, the share of non-ATS OTC (i.e., internalized) volume in the total trading volume of ticker i in the week of date t; *Robinhood ownership breadth, log*$_{i,t}$, the logarithm of the number of Robinhood users holding the ticker i at the end of date t; and *WSB mentions, log*$_{i,t}$, the logarithm of the number of times ticker i was mentioned on the `WallStreetBets` forum on date t. We use the same set of controls for options contracts ($C_{i,t}$) and their underlying ($X_{i,t}$) as in equation (1).

Table III presents results of estimating equation (2). Our first observation is that the measures of retail trading are positively correlated with both *SLIM Share* and *SLIM Imbalance* in the cross-section. This provides some initial validation of our measure of retail trading in options, with the main tests and further supporting evidence presented in Sections I.D and III below. However, along with the ticker-level X and C characteristics and fixed effects, they explain only 7% to 11% of the total variation in *SLIM Share*, showing very limited improvement over the explanatory power documented in Table II.

We note that only `WallStreetBets` mentions exhibit an insignificantly positive correlation with *SLIM Share* (in calls), albeit they have a strong relationship with *SLIM Imbalance*, suggesting that ticker popularity on the investor forum is indeed related to overall buying pressure in both calls and puts, even after conditioning on all the contract and underlying characteristics. The relationship between both *SLIM Share* and *SLIM Imbalance* with `WallStreetBets`

[25] Not all of these trades originate from retail brokerages. FINRA defines it as "non-ATS electronic trading systems and internalized trades." Nonetheless, our results suggest that a significant fraction of these trades do originate from retail brokerages.

Table III

Retail Trading in Options and Other Measures of Retail Activity

This table reports results of estimating (1) on daily data from November 2019 to June 2021. *SLIM Share* and *Small Share* are the ticker-level volume shares of SLIM and small trades, respectively. *SLIM Imbalance* and *Small Imbalance* are the ticker-level volume imbalance for SLIM and small trades, respectively. *Internalized volume in underlying* is the share of non-ATS OTC (i.e., internalized) volume in the total trading volume in the underlying stock or ETF. *Robinhood ownership breadth*, log, is the logarithm of the total number of Robinhood users holding the ticker at the end of each day. *WSB mentions*, log, is the logarithm of the number of mentions a ticker gets on `WallStreetBets` during the day. Underlying controls X and contract controls C are described in Section I.C. All regressions include date and ticker fixed effects. All variables are standardized within contract type (call or put). t-statistics are based on standard errors clustered by ticker and date (in parentheses). $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.1$.

	Retail Trading in Calls				Retail Trading in Puts			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: SLIM Share								
Small Share	0.032***				0.036***			
	(14.04)				(16.58)			
Internalized volume in underlying		0.029***				0.022***		
		(9.77)				(7.93)		
Robinhood ownership breadth, log			0.044***				0.071***	
			(4.22)				(6.65)	
WSB mentions, log				0.000				0.004***
				(0.28)				(3.02)
Underlying controls X	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Contract controls C	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,334,444	1,334,444	538,423	1,170,990	1,107,614	1,107,614	452,762	1,003,262
Adjusted R^2	0.117	0.117	0.110	0.126	0.089	0.088	0.081	0.094

(*Continued*)

Table III—*Continued*

	Retail Trading in Calls				Retail Trading in Puts			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel B: SLIM Imbalance								
Small Imbalance	0.511***				0.501***			
	(260.81)				(219.45)			
Internalized volume in underlying		0.015***				0.003		
		(4.99)				(0.99)		
Robinhood ownership breadth, log			0.045***				0.035***	
			(4.49)				(3.68)	
WSB mentions, log				0.016***				0.010***
				(15.06)				(8.41)
Underlying controls X	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Contract controls C	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,074,569	1,077,136	422,083	980,438	798,755	801,723	324,084	753,268
Adjusted R^2	0.173	0.021	0.026	0.020	0.162	0.023	0.025	0.023

mentions becomes particularly evident and highly statistically significant if we restrict the sample to microtrades ($250 or less), as we show in Section III.C of the Internet Appendix. This suggests that microtrades in options are particularly good in representing the universe of `WallStreetBets` users.

To alleviate the concern that our results in Table II could be driven by false positives (institutional trades) in our measure, Table IA.XVI in the Internet Appendix considers only SLIM trades below $20,000. The results are similar to those in Table II. Furthermore, given that the trading volume in the U.S. options market is highly skewed, one might be concerned that our results hold for only very thinly traded contracts. In Table IA.XVII in the Internet Appendix, we estimate equation (2) for the 354 tickers that constitute the top decile by the total dollar trading volume in our sample. The estimation results are similar to what we document in this section.

D. SLIM Trading During Broker Platform Outages and Trading Restrictions

In this section, we exploit trading restrictions on retail platforms to validate our measure of retail trading. We use both aggregate (time-series) and stock-level (panel) trading restrictions, already introduced in the literature. First, we follow Eaton et al. (2022b) and Barber et al. (2022) to show that the retail trading share, as measured by *SLIM Share*, significantly decreases when retail broker platforms experience outages. Second, we follow Jones, Reed, and Waller (2021) to show that trading restrictions on particular tickers are also associated with a lower *SLIM Share* in those tickers. Combining two types of restrictions allows us to use both time-series and cross-sectional variation to validate SLIM, as well as mitigate concerns related to how we measure restrictions.

Eaton et al. (2022b) and Barber et al. (2022) use the data on outages from DownDetector.com[26] and Robinhood incident history, respectively, to study the effects of retail trading in stock markets. The data of Eaton et al. (2022b) cover more brokers, but are not public. However, DownDetector.com reports the largest outages for each broker in our sample on its Twitter account. We hand-collect these data to construct a sample of outages covering large brokers from public sources. Details on how we construct this sample are presented in Section IV.A of the Internet Appendix. We study the effects of outages on retail trading in a sample of the top 100 most mentioned tickers on `WallStreetBets` during our full sample period.

The unprecedented volatility in certain stocks resulted in many retail brokers restricting trading in January 2021. Jones, Reed, and Waller (2021) study the effect of those restrictions on the overall stock and options trading activity. We identify the timing of restrictions in two ways. First, we precisely follow the timings reported in Table 1 of Jones, Reed, and Waller (2021), that cover the restrictions introduced by Robinhood and TD Ameritrade (and Charles Schwab) and are based on the snapshots from the Internet Archive Wayback Machine.

[26] https://downdetector.com/is the largest consolidator of outage data.

Second, since the snapshots from the Wayback Machine are infrequent, we refine the list of restrictions by manually searching for online posts related to the restrictions on Twitter and reddit.com. This allows us to make the starting and ending time more precise and to add more tickers to the sample. Further details and a table with the resulting restrictions for the second approach are reported in Section IV.B of the Internet Appendix.

To identify the effect of restrictions on the retail trading share, we estimate the panel regression

$$SLIM\ Share_{i,t} = \sum_j \beta_j D(Broker\ j\ restricted)_{j,i,t} + \boldsymbol{\gamma}' X_{i,t} + \alpha_{i,d} + \mu_{tod} + \varepsilon_{i,t}. \quad (3)$$

In the equation above, $SLIM\ Share_{i,t}$ is the share of SLIM volume in the total volume of trading in options on stock i in minute t, and $D(Broker\ j\ restricted)_{j,i,t}$ is a dummy variable equal to one if broker j had a trading restriction on stock i in minute t. Since outages affect trading in all stocks on a broker platform, $D(Broker\ j\ restricted)_{j,i,t}$ equal one for all i if broker j experiences an outage in minute t. Vector $X_{i,t}$ is a set of additional stock-level controls such as the logarithm of total trading volume and the logarithm of stock price two days before minute t, as well as the change in log volume and log price from one day before minute t to minute $t-1$. Ticker by date fixed effects are given by $\alpha_{i,d}$, and time-of-the-day fixed effects by μ_{tod}.[27] We cluster standard errors by ticker and minute. We report estimation results with and without controls $X_{i,t}$, and our results are not sensitive to the exact definition of these controls. When estimating specification (3), we include only days when at least one outage occurred, but results are very similar if all days are included. In contrast, ticker-specific restrictions concentrated in January to March 2021, so we restrict the sample to 30 days before the start of the first restriction and 30 days after the end of the last restriction, although the results do not change if we use narrower estimation windows.

Table IV reports the estimation results. Consistent with SLIM picking up retail trades, we find that *SLIM Share* in a ticker is significantly lower in the minute when broker restrictions are in place, both statistically and economically. Columns (1) to (2) reveal that when the largest retail brokers in options experience outages, *SLIM Share* is 0.72 to 0.81 percentage points lower in stocks and ETFs most popular with retail investors. When ticker-level restrictions are considered, the magnitudes are even larger. Column (3) shows that *SLIM Share* is up to 4.3 percentage points lower when Robinhood restricts trading, 2 percentage points lower when TD Ameritrade or Charles Schwab restrict trading, and 6 percentage points lower when trading is restricted for all of them. This corresponds to a 27% drop relative to the average *SLIM Share* in

[27] When using ticker-level restrictions, we are only able to include α_i with α_d, or ticker and date fixed effects, because of limited intraday variation in the restrictions imposed by TD Ameritrade. Using minute fixed effects instead of time-of-the-day fixed effects for ticker-level restrictions produces similar results.

Table IV

Trading Restrictions and Retail Trading in Options

This table reports results of estimating (3) in a minute-ticker panel. Columns (1) and (2) use outages as restrictions, columns (3) and (4) use ticker-level restrictions from Jones, Reed, and Waller (2021), and columns (5) and (6) use ticker-level restrictions from our sample. $D(RH\,restricted)_{i,t}$ equal one if trading in stock i was restricted by Robinhood in minute t, and zero otherwise. $D(TD\,restricted)_{i,t}$ equal one if trading in stock i was restricted by TD Ameritrade or Charles Schwab (from October 2020) in minute t, and zero otherwise. $D(Both\,restricted)_{i,t}$ equal one if trading in stock i was restricted by both Robinhood and TD Ameritrade/Charles Schwab in minute t, and zero otherwise. *SLIM Share* is the ticker-level volume share of SLIM trades. *Option volume*, lagged, is the two-day lag of the logarithm of the total options volume. *Underlying price*, lagged, is the two-day lag of the logarithm of underlying price in dollars. *Option volume change* is the change in log total options volume from one day before minute t to minute $t-1$. *Underlying price change* is the change in log underlying price from one day before minute t to minute $t-1$. In columns (1) and (2), the sample includes the top 100 most-mentioned tickers on `WallStreetBets` (100 WSB). In columns (3) to (6), we augment that with the restricted tickers. t-statistics are based on standard errors clustered by ticker and minute (in parentheses). $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.1$.

	SLIM Share					
	Outages		Restrictions of Jones, Reed, and Waller (2021)		Refined Restrictions	
	(1)	(2)	(3)	(4)	(5)	(6)
D(RH restricted)	0.083	0.201	-4.258^{*}	-3.713	-2.993^{**}	-2.879
	(0.56)	(1.32)	(-1.96)	(-1.64)	(-2.56)	(-1.63)
D(TD restricted)	-0.260^{**}	-0.180^{*}	-2.175^{***}	-2.468^{***}	-2.298^{***}	-2.134^{***}
	(-2.58)	(-1.80)	(-2.99)	(-2.76)	(-4.00)	(-3.81)
D(Both restricted)	-0.809^{***}	-0.722^{***}	-5.925^{***}	-3.396^{**}	-5.953^{***}	-4.236^{***}
	(-2.97)	(-2.89)	(-3.07)	(-2.45)	(-3.62)	(-3.38)
Option volume, lagged		-0.007		-0.047		0.008
		(-0.45)		(-0.80)		(0.13)
Underlying price, lagged		0.759		-3.254^{***}		-3.161^{***}
		(0.77)		(-3.36)		(-4.52)
Option volume change		-0.284^{***}		-0.491^{***}		-0.328^{***}
		(-10.68)		(-10.73)		(-11.08)
Underlying price change		2.431^{**}		-2.433^{*}		-1.988^{**}
		(2.42)		(-1.66)		(-2.09)
Observations	4,048,647	3,490,708	2,590,917	2,213,626	3,212,667	2,707,402
Adjusted R^2	0.103	0.108	0.110	0.117	0.100	0.104
Fixed effects	Ticker*Date and Time of day		Ticker, Date, Time of day			
Sample	100 WSB		Restricted + 100 WSB			

affected tickers. Volume and price controls do not significantly change the estimates.[28] In columns (5) and (6), we use a refined sample of restrictions and find the same pattern and magnitude of the effects as those reported in columns (3) and (4) (with more precise estimates). Furthermore, in Table IA.XX in the Internet Appendix, we show that the magnitudes estimated in Table IV are

[28] Ticker-level restrictions and especially outages are likely to be exogenous to ticker-level retail trading shares. We include the recent stock price and trading volume changes as well as their lagged values to ensure that the estimates are stable.

even larger for SLIM trades below \$20,000 in size, which are more likely to originate from retail investors.

Earlier in this section, we acknowledge that our measure includes some false positives, that is, institutional trades. We can use the magnitudes of the reduction in SLIM trading revealed by Table IV to back out the fraction of genuinely retail transactions in our measure. The average *SLIM Share* among 100 most-mentioned stocks on `WallStreetBets` is 19.7% (per ticker). This implies that broker outages lead to a relative reduction in trading of $0.809/19.7 = 4.11\%$, with a 95% confidence interval of $(1.40\%, 6.82\%)$. Further assuming that both TD Ameritrade and Robinhood account for about 20% of retail trading volume in options[29] yields the following back-of-the-envelope estimate for the average retail share in SLIM: $4.11\%/0.2 = 20.5\%$, with a confidence interval of $(6.98\%, 34.08\%)$. These estimates, however, are sensitive to the underlying assumptions of the model specification, and could be significantly affected by (i) the fraction of retail investors who have multiple trading apps and could therefore switch to another one in the event of an outage affecting a particular platform, and (ii) measurement error in the exact timing of the outage. Indeed, given our data sources, it is unlikely that we measure the timing of both outages and ticker-level restrictions with perfect precision. Section IV.D of the Internet Appendix further illustrates how model misspecification leads to an attenuation bias in the estimate of the retail share in SLIM. For example, assuming a 50% switching rate among trading app users, and a relative measurement error of 20% in the outage timing (and the same coefficient standard error), leads to an average estimate of retail share in SLIM of 49.28%, with a confidence interval of $(22.18\%, 76.38\%)$. With a relative measurement error of 50%, the average retail share estimate becomes 61.60%, with a confidence interval of $(34.50\%, 88.70\%)$, correspondingly. Finally, there is also measurement error in the *SLIM Share* arising from a sophisticated arbitrage strategy known as dividend play. Benefitting from the growth in retail investor presence, it has become so popular during our sample period that it dramatically inflates overall trading volume and reduces SLIM share in particular retail-popular tickers when it occurs (see Bryzgalova, Pavlova, and Sikorskaya (2022)).

For ticker-level restrictions, our baseline is the sample of restricted stocks augmented with the sample of stocks with the top 100 number of mentions on `WallStreetBets` during the sample period. In Internet Appendix Table IA.XXII, we also report results for two alternative samples: the sample of restricted stocks only and the baseline sample augmented with stocks with at least two retail herding events (frenzies) in the data of Barber et al. (2022).[30] We deem stocks in the baseline sample to be most comparable to each other, although the estimates are stable across the samples.

[29] See the CBOE Insight report "Option Flow 2021 - Retail Rising," available at https://www.cboe.com/insights/posts/option-flow-2021-retail-rising/.

[30] We thank Brad Barber for kindly sharing data on herding events.

E. Alternative Measures of Retail Trading in Options

Our measure provides the first comprehensive classification of retail trades in the options market. Nevertheless, as we show in this section, it captures only a fraction, albeit a sizeable one, of retail trading. Moreover, one may be concerned with the selection into price improvement auctions as opposed to other ways of executing retail orders. To address these concerns, we propose alternative measures of retail trading in options and compare their characteristics to those of SLIM trades. We argue that our findings extend to these more general proxies of retail participation.

We start by considering several alternative measures of retail trading in options. The first measure, also proposed by Ernst and Spatt (2022), takes advantage of another way to "internalize" retail orders, facilitated by exchanges. If an order is routed to a market maker who is a Designated/Primary market maker (formerly a specialist) in a ticker and it currently quotes at the NBBO, this market maker has priority to execute, at NBBO, any order of five contracts or fewer in full.[31] That is, the Designated market maker can effectively internalize these orders. There are 16 options exchanges in the United States, and for most tickers, a wholesaler can route a retail order of up to five contracts to an exchange in which it is a Designated market maker in that ticker. Our empirical proxy for these trades is single-leg electronic trades (OPRA trade type "AUTO") of five contracts or fewer, priced at NBBO. Together with SLIM, these trades form our *All Internalized* measure.

What fraction of retail trading volume do SLIM and All Internalized measures capture? To answer this question, we present a back-of-the-envelope calculation of the wholesaler-intermediated trading volume using Rule 606 (PFOF) disclosures from the brokers in our sample. Specifically, we divide the total monthly dollar PFOF from Rule 606 reports for each order category—market, marketable limit, nonmarketable limit, and other orders—by an average PFOF per contract in that category, which yields the PFOF-implied trading volume.[32] The estimates of the Rule 606 implied trading volume and their splits by order type are presented in Table V. The total Rule 606 implied trading volume computed in column (1) of Table V establishes a useful estimate of the volume of the wholesaler-intermediated retail transactions. Retail trading accounts for 62.6% of the total market volume. There is no estimate of retail volume in the literature to compare this number to, yet to us it is striking that retail investor presence is so high in the market commonly thought to be dominated by sophisticated and/or institutional traders.

By contrasting columns (2) and (6) of Table V, we conclude that the SLIM methodology identifies between 58% (June 2021) and 84% (March 2020) of trading volume from market and marketable limit orders reported in Rule

[31] See, for example, https://www.sec.gov/rules/sro/cboeedgx/2018/34-84697-ex5.pdf, paragraph (g)(2), or https://www.federalregister.gov/documents/2021/05/20/2021-10579/self-regulatory-organizations-box-exchange-llc-notice-of-filing-and-immediate-effectiveness-of-a#citation-17-p27492, Rule 7135(c)(2)(iii).

[32] We thank the anonymous referee for suggesting this calculation to us.

Table V

Trading Volume Implied by Rule 606 Reports and by Our Measures of Retail Trading

This table compares monthly trading volumes across several measures. Column (1) reports the total trading volume implied by the Rule 606 reports (million contracts). This volume is computed as the payment for order flow divided by the average payment per contract aggregated over the four reported order types (market, marketable limit, non-marketable limit, and other orders). Columns (2) to (4) report the weight of individual order types in the total implied volume. Column (5) reports the total OPRA trading volume (million contracts). "SLIM + ≤ 5 Single-Leg Electronic at NBBO" combines SLIM trading volume with that in trades sized up to five contracts that go through trade type "AUTO" (single-leg electronic) and are executed at the best bid or best ask price. "SLIM + Small Single-Leg Electronic at NBBO" combines SLIM trading volume with that in trades sized up to 10 contracts that go through trade type "AUTO" (single-leg electronic). "SLIM + Small + Cheap Single-Leg Electronic at NBBO" combines SLIM trading volume with that in trades sized up to 10 contracts and in trades with dollar value up to $5,000 that go through trade type "AUTO" (single-leg electronic). The data are from SEC Rule 606 reports in columns (1) to (5) and from OPRA otherwise.

	Rule 606 Reports					Retail Volume as % of Implied 606 Volume				
Month	Implied 606 Volume (1)	Market and Market. Limit Orders (2)	Nonmarket. Limit Orders (3)	Other Orders (4)	OPRA Market Volume (5)	SLIM (6)	SLIM + ≤ 5 Single-Leg Electronic at NBBO All Internalized	SLIM + Small Single-Leg Electronic All Retail	SLIM + Small+Cheap Single-Leg Electronic All Retail	Implied 606 Volume as % of Market Volume (1)/(5)
01/20	195.5	41.7%	35.8%	22.5%	348.9	30.5%	44.8%	62.5%	100.8 %	56.0%
02/20	213.8	38.3%	37.6%	24.1%	377.9	29.2%	44.7%	62.9%	97.1%	56.6%
03/20	248.0	30.3%	52.0%	17.7%	448.3	25.6%	41.8%	63.1%	92.6%	55.3%
04/20	260.2	41.8%	42.9%	15.3%	407.4	29.7%	44.0%	62.4%	92.8%	63.9%
05/20	268.6	44.5%	39.4%	16.1%	404.4	31.9%	46.6%	63.4%	91.3%	66.4%
06/20	345.1	44.8%	41.0%	14.2%	519.0	32.2%	48.0%	64.6%	92.0%	66.5%
07/20	298.0	45.9%	39.1%	15.0%	455.9	32.2%	49.9%	66.7%	93.4%	65.4%
08/20	300.8	46.0%	38.1%	15.9%	455.9	30.4%	49.1%	65.8%	92.3%	66.0%
09/20	311.4	44.4%	39.5%	16.0%	497.1	31.4%	51.8%	69.3%	96.2%	62.7%
10/20	288.1	44.5%	38.7%	16.7%	464.7	32.1%	51.6%	68.9%	96.8%	62.0%
11/20	302.4	45.6%	39.5%	14.9%	498.5	31.5%	51.7%	69.4%	98.5%	60.7%
12/20	352.9	46.9%	37.6%	15.4%	554.8	30.6%	51.2%	68.8%	96.9%	63.6%
01/21	395.1	45.0%	39.9%	15.2%	625.7	29.5%	50.6%	68.2%	95.2%	63.1%
02/21	408.6	45.1%	39.5%	15.4%	620.6	28.1%	47.9%	64.2%	90.9%	65.8%
03/21	427.2	45.1%	39.6%	15.3%	676.9	28.3%	48.7%	65.8%	95.0%	63.1%
04/21	345.7	46.2%	37.5%	16.3%	536.1	27.8%	46.8%	63.2%	92.9%	64.5%
05/21	325.9	44.0%	37.6%	18.4%	535.9	27.8%	47.4%	64.5%	96.7%	60.8%
06/21	426.2	46.1%	37.3%	16.6%	655.6	27.0%	46.1%	62.7%	93.7%	65.0%
Average	317.4	43.7%	39.6%	16.7%	504.6	29.8%	47.9%	65.4%	94.7%	62.6%

606 disclosures. To capture the remaining market and marketable limit orders, we next consider the expanded measure, or All Internalized trades. Table V reveals that the All Internalized trading volume exceeds Rule 606 implied volume originating from market and marketable limit orders. We view this as evidence that the internalized trading volume includes some volume from nonmarketable limit orders (from SLIM specifically because the remaining All Internalized trades are all marketable). Barardehi et al. (2021) argue that in equity markets, wholesalers find it profitable to internalize a fraction of nonmarketable orders. Since quoted spreads in equities are much tighter than in options, and since quoted spreads in options are so wide—the average quoted and effective spreads for SLIM transactions are 13.7% and 6.7%, respectively (see Table I)—we expect that a fraction of nonmarketable limit orders in options does get internalized through SLIM.

It is evident from Table V, however, that both the SLIM and All Internalized methodologies do not pick up all retail trades. The omitted trades are likely to be nonmarketable limit orders that wholesalers send to the limit order book on an exchange. We therefore attempt to construct an All Retail measure that captures additionally transactions originating from nonmarketable orders that are not captured by SLIM. The literature to date has not offered a reliable method to classify such trades in the OPRA data, and we therefore propose our own. We start from the measure of retail trading used in the industry—small trades (i.e., transactions of up to 10 contracts). As we discuss in Section I.C, the small trades measure overstates retail presence, and we therefore attempt to reduce the number of false positives. In our *All Retail (small)* measure, we include only a fraction of small trades, namely, single-leg electronic trades under 10 contracts. The latter are our proxy for nonmarketable retail orders sent to the limit order book. We note that we can identify single-leg electronic trades accurately using the new OPRA trade flags. By construction, the All Retail (small) measure includes all of All Internalized transactions.

The new generation of retail options investors is likely to be cash-constrained. FINRA (2021a) reports that more than twice as many new investors who opened brokerage accounts in 2020 held account balances less than $500 (33%) compared to experienced entrants (16%), and more than five times as many compared to existing account owners (6%). This is why we follow Barber, Odean, and Zhu (2009) and Brandt et al. (2010) and use a $5,000 trade size cutoff as an additional way to define retail trades. In our *All Retail (small + cheap)* measure, we broaden our All Retail (small) measure by including "cheap" trades, defined as single-leg electronic transactions of up to $5,000. Table V shows that All Retail (small) captures 65% of the Rule 606 implied trading volume, while All Retail (small + cheap) captures almost all of it, sometimes overshooting it.

To examine whether SLIM transactions are similar to those constituting our broader measures of retail trading, we first compare their descriptive statistics. In Section E of the Internet Appendix, we provide descriptive statistics for All Internalized and All Retail measures and show that they are generally in line with those for SLIM trades, reported in Table I (also reported in Tables IA.VII and IA.VIII in the Internet Appendix). Specifically, they also demonstrate a strong investor preference for ultra short-term (weekly) options and for calls over puts. In terms of trade direction, All Internalized and All Retail (small) measures also show that investors write more options than they buy, although the difference is small and reverses for the All Retail (small + cheap) measure.

We next conduct validation tests, described in Section I.D, in which we seek to check whether All Internalized and both All Retail measures drop during outages experienced by the two largest U.S. retail brokerages. Table IA.XXIX in the Internet Appendix confirms that this is indeed the case. The results are strong for the All Internalized measure. They weaken for our broader measures, All Retail (small) and All Retail (small + cheap). This is to be expected. As we expand the retail trading measures by including more transactions, we inevitably make them noisier. The significance of the coefficients therefore reduces relative to those reported in Table IV. Yet, the coefficients on the dummy variables for TD Ameritrade's and both brokers' outages remain consistently negative, even for our broadest measures. Similarly to SLIM, they all fall by around 1 percentage point.

We obtain similar results for a validation test involving trading restrictions imposed by retail brokerages on a number of tickers that are popular with retail investors. Specifically, we estimate regression (3) using our broader measures of retail trading in options rather than SLIM. Table IA.XXX in the Internet Appendix reports the results. Similar to SLIM, all the measures of retail trading are more than 6 percentage points lower when broker restrictions are in place. We find mostly negative but insignificant reductions in retail share under TD Ameritrade restrictions, although the coefficients on D(TD restricted) are not significantly different from those for SLIM. The results are similar irrespective of the chosen sample of tickers (see Tables IA.XXXI and IA.XXXII in the Internet Appendix).

Finally, we look at comovement of our All Internalized and All Retail measures with established retail investor popularity indicators. The results are reported in Tables IA.XXXIII, IA.XXXIV, and IA.XXXV in the Internet Appendix, which are the analogs of Table III for SLIM. Panels A of the tables show that our broader measures are, like SLIM, mostly positively correlated with measures of retail activity, such as *Small Share*, internalized volume in equities, Robinhood breadth of ownership, and `WallStreetBets` mentions. As evident from Panel B, imbalances in our All Internalized and All Retail measures, for the most part, are also positively correlated with the measures of retail activity. We attribute the weakening of these results relative to their analogs for SLIM to the fact that our broader proxies for retail trading—All Internalized, All Retail (small), and All Retail (small + cheap)—are noisier measures of retail trading than SLIM.

Overall, our alternative measures of retail trading are consistent with what we find for SLIM. Yet, the evidence in favor of them representing a clean cross-section of retail transactions is weaker. To date, there is no reliable identification method for nonmarketable retail orders submitted to the limit order book. Our main concern with the broader measures we propose above is that, while they include limit orders of retail investors, they contain false positives as well. In particular, they may include institutional trades of smaller sizes. Fortunately, OPRA trade flags can help detect some institutional orders broken into smaller trades by execution algorithms, such as the ISO flag we discussed in Section I.C above and Section I.F of the Internet Appendix. However, other split orders are likely to appear in our data under the plain-vanilla flags such as single-leg electronic trades. Furthermore, our measures likely pick up genuine small trades of professional or semiprofessional investors, such as those we see in index options. In the analysis that follows, to reduce false positives, we stick to our SLIM methodology for identifying retail transactions.

II. Aggregate Performance of Retail Investors in the U.S. Options Market

In this section, we examine the aggregate performance of retail investors in the U.S. options market. We document that investors lose money after transaction costs, with most of the losses concentrating in long positions in short-term options. Finally, we show that call imbalances in SLIM trading positively predict next-day returns on the underlying stocks.

A. Dollar Performance of SLIM Trades

We compute dollar performance of each retail trade j over the horizon of h days,

$$\$Perf_{hj} = Direction_j \times Size_j \times 100 \times (Price_{j,t+h} - Price_{j,t}), \tag{4}$$

where $Size_j$ is the size of the trade in contracts,[33] $Price_{j,t+h}$ is the price of the traded contract at $t + h$, $Price_{j,t}$ is the price of the traded contract at t,[34] and $Direction_j$ is the trade direction sign: 1 for buy trades and -1 for sell trades. We consider horizons h of one, two, five, and 10 days, as well as intraday and until the contract expiration.[35] We also report the intraday performance, which is until the close of the trade day.

We evaluate the contribution of gross performance and transaction costs separately. To compute gross performance, we use midpoint prices: $Trade\,midquote_{j,t}$, or the bid-ask midquote at the time of the trade, for $Price_{j,t}$ and $Close\,midquote_{j,t+h}$, or the close midquote of the traded contract on day $t + h$ as reported by OptionMetrics, for $Price_{j,t+h}$. To compute net performance,

[33] We winsorize trade sizes as in our earlier analysis at the 99.5$^{\text{th}}$ percentile each day. Results are not sensitive to the winsorization.

[34] In the reported results, we apply price adjustment factors related to corporate actions such as stock splits. Results are very similar, especially for shorter holding horizons, if we ignore the adjustment factors.

[35] We use the last available price when the data for a certain horizon are not available. Note that at the time of writing, the OptionMetrics data ran only up to December 31, 2021. We therefore exclude contracts expiring after that date.

we assume that all transaction costs are paid when the trade is open, so we use the actual trade price for $Price_{j,t}$ and $Close\,midquote_{j,t+h}$ for $Price_{j,t+h}$. We do not explicitly consider trading costs paid as investors close their positions because some of them are held to expiration. In Section I, we show that retail investors in our sample prefer ultra short-term options, and thus it is likely that many of them are held to expiration. By ignoring trading costs at the end of the performance evaluation horizon, we provide an upper bound for investor net performance.

We aggregate the trade-level performance defined in equation (4) into the total retail portfolio and report its daily average dollar performance in Table VI (Panel A). We also compute the performance of the buy and sell portfolios separately (Panel B) by summing up the dollar performance of trades with the implied buy and sell direction, correspondingly. These calculations are consistent with the buy, sell, and buy-minus-sell portfolio performance calculations in Barber et al. (2009). We also report performance of trades aggregated over several dimensions specific to options such as contract type (call retail portfolio versus put retail portfolio), moneyness, and time to expiration.

Table VI summarizes the daily mean performance of retail investor options trades. Even though performance before transaction costs of the buy-minus-sell portfolio in Panel A is positive across horizons, ranging from \$10.4 to \$12.9 million per day, adding the observed transaction costs makes it significantly negative, between −\$5.0 and −\$1.6 million per day.

The literature has documented that option writing strategies generally deliver positive average returns and large CAPM alphas (see, e.g., Broadie, Chernov, and Johannes (2009) and references therein for a recent study and Jagannathan and Korajczyk (1986) for an earlier contribution). Consistent with this result, the average gross performance of the sell portfolio in our sample is positive.[36] The average performance of the sell portfolio is positive even net of the observed transaction costs, although, with the exception of intraday performance, not statistically different from zero. On the other hand, the buy portfolio incurs losses on average, even on a gross basis. Directionally, this is exactly what one would expect from the theta exposure: Because a long option position loses its value as time passes, buy (sell) trades should have negative (positive) performance, on average.

Table IA.XXXVI in the Internet Appendix reports the aggregate performance between November 2019 and June 2021. Under the assumption of a 10-day holding period, retail investors lost \$2.10 billion on their options trades. Similar to the mean daily results in Table VI, the aggregate losses

[36] We find the opposite for performance to expiration: Investors lose on their short positions and gain on their long positions. This sign flip is driven mostly by large price movements affecting contracts expiring in 3–12 months (see Table IA.XLI in the Internet Appendix, which decomposes performance by contract type, time to expiration, and trade direction). This is consistent with Broadie, Chernov, and Johannes (2009), who find that options returns might be strongly skewed in small samples and recommend studying delta-hedged returns instead. Accordingly, we find no sign flip in delta- and fully hedged reported performance in Section VI.I of the Internet Appendix.

Table VI

SLIM Daily Performance by Trade Direction and Contract Characteristics

This table reports mean daily performance of SLIM trades from November 2019 to June 2021. Gross and net performance of each type is computed as explained in Section II. t-statistics based on Newey-West standard errors with the optimal number of lags are in parentheses.

	Gross Performance, $ mln.						Net Performance, $ mln.					
Horizon h	Intraday	1 Day	2 Days	5 Days	10 Days	Expiration	Intraday	1 Day	2 Days	5 Days	10 Days	Expiration
Panel A: All contracts												
	10.46	11.86	10.91	10.59	10.36	12.90	−4.92	−3.52	−4.47	−4.80	−5.03	−1.63
	(14.23)	(13.59)	(9.50)	(5.81)	(5.76)	(3.42)	(−11.18)	(−5.18)	(−3.86)	(−2.56)	(−2.63)	(−0.39)
Panel B: By trade direction												
Sell	12.86	18.29	22.07	20.21	16.78	−59.73	3.79	9.22	13.00	11.15	7.71	−68.33
	(7.46)	(2.81)	(2.11)	(1.10)	(0.70)	(−1.69)	(2.36)	(1.42)	(1.25)	(0.61)	(0.32)	(−1.95)
Buy	−2.40	−6.43	−11.16	−9.63	−6.42	72.63	−8.71	−12.74	−17.47	−15.94	−12.74	66.71
	(−1.49)	(−0.99)	(−1.10)	(−0.54)	(−0.27)	(2.03)	(−5.22)	(−1.96)	(−1.71)	(−0.88)	(−0.53)	(1.82)
Panel C: By contract type												
Call	7.48	8.34	7.28	6.68	6.08	8.94	−3.48	−2.61	−3.68	−4.28	−4.87	−1.33
	(13.25)	(11.15)	(6.51)	(3.65)	(3.36)	(2.70)	(−10.89)	(−3.90)	(−3.13)	(−2.22)	(−2.45)	(−0.36)
Put	2.98	3.52	3.63	3.91	4.27	3.96	−1.45	−0.91	−0.79	−0.52	−0.16	−0.30
	(15.03)	(10.35)	(8.90)	(6.68)	(6.13)	(3.17)	(−7.91)	(−3.69)	(−2.28)	(−0.95)	(−0.24)	(−0.23)

(*Continued*)

Table VI—*Continued*

	Gross Performance, $ mln.						Net Performance, $ mln.					
Horizon h	Intraday	1 Day	2 Days	5 Days	10 Days	Expiration	Intraday	1 Day	2 Days	5 Days	10 Days	Expiration
Panel D: By moneyness												
Below −2	0.06	0.06	0.07	0.07	0.08	0.07	−0.02	−0.02	−0.02	−0.02	−0.01	0.01
	(5.16)	(5.98)	(5.90)	(5.21)	(5.32)	(4.66)	(−6.70)	(−4.25)	(−4.00)	(−4.15)	(−1.93)	(1.26)
−2 to −1	0.07	0.07	0.07	0.07	0.09	0.09	−0.04	−0.04	−0.03	−0.03	−0.01	0.01
	(8.16)	(7.90)	(7.79)	(8.55)	(7.71)	(7.65)	(−12.16)	(−6.69)	(−7.18)	(−4.43)	(−1.45)	(1.24)
−1 to −0.1	2.79	3.35	3.37	3.94	4.28	6.22	−1.14	−0.57	−0.55	0.02	0.36	2.69
	(12.33)	(13.09)	(11.73)	(10.87)	(9.78)	(5.10)	(−8.66)	(−3.66)	(−2.24)	(0.06)	(0.97)	(2.06)
At the money	6.69	7.33	6.46	5.67	5.17	6.20	−3.17	−2.53	−3.40	−4.19	−4.69	−3.43
	(13.79)	(11.49)	(7.21)	(3.47)	(3.17)	(2.66)	(−10.76)	(−3.92)	(−3.79)	(−2.52)	(−2.78)	(−1.37)
0.1 to 1	0.90	1.11	1.03	0.88	0.86	0.41	−0.40	−0.19	−0.27	−0.42	−0.44	−0.73
	(11.16)	(9.29)	(7.79)	(3.82)	(3.01)	(0.45)	(−6.57)	(−1.71)	(−1.97)	(−1.75)	(−1.40)	(−0.80)
1 to 2	0.03	0.02	0.03	0.05	−0.01	−0.17	−0.04	−0.05	−0.04	−0.02	−0.08	−0.22
	(1.80)	(0.72)	(1.19)	(1.22)	(−0.13)	(−0.95)	(−1.82)	(−1.65)	(−1.54)	(−0.70)	(−1.78)	(−1.24)
Above 2	−0.09	−0.09	−0.12	−0.09	−0.12	0.07	−0.12	−0.13	−0.16	−0.13	−0.16	0.05
	(−3.06)	(−3.16)	(−2.15)	(−1.55)	(−2.00)	(0.39)	(−3.74)	(−4.00)	(−2.52)	(−2.02)	(−2.41)	(0.26)
Panel E: By time to expiration												
Less than a week	4.12	4.38	3.68	3.17	3.17	3.17	−2.14	−1.89	−2.58	−3.09	−3.09	−3.10
	(12.28)	(8.19)	(5.19)	(3.40)	(3.40)	(3.39)	(−9.78)	(−4.54)	(−3.38)	(−3.08)	(−3.08)	(−3.08)
1–2 weeks	1.33	1.38	1.22	0.70	0.41	0.42	−0.45	−0.41	−0.57	−1.09	−1.38	−1.36
	(11.84)	(7.15)	(4.54)	(0.95)	(0.57)	(0.59)	(−7.63)	(−2.42)	(−2.09)	(−1.45)	(−1.88)	(−1.87)
2–4 weeks	1.78	2.03	1.91	1.86	1.52	1.14	−0.63	−0.38	−0.51	−0.55	−0.89	−1.27
	(12.70)	(11.09)	(8.89)	(5.30)	(3.53)	(1.49)	(−8.51)	(−3.32)	(−2.95)	(−1.69)	(−2.08)	(−1.69)
1–3 months	1.65	2.03	2.00	2.24	2.34	2.66	−0.69	−0.31	−0.34	−0.10	0.00	0.32
	(15.32)	(15.33)	(14.12)	(11.26)	(9.27)	(4.25)	(−8.56)	(−3.02)	(−3.02)	(−0.52)	(0.02)	(0.46)
3–12 months	1.16	1.47	1.49	1.91	2.16	1.84	−0.70	−0.40	−0.38	0.04	0.30	0.18
	(11.46)	(10.14)	(9.45)	(6.61)	(4.86)	(1.07)	(−8.46)	(−5.24)	(−3.71)	(0.21)	(0.75)	(0.10)
Over a year	0.41	0.57	0.61	0.71	0.75	3.67	−0.31	−0.14	−0.11	−0.01	0.04	3.60
	(17.33)	(14.36)	(12.23)	(8.82)	(6.01)	(2.17)	(−10.80)	(−4.29)	(−2.44)	(−0.07)	(0.27)	(2.18)

were concentrated in buy trades, at-the-money contracts, call contracts, and in contracts with less than a week to expiration.

In Table IA.XXXVII in the Internet Appendix, we report the overall trade performance by month and day of the week. Retail investor losses are not concentrated in any particular month, while January 2021, February 2021, and December 2020 are the worst months in our sample, corresponding to losses of \$672, \$358, and \$321 million, respectively (using net performance at a 10-day horizon). The same table reveals that, on average, investor performance seems to be lower when the holding period includes the end of the week.

Table IA.XXXVIII in the Internet Appendix reveals the top and bottom 10 tickers, based on the aggregate net performance of trades originated by retail customers and those of the whole market. Similar to the latter, retail investors realized a gain on such large-cap names as Nvidia (NVDA), Apple (AAPL), and Moderna (MRNA). Interestingly, however, in contrast to the market, they lost on trading in "meme" stocks, such as GameStop (GME) and AMC Entertainment (AMC), and on some popular mega-cap names such as Tesla (TSLA) and Amazon (AMZN). In general, 100 most retail-popular companies as measured by their mentions on the `WallStreetBets` forum account for more than 50% of investor losses in our sample (see Table IA.XXXIX in the Internet Appendix).

To better understand the sources of retail performance in options, we provide a more granular decomposition by contract type, trade direction, and time to expiration in Section VI.E of the Internet Appendix. We document that investor losses are concentrated primarily in long positions in short-term (weekly) options, both calls and puts. In contrast, investors who wrote those options made money, even on a net basis. This observation suggests that there are potentially two distinct groups of retail options traders: (i) those who buy short-term (weekly) options and lose money and (ii) those who sell these options and earn a premium most of the time.

The dollar performance measure, considered so far, is our preferred performance indicator because it reveals where the aggregate retail losses come from and also allows us to compare performance in the types of contracts SLIM investors prefer trading, or in other words, where most of SLIM trading volume is.

B. Profitability of SLIM Trades

To compare profitability of SLIM trades relative to that of our broader proxies for retail trading, All Internalized and All Retail, which include more trades, we need to appropriately scale the dollar performance measure. We therefore compute per-dollar performance of retail trades, that is, investor returns or profitability of their trades. As noted in Barber et al. (2009), such a measure would be artificially high if high dollar performance was earned on days with low trading volume. We proceed with this caveat in mind and compute two measures of mean daily profitability: with and without leverage. Our measure of profitability with leverage ignores any collateral/margin requirements that investors may face on the options they write, that is, it is as options textbooks would define it. Short positions can be netted against long. Formally, the daily gross/net profitability with leverage is computed as the daily gross/net performance of a portfolio at a given horizon divided by the absolute value of the net position of that portfolio (total purchased minus total sold). Our measure without leverage follows that in Barber et al. (2009) and assumes that each short position requires the investor to deposit the entire proceeds from shorting as collateral, which earns zero interest. Under this definition, no netting is allowed and even a fully hedged short option position requires the same collateral as a naked one. Formally, *the daily gross/net profitability without leverage* is computed as the daily gross/net performance of a portfolio at a given horizon divided by the absolute value of daily dollar trading volume in that portfolio.

We view the definitions of profitability above as two extremes. It is clearly not possible for a retail investor's portfolio to have unlimited leverage, which the first definition implicitly permits. At the same time, the second definition could be too conservative. For example, covered calls are common retail investor strategies, which were already popular in the 1990s (see Lakonishok et al. (2007)) and are viewed by the new generation of retail investors as a way to earn extra income for a user who is "holding the underlying anyway" (see Section VI.H of the Internet Appendix for more evidence from investor forums). Retail brokers would net the option position from the position in the underlying and deposit the proceeds from selling a covered call option at the time of the sale.

Tables IA.XLII and IA.XLIII in the Internet Appendix present retail trades profitability under both definitions. Under the first definition that permits leverage, investors' returns over any horizon are hugely volatile and large in absolute value (Table IA.XLII). The magnitudes of mean daily returns range from −284% to 488% for gross profitability and from −177% to −23% for net profitability over the same return horizons that we have assumed for dollar performance. These return patterns are consistent with the literature. For example, Broadie, Chernov, and Johannes (2009) argue that because options embed leverage and have highly nonlinear payoffs, standard statistics applied to options portfolios look rather extreme. We find that gross profitability is positive and significant at the intraday and expiration horizons and is statistically indistinguishable from zero for the other horizons. Net profitability is also highly negative and significant for horizons of up to two days and then becomes indistinguishable from zero.

Under the assumption of no leverage, SLIM investors lose between 28 and 40 cents per 100 dollars of trading over the same return horizons that we have assumed for dollar performance (Table IA.XLIII), while net profitability to expiration is a positive 37 bps, yet not statistically different from zero. If we consider portfolios by trade and contract features, net profitability is mostly indistinguishable from zero. A notable exception is the portfolio of contracts with less than a week to expiration, which incurs significant losses at all holding periods.

The differences between the results delivered by the two definitions are quite drastic. It seems to us that the definition without leverage is perhaps too conservative for an options portfolio and actual investor portfolio returns are closer to those in the definition with leverage (although they would not be so extreme, given that in reality retail brokerage platforms do impose some margin/collateral requirements).

One important limitation of our performance calculation is that, as we have remarked earlier, SLIM captures primarily market and marketable limit orders and leaves out the majority of nonmarketable limit orders. By using liquidity-demanding marketable orders as our proxy for retail orders, we are biasing our sample toward costlier transactions and hence are potentially overestimating the extent of investor losses. We acknowledge this concern and attempt to address it by comparing the profitability of SLIM trades to that of broader measures of retail trading that we introduced in Section I.E. To compare profitability of SLIM trades to that of All Internalized and All Retail trades, we adopt the profitability definition that involves leverage, as it delivers options returns that are more consistent with the literature. Table IA.XLIV in the Internet Appendix reports the results of the difference in means tests of daily net profitability of each of our broader measures and that of SLIM. It is clear from the tables that profitability of All Internalized and both All Retail trades is not statistically different from that of SLIM trades at the 1% level. This evidence lends additional support to the claim that our SLIM measure of retail trading is similar to the alternative, albeit noisier, proxies.

C. Trading Costs and Other Drivers of Underperformance

In our data, we do not observe stock holdings of investors, and they may possibly be engaging in strategies involving both options and the underlying stocks. For example, they may fully hedge their short options positions due to the restrictions on naked short positions typically imposed by brokerages. By full hedging, we mean delta-hedging with hedge ratio equal to one at all times. Furthermore, from statistical viewpoint, options returns are quite extreme and standard statistics computed based on raw returns in finite samples are problematic, while those based on delta-hedged returns are more informative (see Broadie, Chernov, and Johannes (2009), Zhan et al. (2022), and references therein). In Section VI.I of the Internet Appendix, we compute fully hedged and delta-hedged performance of SLIM trades in our sample. Tables IA.XLV and IA.XLVI, which are analogous to Table VI, summarize our results for those two performance measures and demonstrate that they both deliver similar results to our baseline results. The main exception is that the performance of the buy and sell portfolios, which now contain a stock leg, is more extreme than in our baseline analysis. We attribute this to the run-up in the stock market during our sample period. As a robustness check, we compute market-adjusted performance instead, and the performance of both the buy and sell portfolios is much more in line with that in Table VI. As for aggregate dollar performance, if all SLIM investors were delta-hedged (fully hedged), their 10-day net performance in our sample would have been −\$2.2 billion (−\$4.5 billion).

Regardless of the chosen measure of performance, the losses in short-term options contracts are significant and contribute the most to aggregate retail performance. We therefore study retail performance in these contracts in a multivariate setup. In Section VI.J of the Internet Appendix, we estimate regressions similar to specification (2) in Section I.C but with SLIM performance as a dependent variable. We find that, even conditional on ticker and contract characteristics, retail investors who buy the short-term contracts are likely to experience losses. Equity-based retail activity proxies are positively associated with performance, but only on a gross basis: They turn negative and mostly insignificant as soon as trading costs are taken into account. Finally, our estimates also suggest that contracts with a larger retail presence, as measured by *SLIM Share*, have negative net performance on average.

Our analysis thus far has not taken *direct* transaction costs into account. Some of the brokerages in our sample, such as Robinhood, offer commission-free options trading. However, the majority of brokerages still charge around \$0.65 per contract.[37] Using the fraction of PFOF in options paid to Robinhood as the upper bound of their share in the retail options trading (the share based on Rule 606 implied trading volume is very similar), we can estimate the aggregate *direct* transaction costs paid by retail investors. Using 1.93 million contracts as the aggregate SLIM volume and 25% as Robinhood's average share in PFOF for options, the direct transaction costs of retail trades in our sample period amount to $\$0.65 \times 1.82 \times 10^6 \times 0.75 \approx \$887$ million.

Even though *indirect* transaction costs are already included in the net performance figures we report, we find it useful to highlight their total value in our sample. It is computed by summing up the products of effective half-spread and trade size across all SLIM trades, resulting in around \$6.4 billion.[38] These costs are not as transparent as brokerage fees and are likely to be overlooked by retail investors. Furthermore, they become revenue for market makers and exchanges executing retail orders (rather than for retail brokerages). These costs are economically large, almost seven times the direct costs of retail trading. Our calculation approach captures the actual gains and losses of retail trading and does not require any assumptions regarding their opportunity costs.

One limitation of our data is that some trades might come from multileg strategies involving options as well as underlying equities (e.g., a covered call), and we do not observe equity legs of these transactions. However, since the retail investor boom in our sample is driven largely by novice investors, we believe that only a small fraction of them uses such sophisticated strategies.

[37] As of March 2022, TD Ameritrade, Charles Schwab, E*TRADE, and Fidelity all charge \$0.65 per contract, according to their websites. Some of the brokers provide commission discounts for frequent traders or for large transactions. However, given the stylized features of retail trading highlighted in Table I, these discounts are unlikely to have a material impact on our estimates.

[38] To put this number into perspective, the total PFOF in options in our sample is around \$2.8 billion.

It should therefore have little impact on our aggregate retail performance estimates.

The literature has suggested that investors may learn through trading (see, e.g., Seru, Shumway, and Stoffman (2010) and Linnainmaa (2011)). We use the results presented in Table IA.XXXVII in the Internet Appendix to study whether retail investor performance in the later part of the sample is better than in the earlier part. We find that, on the contrary, retail investors lost *more* money in the later subsample, especially in January and February of 2021, around the GameStop frenzy. This could happen if retail investors do not learn from their trading experience.[39] A more likely explanation, however, is the changing composition of the investor base. While some of the poor-performing early investors could have exited the sample, it seems that their attrition was more than compensated by the entry of new retail investors in later months. After all, in 2021 alone, the account base of Robinhood almost doubled, increasing from 11.7 to 21.3 million, according to the company's quarterly reports.

D. SLIM Trading and Stock Return Predictability

Recent findings on retail investor frenzies during the pandemic indicate that retail order imbalances in equities positively predict next-day returns (see Jones, Zhang, and Zhang (2022)). Yet, no study evaluates the spillover of retail trading in options on the returns of the underlying. At the same time, a large and growing literature documents that information contained in option returns has predictive power for the dynamics of the underlying assets, typically by reflecting informed trading or due to the relaxation of leverage constraints (see Pan and Poteshman (2006), Cremers and Weinbaum (2010), Xing, Zhang, and Zhao (2010), An et al. (2014), Ge, Lin, and Pearson (2016), Augustin, Brenner, and Subrahmanyam (2019), Weinbaum et al. (2023)). Is SLIM trading indicative of the future returns on the underlying stocks? Since our sample of data are fairly short, to answer this question, we focus on the daily predictability of stock returns driven by SLIM trade imbalances.

Table VII reports the predictability of daily stock returns by *SLIM Imbalance* in call and put options estimated via panel regressions with fixed effects and double-clustered standard errors (by ticker and date). We consider several versions of the key independent variable: the level of *SLIM Imbalance*, its innovation relative to the previous day, computed as the change in *SLIM Imbalance* over two days with available imbalances, and the ticker-specific quantile relative to its levels over the previous trading month. The latter proxy allows us to better reflect the level of the previous day's *SLIM Imbalance* compared to the overall directional retail trading over the recent period. All of our specifications also control for the options trading volume, implied volatility, the

[39] Prior studies also suggest that investors learn worse after experiencing financial losses, in active trading (relative to observing other people decisions), and when they are emotionally involved in decision making. See Kuhnen (2015) and references therein. It would be interesting to extend our data and test these potential mechanisms for the performance of the new generation of retail investors.

Table VII

Stock Return Predictability via SLIM Imbalance

This table reports daily stock return predictability by various measures of *SLIM Imbalance* in call and put options. Our sample is from November 2019 to June 2021. The dependent variable is the next-day stock return, adjusted for delisting (Shumway (1997)). The key independent variable in columns (1) to (3) is the raw level of *SLIM Imbalance* (as defined in Section I.C), while in columns (4) to (6) it is the change in *SLIM Imbalance* relative to the previous day with available *SLIM Imbalance*. In columns (7) to (9), the independent variable is the monthly quantile of the previous-day *SLIM Imbalance*. Controls include the previous-day volume-weighted trade-implied volatility reported by OPRA, previous-day (log) options trading volume per ticker, (log) market capitalization from the previous day, contemporaneous market rate of return (using CRSP value-weighted index), and previous-day Amihud (2002) illiquidity measure. t-statistics are based on standard errors clustered by ticker and day (in parentheses). $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.1$.

	SLIM Imbalance (level)			SLIM Imbalance (innovation)			Monthly Quantile of SLIM Imbalance		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
SLIM Call Imbalance	0.0005**	0.0006***	0.0005***	0.0002**	0.0002**	0.0002**	0.0009**	0.0009**	0.0006**
	(2.33)	(2.89)	(3.23)	(2.59)	(2.39)	(2.53)	(2.54)	(2.43)	(2.38)
SLIM Put Imbalance	−0.0004***	−0.0004***	−0.0003***	−0.0001**	−0.0001*	−0.0001	−0.0010***	−0.0009***	−0.0005**
	(−3.42)	(−3.64)	(−3.00)	(−2.01)	(−1.86)	(−1.09)	(−3.09)	(−2.70)	(−2.20)
Observations	680,884	680,775	680,775	676,5847	676,767	676,767	609,722	609,709	609,709
Adjusted R^2	0.126	0.145	0.184	0.127	0.145	0.185	0.132	0.154	0.194
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Ticker FE	N	Y	Y	N	Y	Y	N	Y	Y
Date FE	N	N	Y	N	N	Y	N	N	Y

market capitalization of the stock, as well as the contemporaneous market return. We also include Amihud (2002) liquidity measure because of the short prediction horizon.

All of the specifications in Table VII indicate that a higher *SLIM Imbalance* in calls tends to forecast a higher return, and a higher *SLIM Imbalance* in puts tends to forecast a lower return on the underlying stock over the next trading day. While this effect is present for both levels and innovations in *SLIM Imbalance*, it is particularly pronounced for the monthly quantile of *SLIM Imbalance*. We see no significant impact of the order imbalance on weekly or monthly returns, although the signs of the coefficients remain the same. Either this predictability is very short-lived or it could be due to the low statistical power of the tests, given a relatively short sample.

There are several channels through which volume imbalance in options could impact the returns of the underlying stocks: hedging demand by wholesalers and/or intermediaries, the relaxation of short-selling constraints, and the reflection of informed trading by retail investors. Given the short-term nature of predictability, its sign for call and put imbalances, and all of our other findings regarding SLIM behavior and performance in Sections II and III, this predictability relationship seems to be more in line with the price pressure caused by the hedging demand of the intermediaries servicing retail order flow.

III. Additional Support for SLIM as a Measure of Retail Trading

In this section, we offer additional suggestive evidence that our measure captures *retail* trading in the U.S. options market and discuss remaining limitations.

A. SLIM Trading on Option Expiration Days

First, we exploit the fact that some U.S. retail brokerages handle expiring options on their clients' accounts in a rule-based manner. For example, Robinhood attempts to exercise in-the-money options (if the account has enough buying power) or sells the contract approximately one hour before the market close (if it does not).[40] This gives us a testable prediction for our measure of retail trading in contracts on their expiration day: We expect to see an imbalance in the direction of sell trades in the last one or two trading hours of the day. To test this prediction, we study volume share of buy and sell trades in each trading hour on option expiration day.

On expiration days, as Table IA.XLIX in the Internet Appendix reports, there is significantly larger sell volume share in SLIM trades in the last two hours of the trading day. Notably, this pattern does not emerge on nonexpiration days. These features of SLIM trades are consistent with retail brokerages taking an automated action to close retail positions prior to the option's expiration. At

[40] See Robinhood's rules here: https://robinhood.com/us/en/support/articles/expiration-exercise-and-assignment/ accessed on March 21, 2022.

the same time, there is no pattern like this for MLIM trades and other multileg trades, which are more likely to be institutional. We test these differences more formally in Table IA.L and find them to be highly statistically significant.

B. SLIM Trading during Robinhood Herding Events

Second, we study directional order imbalances across trade types during the Robinhood herding events (frenzies) uncovered in Barber et al. (2022). In particular, we estimate equation (2) using a dummy for the Robinhood herding event in ticker i on date t instead of $Retail_{i,t}$. This analysis is performed on a subsample of our data (November 4, 2019, to August 10, 2020) due to availability of Robintrack data with which the investor frenzies are identified.

Table IA.LI in the Internet Appendix documents higher *SLIM Imbalance* during Robinhood herding events. We also find that the correlation is the highest for SLIM trades sized below \$250. Importantly, imbalances in multileg price improvement auctions (MLIM), all multileg and large trades are not positively related to frenzies. Our results even show negative correlations, suggesting that other types of investors, most likely professional traders or institutions, trade against retail investors during such events. Overall, we document that during the well-publicized investor frenzies, there were directional order imbalances in retail trading in options as well.

C. SLIM Trading around Stock Splits

As we discuss earlier, the new generation of retail options investors is also more likely to be cash-constrained. Micro SLIM trades (below \$250) should therefore reflect the activity of cash-constrained investors, and we expect to see large changes in trading volume in these transactions around stock splits.[41] Note that stock splits should have minimal effect on investor positions in the underlying, because trading fractional shares is permitted on most popular investment platforms during our sample period. In contrast, stock splits may still affect retail investors in options because trading fractional options contracts is not permitted. We perform a simple event study, reported in Section VII.C of the Internet Appendix, where we focus on two companies popular with retail investors—Apple (AAPL) and Tesla (TSLA)—that executed stock splits on the same day, August 28, 2020. We find that microsized SLIM trading volume on these two names went up significantly relative to a control group of companies popular with retail investors that did not go through a stock split. Figure IA.6 in the Internet Appendix also documents that the distribution of trade dollar sizes *within* SLIM trades changes after the split, consistent with the presence of cash constraints: After the split, we see a significantly larger share of trades of smaller sizes, corresponding to an increase in the skewness of trade size distribution of 48% and 73% for AAPL and TSLA, respectively. In Section VII.C of the Internet Appendix, we also consider all

[41] We thank Yang Liu for suggesting this test.

stocks splits in our sample period and document that an increase in micro SLIM volume is positively related to the size of the split. In this full sample of splits, we find similar changes in the distribution of SLIM trade sizes after the event as for AAPL and TSLA. All of this evidence strongly suggests that SLIM trades, especially of microsizes, are likely to be originated by cash-constrained investors.

D. Suboptimal Exercise by SLIM Investors

In our last validation exercise, we show that SLIM investors are less likely to exercise their options optimally.[42]

We rely on the Black-Scholes-Merton option pricing formula to determine whether it is optimal to exercise a call option early, before the underlying goes ex-dividend. Denote the expected ex-dividend price of an option by c_{ex}, its strike by K, and the current (cum-dividend) underlying stock price by S. The expected option ex-dividend price represents the expected time value of the option. The variable *early exercise value (EEV)* is therefore the difference between the current stock price, strike, and this expected time value of the option: $S - K - c_{ex}$. Details on the computation of c_{ex} are in Section VII.D of the Internet Appendix.

In the following analyses, we restrict our sample to call option contracts that are optimal to exercise on cum-dates and refer to the resulting sample as the early exercise sample. Details on its construction are provided in Section VII.E of the Internet Appendix, and Table IA.LIII in the Internet Appendix presents descriptive statistics.

Let $t-1$ denote the day before the last cum-dividend date and let OI_{t-1} be OI on that date (measured after all trades, exercises, and assignments on that date). To test the hypothesis that retail investor presence increases the fraction of OI remaining (suboptimally) unexercised, we run the regression

$$f_{c,t} = \beta\, share^{SLIM}_{c,t} + \boldsymbol{\gamma}' X_{c,t} + \alpha_{i,t} + \varepsilon_{c,t}, \tag{5}$$

where $f_t \equiv OI_t/OI_{t-1}$ is the fraction of OI remaining unexercised, and $share^{SLIM}_{c,t}$ is the average dollar volume share of SLIM trades over one trading week before the last cum-dividend date t, which captures interest of retail investors. In some specifications, we also use *Small Share* ($share^{small}_{c,t}$) and ticker-level measures of retail investor popularity such as Internalized volume in underlying and WSB mentions (log) all computed over one trading week before date t.[43] These measures are defined in the paragraph beneath equation (2). The vector of controls $X_{c,t}$ includes the following contract-level variables: log

[42] Previous research documents that not all American options are exercised rationally (e.g., Poteshman and Serbin (2003)). Focusing on early exercise decisions, Battalio, Figlewski, and Neal (2020), Cosma et al. (2020), Jensen and Pedersen (2016), and Barraclough and Whaley (2012) show in more recent data that a fraction of investors still fail to exercise their options optimally.

[43] We also explore an alternative specification in which we measure retail trading over two weeks preceding the last cum-dividend date. Our results are quantitatively similar.

OI, EEV, log dollar trading volume, relative spread, implied volatility, moneyness, and days to expiration. Finally, our specification also includes the ticker by date fixed effects $\alpha_{i,t}$, as we aim to compare contracts within the same ticker but with different *SLIM Shares*.

Table VIII reports results of the regression in (5). We find a strong positive relationship between retail investor trading, as measured by *SLIM Share*, and the fraction of options that were suboptimally not exercised on the last cum-dividend day. This effect is highly significant regardless of whether we also include other measures of retail trading such as *Small Share*, internalized volume in the underlying, or WSB mentions in the model. A one-standard-deviation increase in the share of SLIM trades in the contract in the week preceding the cum-date raises the fraction unexercised by about 1 percentage point, depending on the specification. This result is robust, and the magnitudes of the coefficients of interest do not significantly change as we relax the specification of fixed effects and switch on ticker-level controls instead (see columns (4) and (5)).

In sum, we conclude that a higher *SLIM Share* is associated with a higher fraction of OI left suboptimally unexercised by the ex-dividend date. We also see that there is no such association for other trade types such as MLIM, all multileg, and large trades. Table IA.LIV in the Internet Appendix summarizes these results.

E. Further Limitations of the SLIM Methodology

Finally, we discuss the remaining limitations of using SLIM trades to detect retail trading in the U.S. options market. First, our methodology likely omits trades of semiprofessional traders, such as those that do not go through a wholesaler and instead are sent directly to exchanges (e.g., those originated on Interactive Brokers) and those that constitute complex strategies (e.g., bull spreads, straddles, and butterfly spreads). Complex strategies typically require multileg transactions, and hence wholesalers looking for price improvement would usually execute them via multileg price improvement auctions, as opposed to single-leg ones. In the OPRA data, these transactions appear as trade type "MLAN" (multileg non-ISO price improvement mechanism), and we refer to them as MLIM for consistency. These MLIM trades correspond to about 4% of total market volume, and they consist primarily of trades of "protail" investors—small professional investors and hedge funds—albeit some may be those of retail investors. We also compute mentions of multileg strategies on `WallStreetBets` in our sample period and find that they constitute a small number relative to the mentions of individual tickers and comments overall. In addition, in Section VII.G of the Internet Appendix, we report descriptive statistics and cross-sectional correlations of MLIM with the equity-based measures of retail activity. These results further demonstrate that these trades are clearly quite different in nature from those going through single-leg actions. Since we want to capture trading of the new

Table VIII

Suboptimal Exercise and Retail Investor Popularity

This table reports estimates of equation (5) in our early exercise sample. *SLIM Share* and *Small Share* are the contract-level volume shares of SLIM and small trades, respectively, averaged over one trading week before the cum-dividend date. *Internalized volume in underlying* is the share of non-ATS OTC (i.e., internalized) volume in the total trading volume in the underlying stock or ETF, averaged over one trading week before the cum-dividend date. *WSB mentions*, log, is the logarithm of total mentions of the ticker on `WallStreetBets` forum. Contract controls include log dollar trading volume, relative spread, IV, moneyness, days to expiration, log OI, and EEV. Ticker controls include underlying price, underlying volatility, underlying relative bid-ask spread, and underlying market cap. Since specification (5) includes ticker-level variables, in column (5) we use ticker and date fixed effects, as opposed to ticker by date. Standard errors are clustered by ticker and date. Robust t-statistics are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.1$.

	Fraction of OI Not Exercised				
	(1)	(2)	(3)	(4)	(5)
SLIM share	4.906***	4.854***	5.547***	5.094***	5.330***
	(5.58)	(5.55)	(3.86)	(5.79)	(5.83)
Small share		3.539***			
		(3.40)			
Internalized volume in underlying					25.223***
					(2.93)
WSB mentions, log					0.469**
					(2.34)
Observations	41,735	41,735	13,758	41,735	40,181
Adjusted R^2	0.206	0.206	0.286	0.183	0.185
Sample	All	All	Top EEV tercile	All	All
FE	Ticker*Date	Ticker*Date	Ticker*Date	Ticker and Date	Ticker and Date
Contract controls	Y	Y	Y	Y	Y
Ticker controls	N	N	N	Y	Y

generation of retail investors, we are hesitant to include MLIM trades in our analysis.[44]

Second, our measure likely includes some false positives. Of the SLIM volume, 10.8% is concentrated in transactions with over $20,000 in value (see Table I), which is considered a cutoff for retail trades in related literature on equities (see, e.g., Lee and Radhakrishna (2000)). We therefore exclude trades above $20,000 in our robustness checks. Table IA.XVI in the Internet Appendix confirms that the results are virtually the same. Furthermore, the validation evidence in Section I.D and above strongly suggest that the majority of the trades we capture indeed originate from retail investors.

It is reassuring, however, that in independent contemporaneous work, Ernst and Spatt (2022) rely on the same empirical strategy to classify retail trades in the options market. Their findings are complementary to ours, as they focus on order execution quality and market microstructure.

IV. Concluding Remarks

This paper focuses on the recent boom in retail investor trading in options, driven by young and tech-savvy, yet inexperienced, investors. Exploiting a new OPRA reporting requirement, we develop a novel measure of retail investor trading in options and document a rapid rise in retail investor trading in our sample. We argue that retail investors enter the options market for speculative reasons. They prefer options with very short maturities, primarily calls. These contracts have high relative bid-ask spreads, making the options business a very lucrative one for wholesalers that execute retail order flow. This is further supported by the ballooning PFOF for options received by retail brokerages.

Our paper calls for more transparency in reporting wholesaler activities in the options market, consistent with the current requirement by FINRA in equities. In particular, it would be useful to know how often market makers affiliated with wholesalers get order allocations through price improvement auctions. One particularly fruitful avenue for future research is uncovering the barriers to entry in this market and characterizing the optimal market structure.

We would not be the first to call for more transparency in trading costs in zero-commission offers of retail brokerages.[45] However, most prior calls were related to equities. Trading costs in options are orders of magnitude higher, so a regulatory requirement to disclose these costs to investors would be a welcome first step.

[44] Furthermore, Tables IA.LVII and IA.LVIII in the Internet Appendix demonstrate that all multileg trades taken together and trades above $50,000 are also clearly different from SLIM trades.

[45] Regulators have long been interested in various aspects of the system of PFOF and, in particular, whether internalization of orders really provides price improvement for the clients. In 2017, the SEC found that some of the algorithms used by Citadel Securities to route retail orders did not seek to obtain the best price on the marketplace, leading to a settlement fee of $22.6 mln (see https://www.sec.gov/news/pressrelease/2017-11.html).

Frequent trading produces large order flow and revenue from PFOF for retail investing platforms. Trading assets that are less liquid, such as options, enhances these profits further. This may create an incentive for retail brokerages to encourage more trading in less liquid asset classes or securities. Policymakers should be aware of this potential conflict of interest.

An advantage of our retail trading measure is that it allows us to capture a large swath of retail transactions in the U.S. options market. A disadvantage is that we do not know who is making these transactions. It is therefore difficult for us to identify specific behavioral mechanisms driving retail investor choices. In particular, it would be important to understand whether ultra short-term options are popular with retail investors because of their preferences for lotteries or because these options are the default choice on the trading apps. Policy implications of these two theories are very different. If investor choices are driven by preferences, there is no reason for regulatory intervention. If they are driven by the default choice, however, there could be a case for intervention because a brokerage may be incentivizing too much churning. A regulator may engage with brokerages and run a simple controlled experiment in which the default option expiration choice is presented differently to investors. Naturally, to better understand retail investor strategies, their potential pitfalls, or investor protection policies, it would be ideal to couple our analysis with account-level data from retail brokerages.

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REFERENCES

Amihud, Yakov, 2002, Illiquidity and stock returns: Cross-section and time-series effects, *Journal of Financial Markets* 5, 31–56.

An, Byeong-Je, Andrew Ang, Tarun G. Bali, and Nusret Cakici, 2014, The joint cross section of stocks and options, *Journal of Finance* 69, 2279–2337.

Augustin, Patrick, Menachem Brenner, and Marti G. Subrahmanyam, 2019, Informed options trading prior to takeover announcements: Insider trading? *Management Science* 65, 5697–5720.

Barardehi, Yashar, Dan Bernhardt, Zhi Da, and Mitch Warachka, 2021, Internalized retail order imbalances and institutional liquidity demand, Working paper, University of Warwick, Department of Economics.

Barber, Brad M., Xing Huang, Terrance Odean, and Chris Schwartz, 2022, Attention-induced trading and returns: Evidence from Robinhood users, *Journal of Finance* 77, 3141–3190.

Barber, Brad M., Yi-Tsung Lee, Yu-Jane Liu, and Terrance Odean, 2009, Just how much do individual investors lose by trading? *Review of Financial Studies* 22, 609–632.

Barber, Brad M., and Terrance Odean, 2001, Boys will be boys: Gender, overconfidence, and common stock investment, *Quarterly Journal of Economics* 116, 261–292.

Barber, Brad M., Terrance Odean, and Ning Zhu, 2009, Do retail trades move markets? *Review of Financial Studies* 22, 151–186.

Barberis, Nicholas, and Ming Huang, 2008, Stocks as lotteries: The implications of probability weighting for security prices, *American Economic Review* 98, 2066–2100.

Barraclough, Kathryn, and Robert E. Whaley, 2012, Early exercise of put options on stocks, *Journal of Finance* 67, 1423–1456.

Battalio, Robert, Stephen Figlewski, and Robert Neal, 2020, Option investor rationality revisited: The role of exercise boundary violations, *Financial Analyst Journal* 76, 82–99.

Battalio, Robert, Todd Griffith, and Robert Van Ness, 2021, Do (should) brokers route limit orders to options exchanges that purchase order flow? *Journal of Financial and Quantitative Analysis* 56, 183–211.

Battalio, Robert, Andriy Shkilko, and Robert Van Ness, 2016, To pay or be paid? The impact of taker fees and order flow inducements on trading costs in U.S. options markets, *Journal of Financial and Quantitative Analysis* 51, 1637–1662.

Bauer, Rob, Mathijs Cosemans, and Piet Eichholtz, 2009, Option trading and individual investor performance, *Journal of Banking & Finance* 33, 731–746.

Beshears, John, James J. Choi, David Laibson, and Brigitte C. Madrian, 2009, The importance of default options for retirement saving outcomes: Evidence from the United States, Brown, J. R., J. B. Liebman, and D.A. Wise, eds.: Social Security Policy in a Changing Environment (University of Chicago Press, Chicago, IL).

Beshears, John, James J. Choi, David Laibson, Brigitte C. Madrian, and William L. Skimmyhorn, 2021, Borrowing to save? The impact of automatic enrollment on debt, *Journal of Finance* 77, 403–447.

Boehmer, Ekkehart, Charles M. Jones, Xiaoyan Zhang, and Xinran Zhang, 2021, Tracking retail investor activity, *Journal of Finance* 76, 2249–2305.

Boyer, Brian H., and Keith Vorkink, 2014, Stock options as lotteries, *Journal of Finance* 69, 1485–1527.

Brandt, Michael W., Alon Brav, John R. Graham, and Alok Kumar, 2010, The idiosyncratic volatility puzzle: Time trend or speculative episodes? *Review of Financial Studies* 23, 863–899.

Broadie, Mark, Mikhail Chernov, and Michael Johannes, 2009, Understanding index option returns, *Review of Financial Studies* 22, 4493–4529.

Bryzgalova, Svetlana, Anna Pavlova, and Taisiya Sikorskaya, 2022, Profiting from investor mistakes: Evidence from suboptimal option exercise, Working paper, London Business School.

Cai, Jinghan, Jibao He, Wenxi Jiang, and Wei Xiong, 2021, The whack-a-mole game: Tobin taxes and trading frenzy, *Review of Financial Studies* 34, 5723–5755.

Chapkovski, Philipp, Mariana Khapko, and Marius Zoican, 2021, Does gamified trading stimulate risk taking?, Working paper, University of Toronto.

Choi, James J., David Laibson, Brigitte C. Madrian, and Andrew Metrick, 2004, For better or for worse: Default effects and 401(k) savings behavior, David A. Wise, ed., Perspectives on the Economics of Aging (University of Chicago Press, Chicago, IL).

Christoffersen, Peter, Ruslan Goyenko, Kris Jacobs, and Mehdi Karoui, 2018, Illiquidity premia in the equity options market, *Review of Financial Studies* 31, 811–851.

Cosma, Antonio, Stefano Galluccio, Paola Pederzoli, and Olivier Scaillet, 2020, Early exercise decision in american options with dividends, stochastic volatility, and jumps, *Journal of Financial and Quantitative Analysis* 55, 331–356.

Cremers, Martijn, and David Weinbaum, 2010, Deviations from put-call parity and stock return predictability, *Journal of Financial and Quantitative Analysis* 45, 335–367.

de Silva, Tim, Kevin Smith, and Eric C. So, 2022, Losing is optional: Retail option trading and earnings announcement volatility, Working paper, MIT.

Eaton, Gregory W., T. Clifton Green, Brian Roseman, and Yanbin Wu, 2022a, Retail option traders and the implied volatility surface, Working paper, Emory University.

Eaton, Gregory W., T. Clifton Green, Brian S. Roseman, and Yanbin Wu, 2022b, Retail trader sophistication and stock market quality: Evidence from brokerage outages, *Journal of Financial Economics* 146, 502–528.

Ernst, Thomas, and Chester S. Spatt, 2022, Payment for order flow and asset choice, NBER Working Paper 29883.

Fedyk, Valeria, 2021, This time is different: Investing in the age of Robinhood, Working paper, London Business School.

FINRA, 2021a, Investing 2020: New accounts and the people who opened them, FINRA Foundation and NORC at the University of Chicago.

FINRA, 2021b, Options account approval, supervision and margin, Regulatory Notice 21-15.

Ge, Li, Tse-Chun Lin, and Neal Pearson, 2016, Why does the option to stock volume ratio predict stock returns?, *Journal of Financial Economics* 120, 601–622.
Hagströmer, Björn, 2021, Bias in the effective bid-ask spread, *Journal of Financial Economics* 142, 314–337.
Hendershott, Terrence J., Saad Khan, and Ryan Riordan, 2022, Option auctions, Working paper, University of California, Berkeley.
Jagannathan, Ravi, and Robert A Korajczyk, 1986, Assessing the market timing performance of managed portfolios, *Journal of Business* 59, 217–235.
Jensen, Mads V., and Lasse H. Pedersen, 2016, Early option exercise: Never say never, *Journal of Financial Economics* 121, 278–299.
Jones, Charles M., Adam V. Reed, and William Waller, 2021, When brokerages restrict retail investors, does the game stop?, Working paper, Columbia University.
Jones, Charles M., Xiaoyan Zhang, and Xinran Zhang, 2022, Retail investors in the pandemic, Working paper, Columbia University.
Kalda, Ankit, Benjamin Loos, Alessandro Previtero, and Andreas Hackethal, 2021, Smart(phone) investing? A within investor-time analysis of new technologies and trading behavior, NBER working paper 28363.
Kuhnen, Camelia M., 2015, Asymmetric learning from financial information, *Journal of Finance* 70, 2029–2062.
Lakonishok, Josef, Inmoo Lee, Neil D. Pearson, and Allen M. Poteshman, 2007, Option market activity, *Review of Financial Studies* 20, 813–857.
Lee, Charles M. C., and Balkrishna Radhakrishna, 2000, Inferring investor behavior: Evidence from TORQ data, *Journal of Financial Markets* 3, 83–111.
Lee, Charles M. C., and Mark J. Ready, 1991, Inferring trade direction from intraday data, *Journal of Finance* 46, 733–746.
Li, Xindan, Avanidhar Subrahmanyam, and Xuewei Yang, 2021, Winners, losers, and regulators in a derivatives market bubble, *Review of Financial Studies* 34, 313–350.
Linnainmaa, Juhani T., 2011, Why do (some) households trade so much?, *Review of Financial Studies* 24, 1630–1666.
Liu, Hongqi, Cameron Peng, Wei A. Xiong, and Wei Xiong, 2022, Taming the bias zoo, *Journal of Financial Economics* 143, 716–741.
Madrian, Brigitte C., and Dennis F. Shea, 2001, The power of suggestion: Inertia in 401(k) participation and savings behavior, *Quarterly Journal of Economics* 116, 1149–1187.
Mayhew, Stewart, 2002, Competition, market structure, and bid-ask spreads in stock option markets, *Journal of Finance* 57, 931–958.
Muravyev, Dmitriy, 2016, Order flow and expected option returns, *Journal of Finance* 71, 673–708.
Muravyev, Dmitriy, and Neil D. Pearson, 2020, Options trading costs are lower than you think, *Review of Financial Studies* 33, 4973–5014.
Pan, Jun, and Allen Poteshman, 2006, The information in option volume for future stock prices, *Review of Financial Studies* 19, 871–908.
Pearson, Neil D, Zhishu Yang, and Qi Zhang, 2021, The Chinese warrants bubble: Evidence from brokerage account records, *Review of Financial Studies* 34, 264–312.
Poteshman, Allen M., and Vitaly Serbin, 2003, Clearly irrational financial market behavior: Evidence from the early exercise of exchange traded stock options, *Journal of Finance* 58, 37–70.
Ramachandran, Lakshmi S., and Jitendra Tayal, 2021, Mispricing, short-sale constraints, and the cross-section of option returns, *Journal of Financial Economics* 141, 297–321.
Savickas, Robert, and Arthur J. Wilson, 2003, On inferring the direction of option trades, *Journal of Financial and Quantitative Analysis* 38, 881.
SEC, 2022, Equity and options market structure conditions in early 2021, SEC Staff Report.
Seru, Amit, Tyler Shumway, and Noah Stoffman, 2010, Learning by trading, *Review of Financial Studies* 23, 705–739.
Shumway, Tyler, 1997, The delisting bias in CRSP data, *Journal of Finance* 52, 327–340.
Weinbaum, David, Andrew Fodor, Dmitriy Muravyev, and Martijn Cremers, 2023, Option trading activity, news releases, and stock return predictability, *Management Science* 69, 4810–4827.
Welch, Ivo, 2022, The wisdom of the Robinhood crowd, *Journal of Finance* 77, 1489–1527.

Xing, Yuhang, Xiaoyan Zhang, and Rui Zhao, 2010, What does individual option volatility smirk tell us about future equity returns?, *Journal of Financial and Quantitative Analysis* 45, 641–662.

Xiong, Wei, and Jialin Yu, 2011, The Chinese warrants bubble, *American Economic Review* 101, 2723–2753.

Zhan, Xintong (Eunice), Bing Han, Jie Cao, and Qing Tong, 2022, Option return predictability, *Review of Financial Studies* 35, 1394–1442.

Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.
Replication Code.