Speculation by Subscription:
Finfluencers and Retail Option Trading

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Abstract

We examine the market impact, investment performance, and incentives of subscription-based option recommendation services on Discord. Recommendations emphasize speculative, short-dated contracts with low premiums and high leverage. Signed retail trading volume jumps immediately around callouts and turns negative after exit recommendations, consistent with subscribers following trade recommendations. Option prices rise following callouts but reverse over the next two hours. After accounting for transaction costs, subscribers earn significantly negative returns. Losses are largest for recommendations involving speculative, high-transaction-cost option contracts. These characteristics attract greater subscriber trading, suggesting that the incentives of subscription-based trade recommendation services may conflict with subscriber performance.

Keywords: Retail investors, options markets, social media, investment recommendations, financial advice, speculative trading

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1. Introduction

Retail option trading has grown rapidly in recent years, often accounting for a large share of trading activity and affecting market outcomes (Bryzgalova, Pavlova, and Sikorskaya, 2023; Eaton et al., 2026). Despite this growth, little is known about retail investor behavior and performance in options markets, where the distinctive features of derivatives may have important welfare implications. Unlike stocks, which provide exposure to the equity premium and allow investors to share in aggregate value creation, options offer leveraged exposure to specific price movements over short horizons and often involve high transaction costs. These features can magnify the costs of poor decisions, making it important to understand what shapes retail option trading and whether investors can profitably act on the guidance they receive.

One increasingly prominent source of financial advice is social media. Financial influencers, or "finfluencers," provide a broad range of financial guidance, and survey evidence indicates that less experienced investors are especially willing to rely on their content (Lin et al., 2025). These influencers may therefore serve as an important mechanism of social transmission, channeling information, trading ideas, and investor attention across networks (e.g., Hirshleifer, 2020).[1] In this article, we study an economically significant segment of this market: subscription-based services that provide real-time option trade recommendations. Our analysis examines the types of contracts recommended through these services, how retail traders respond to their entry and exit signals, the returns available to subscribers, and whether recommendations that attract greater engagement also deliver better performance.

[1] Cookson, Mullins, and Niessner (2024) survey the literature on the role of social media in the broader financial information environment.

The economic implications of option finfluencers are ambiguous. Skilled finfluencers may broaden access to sophisticated trading ideas and contribute to price discovery. At the same time, subscription-based business models create incentives to attract and retain subscribers, which may favor recommendations that generate engagement rather than investor returns. This tension is particularly acute in option markets, where short maturities, wide bid-ask spreads, and execution delays can quickly erode performance.

We evaluate these competing possibilities using a novel dataset of option trade recommendations from major subscription-based Discord trading services, referred to as servers, merged with high-frequency option trades and quotes. The recommendations contain precise timestamps and contract-level details, which let us track retail trading and option prices around each alert at minute- and second-level frequencies. We use the full message histories available in the relevant Discord servers to identify subsequent trims and exits and estimate subscriber returns under execution assumptions that vary with entry speed and trading costs. The setting allows us to test whether finfluencer recommendations shape retail option order flow, whether subscribers can profitably implement the recommendations, and whether the characteristics that attract subscriber engagement are also associated with subscriber outcomes.

In our sample of 20,793 position-opening announcements, referred to as callouts, from 15 Discord servers, we find evidence that option trade recommendations concentrate in particularly speculative contracts. The median contract expires in three days, has a premium of $1.25, and has embedded leverage of roughly 30. Relative to broader retail option trading, the tilt toward speculative contracts is pronounced. Roughly 79% of callout contracts expire within one week, compared with 48% of overall retail trades, as proxied using the algorithm in Bryzgalova, Pavlova, and Sikorskaya (2023) (BPS). Moreover, average leverage is roughly five times as large as in the broader sample. These patterns suggest that option finfluencers do not simply mirror retail option trading. They select a subset of the contracts retail investors already favor that are cheaper to enter, more sensitive to short-horizon price movements, and more capable of producing salient gains.

We find that retail traders respond to callouts almost immediately. Using minute-level event-time tests, retail volume in the recommended contract rises to roughly 14.5 standard deviations above the baseline level in the first minute after publication and signed retail volume rises by more than four standard deviations. Second-level data show that the response peaks 30-45 seconds after the callout, consistent with subscribers quickly buying the recommended contracts. Notably, retail traders also respond to subsequent trade-management guidance. Signed retail volume becomes negative after trim and exit messages, suggesting that followers reduce positions when server administrators advise them to do so. The reversal from buying after entries to selling after trims and exits supports a follower-response interpretation over explanations based only on contemporaneous market conditions.

The price effects are large but short-lived. Recommended options appreciate immediately after callouts, with midpoint prices rising 1.6% in the first 15 seconds and 3.0% in one minute, consistent with the sudden increase in retail buying pressure. However, midpoint returns decline over the next two hours and become slightly negative by the end of the event window. The reversal suggests that much of the initial price movement reflects temporary demand pressure rather than permanent information.

The timing of position entry is therefore an important driver of subscriber performance. Investors who enter immediately after a callout capture only a short-lived price response, and performance deteriorates sharply as entry is delayed. Using a dynamic 60-minute exit strategy, midpoint returns fall from 1.00% for subscribers entering within the first 15 seconds to -0.19% for those entering within the first minute and -2.19% for those entering within the first five minutes. Once realistic execution costs are incorporated, the realized returns are negative throughout, declining from -1.96% to -2.88% and -4.88%, respectively. Scaling these returns by abnormal retail trading volume in the five minutes after each callout implies aggregate subscriber losses of approximately $58 million.

We next examine which recommendation characteristics attract the strongest subscriber trading and whether those same characteristics are associated with better subscriber outcomes. We focus on two key contract features. First, we consider the speculativeness of the recommended contract. Motivated by evidence that retail investors are attracted to speculative securities and skewed option payoffs (Barberis and Huang, 2008; Kumar, 2009; Bali, Cakici, and Whitelaw, 2011; Boyer and Vorkink, 2014; Byun and Kim, 2016), we conjecture that traders will be drawn to callouts that involve inexpensive, short-dated contracts with high leverage, written on smaller and lower-priced firms. Accordingly, we construct a Speculative Index that combines these five contract characteristics. The second dimension is the contract's bid-ask spread, which captures the cost of implementing a recommendation. If subscribers account for implementation costs when deciding whether to follow a recommendation, retail demand should be weaker for contracts with wider spreads.

We find that retail demand is stronger for more speculative callouts. Retail volume also increases with bid-ask spreads, contrary to the hypothesis that subscribers account for implementation costs. Signed-volume tests show that both patterns reflect directional buying rather than elevated two-sided trading. We then examine whether the two contract features that attract the strongest subscriber trading, speculativeness and bid-ask spreads, are also associated with better subscriber outcomes. We find that more speculative recommendations earn significantly lower realized returns. A one-standard-deviation increase in speculativeness predicts roughly two percentage points lower realized returns. Bid-ask spreads have a separate negative relation with realized performance. A one-standard-deviation increase in spreads predicts an additional 1.6 percentage point decline in realized returns. Thus, the recommendations that generate stronger retail demand also deliver weaker subscriber outcomes.

The final set of tests examines whether recommendation styles differ systematically across servers in ways that are consistent with catering to subscriber demand. We measure a server's recent recommendation style using the average speculativeness or bid-ask spread of its previous 50 callouts, excluding same-day callouts, and then examine subsequent recommendations. We find that contract recommendation styles are persistent. Servers with more speculative recent callouts continue to issue more speculative recommendations, and servers with wider-spread recent callouts continue to recommend less liquid contracts.

More speculative servers generate stronger retail trading responses but weaker subscriber returns. Average standardized retail volume rises from 10.7 among low-speculativeness server-days to 26.6 among high-speculativeness server-days, while realized dynamic returns decline from -2.60% to -7.68% when entry is measured over the first five minutes after publication. Sorting servers on their past bid-ask spreads yields a similar pattern, with retail volume increasing from 10.0 to 24.2 and realized returns falling from -3.77% to -7.11%. The evidence points to a conflict between subscriber engagement and subscriber outcomes, with the styles that attract the strongest response also producing the weakest performance.

Our findings contribute to several strands of literature. Prior work studies how investors respond to analysts, newsletters, and investment-research platforms, and emphasizes that recommendation value depends on incentives, investor sophistication, implementation costs, and the timing of investor responses (Womack, 1996; Graham and Harvey, 1996; Barber et al., 2001; Malmendier and Shanthikumar, 2007; Mehran and Stulz, 2007; Dyer and Kim, 2021; Reuter and Schoar, 2024). The servers we study are distinctive because they combine contract-specific option alerts with ongoing trade-management instructions in a real-time subscription environment. This setting allows us to examine whether recommendations that elicit stronger subscriber trading also improve subscriber performance. Instead, we find that recommendations attracting greater retail participation perform worse, suggesting that the incentives of paid advice services and their subscribers may not be fully aligned.

The paper also speaks to the literature on financial social media. Previous work shows that social media plays an important role in the financial information environment, affecting how investors acquire information, allocate attention, and interact with other investors (e.g., Chen, De, Hu, and Hwang, 2014; Campbell et al., 2019; Cookson and Niessner, 2020; Farrell et al., 2022; Han, Hirshleifer, and Walden, 2022; Cookson, Engelberg, and Mullins, 2023; Bradley et al., 2024; Kakhbod et al., 2025). We extend this literature to retail option markets, where the distinctive features of derivative securities, including leverage, short maturities, and substantially higher transaction costs, make the consequences of trading guidance potentially very different from those documented in equity markets.

A related literature examines retail participation in option markets. Prior studies show that retail investors are active option traders and that their activity is often concentrated in simple, speculative contracts (Lakonishok, Lee, Pearson, and Poteshman, 2007; Boyer and Vorkink, 2014; Hu, Kirilova, Park, and Ryu, 2024). For example, Bryzgalova, Pavlova, and Sikorskaya (2023) show that retail option trading is sizable and concentrates in contracts suited to speculation, while de Silva, So, and Smith (2026) provide evidence that retail investors speculate around earnings announcements. Other work shows that option prices can reflect demand pressure when intermediaries cannot fully hedge order flow.[2] We complement this literature by shifting attention from the option trades investors ultimately place to the paid recommendation services that help shape them. Our analysis connects the source of retail trading ideas to both retail option demand and short-lived price pressure in the recommended contracts.

2. Institutional Setting and Recommendation Sample

2.*1 Finfluencers and Subscription-Based Trading Services*

Financial influencers, or “finfluencers,” have become an increasingly important source of investment-related content for retail investors. The term describes a broad range of content creators who provide financial education or advice on topics such as budgeting, credit, investing, and trading. Social media platforms have made it easier for individuals to produce and distribute financial commentary, and investors increasingly use this content when making financial decisions. For example, in FINRA Foundation’s 2024 Investor Survey, 26% of investors report using recommendations from social media finfluencers when making investment decisions, including 61% of investors under 35 and 57% of investors with less than two years of investing experience (Lin et al., 2025).

Our study focuses on a narrower segment of this market: finfluencers who sell specific option trade guidance to paying subscribers. These services differ from both traditional investment research and open online investment platforms. Traditional analysts typically produce formal research reports for institutional investors, whereas platforms such as StockTwits and Seeking Alpha host public posts and decentralized commentary. Neither is organized to provide retail

[2] See for example Bollen and Whaley (2004), Gârleanu, Pedersen, and Poteshman (2009), Choy and Wei (2023), and Eaton et al. (2026).

traders with real-time, position-level guidance on when to enter, manage, and exit specific trades. By contrast, the services we study operate through private online communities centered on identifiable trading personalities and sell access to a continuing stream of recommendations. To our knowledge, ours is the first study of real-time option recommendations directed at retail traders.

Potential subscribers can encounter these services through public social-media content, referral links, or marketplaces such as Whop that list paid trading services. Marketing materials often emphasize selected indicators of successful performance, including screenshots of profitable trades or claimed success such as a "+80-90% win rate." These claims may be especially salient in option markets because individual successful trades can generate large percentage returns over short horizons. However, promotional materials may not reflect the full distribution of recommendation performance, the timing at which ordinary subscribers could have entered the trade, or the trading costs required to implement the recommendation. After subscribing, investors typically receive access to a private Discord server, where administrators or designated moderators post trade alerts, market commentary, and follow-up guidance. Services monetize through recurring subscription fees, which frequently exceed \$100 per month for tiers that include additional tools or greater interaction with the trading community.

These services operate in a regulatory gray area between informed social-media commentary and registered investment advice. Many services describe their content as educational, informational, or entertainment-oriented, but regulatory concerns generally depend on the underlying conduct rather than the labels used by the service. Relevant issues include whether subscribers pay for access, whether administrators provide specific and time-sensitive securities recommendations, whether performance advertising gives an incomplete impression of likely subscriber outcomes, and whether administrators trade around their own recommendations. We do not evaluate whether the conduct of any service or administrator in our sample violates securities law. Internet Appendix A provides additional discussion of the legal and regulatory setting, including performance advertising and potential trading conflicts.

The core paid content in many of these trading services is a sequence of actionable trade recommendations, commonly referred to as "callouts." In contrast to broad market commentary or long-form reports, callouts are framed as specific trading opportunities. In options-focused servers, a callout commonly identifies an underlying security, option type, strike price, expiration date, and trade direction. These recommendations are often short horizon and frequently presented in a style that emphasizes rapid trade execution and the possibility of large percentage gains. This format differs from traditional analyst recommendations, which are typically lower frequency and oriented around firm fundamentals, and from many open social-media posts, which may express opinions without providing a specific trade to implement.

Another distinctive feature is that administrators often provide ongoing trade-management guidance after the initial recommendation, indicating that subscribers should take partial profits, commonly referred to as trims, or exit the position entirely. Subscribers therefore do not only purchase access to an initial recommendation, but to a stream of investment guidance from server administrators. In the servers we study, subscription access also includes archived trade logs that record prior callouts and subsequent trade-management messages.

Given the nontrivial subscription fees, subscribers likely believe that administrators possess option-trading skill that would be difficult to replicate independently. However, evaluating skill is challenging in this setting. Option returns are highly volatile, individual winners are salient, and feasible subscriber performance depends on execution timing, exit timing, and transaction costs. These features make it difficult to distinguish skill from noise, especially when promotional materials highlight successful trades rather than the full history of recommendations.

A central economic feature of the subscription model is the potential tension between attracting subscriber engagement and generating profitable recommendations. Subscription revenues depend on attracting and retaining paying subscribers, which may lead services to emphasize trades that are salient, easy to follow, and appealing to retail investors. In particular, the characteristics that make a recommendation appealing to subscribers may not be the same characteristics that maximize subscriber returns. This potential misalignment is central to our setting and motivates our analysis of both retail trading responses and subscriber outcomes.

2.2. The Option Callout Sample and Variable Construction

Our sample consists of option trade recommendations between March 2020 and December 2025 in subscription-based options-trading servers hosted on Discord. To identify candidate services, we search Whop, an online marketplace for paid trading communities, using combinations of day-trading-related keywords such as "options trading," "trade alerts," and "day trading." We retain results that advertise live trading or real-time trade alerts. The full list of search terms is reported in Internet Appendix B. To exclude unrelated, inactive, or very small communities, we require servers to have at least 500 active subscribers or, when subscriber counts are not publicly available, at least 75 posted reviews. We further require there to be a monthly subscription fee with a price below $500. From the resulting set of candidate communities, we collect data from 15 representative active options-trading servers. To preserve anonymity, we do not disclose the names of the servers in our sample.

For each server, we download the complete message history through the Discord API, including message content, timestamps, and author identifiers. We standardize message formatting and convert all timestamps from UTC to U.S. Eastern Time. We then identify messages posted by server administrators and define a callout as a message in which an administrator recommends a specific option trade to subscribers by announcing the initiation of a position.

To identify callouts, we use a rule-based parser that extracts four contract characteristics from each message: the underlying ticker, strike price, option type (call or put), and expiration date. Messages are classified as callouts only if they uniquely identify a single option contract and contain language indicating the initiation of a new position. To distinguish callouts from trade updates and other discussions, we exclude messages containing language associated with exits, trims, watchlists, existing positions, or profit updates. Detailed classification rules and keyword lists are reported in Internet Appendix B.

After entering a position, administrators often provide updates regarding the trade's performance and management. Using a separate set of classification rules, we identify messages indicating partial profit-taking (trims) and complete position exits. We use these messages to reconstruct the lifecycle of each recommendation and record whether a position is trimmed, the number of trims prior to exit, whether the position is explicitly closed, and the time elapsed before trim and exit recommendations. The classification approach is described in Internet Appendix B.

Finally, we match each callout to the corresponding intraday option quotes from OPRA and to underlying-security information from TAQ and CRSP. We restrict the sample to callouts on options written on individual equities and exclude recommendations involving ETFs or indices (CRSP SHRCD 73 and equity index options listed on the CBOE website[3]). Using the recommendation timestamp, we identify the corresponding option contract and record contemporaneous option and underlying-stock characteristics, including option premiums, bid-ask

[3] https://www.cboe.com/tradable-products/product-list

spreads, moneyness, leverage, days to expiration, underlying prices, and market capitalizations. Detailed variable definitions are reported in Appendix A. Applying these filters yields 20,793 callouts on equity options spanning March 2020 through December 2025.

2.3. Descriptive Statistics

Callout activity increases over our sample, rising from 5,106 callouts in 2020–2021 to 9,261 callouts in 2024–2025. Activity is concentrated across servers, with the two largest contributors accounting for roughly half of all callouts. Table 1 reports the distribution of option characteristics at the callout level. Callouts predominantly involve short-dated options, with a median of 3 days to expiration. We define signed moneyness as $(Spot - Strike)/Strike \times Sign$, where *Sign* equals one for call options and negative one for put options. The median signed moneyness is -0.02, and the 90th percentile is approximately zero, indicating that the vast majority of callouts involve at-the-money or out-of-the-money contracts. Callouts have modest prices (median premium = \$1.25), allowing investors to obtain substantial embedded leverage. The median leverage is approximately 30, while the 90th percentile exceeds 75.

Many of these contract characteristics are jointly associated with speculative trading. To summarize them, we construct a speculative index from contract maturity, option premium, embedded leverage, and the price and market capitalization of the underlying firm. We standardize each component, sign it so that higher values correspond to more speculative contracts, sum the components, and standardize the index. By construction, the index has a mean of zero and a standard deviation of one. Across recommendations, the middle 50% of observations range from −0.71 to 0.69, while the 10th and 90th percentiles are −1.18 and 1.33, respectively.

Trade-management activity is prevalent but heterogeneous across callouts. The median callout includes no trims, 23% of callouts involve at least one trim recommendation, while 41%

include a formal exit signal. Among callouts with an exit signal, the median time to exit is 21 minutes, highlighting the very short-term trading horizon reflected in these callouts. Finally, callouts are written on large, liquid underlying stocks, with a median share price of $125 and a median market capitalization of approximately $119 billion.

2.4. Comparison with Retail Option Trading

Table 2 benchmarks the server callouts against the broader universe of retail option trading, using the SLIM classification developed by Bryzgalova, Pavlova, and Sikorskaya (2023). SLIM trades are single-leg improvement mechanism trades, executed through exchanges auctions that predominantly process retail order flow, and serve as a useful proxy for retail option trading. Columns 2–3 summarize the characteristics of SLIM trades based on trade- and volume-share classifications, while Columns 4–5 report analogous statistics for non-SLIM trades. Columns 6–7 compare callout contracts with the SLIM trade-share sample, reporting estimated differences and associated t-statistics based on standard errors two-way clustered by underlying ticker and callout date.

The results indicate that callouts are considerably more speculative than even SLIM trades. Relative to the SLIM trade-share sample, callout contracts are significantly more likely to be 0 DTE or expire within one week and substantially less likely to have maturities exceeding one month. They also exhibit considerably lower option premiums ($2.93 versus $7.65) and much higher embedded leverage (23.5 versus 7.9). These differences translate into a significantly higher speculative index for callout contracts.[4] Callout recommendations are also more likely to involve

[4] The speculative index in Table 2 is constructed by standardizing the underlying characteristics using the full sample of retail trading before averaging them. Accordingly, the mean of the index need not equal zero within subsamples.

call options (82% versus 66%), while exhibiting lower bid-ask spreads than the average retail option trade.

Overall, Table 2 shows that callouts do not simply mirror broader retail option trading. Instead, they systematically recommend a more speculative subset of the contracts already preferred by retail investors. Relative to the typical retail option trade, Discord callouts are more heavily concentrated in call options, involve shorter maturities, lower premiums, and provide substantially greater embedded leverage.

3. Retail Trading around Option Callouts

In this section, we examine how retail investors trade around callouts. Section 3.1 analyzes whether retail trading volume and order imbalances increase following the publication of a callout. Section 3.2 investigates whether retail investors also follow server administrators' execution-management suggestions, including trim and exit recommendations.

3.1. Retail Trading around Server Callouts

3.1.1. Trading Volume around Callouts

A challenge in measuring the influence of callouts on retail option trading activity is that recommendations are issued in near real time and may themselves respond to contemporaneous market developments, making it difficult to separate the effects of the recommendation from the underlying information environment. The high-frequency data, however, also provides the precise timestamps of callouts allowing us to examine trading behavior at minute- and second-level frequencies. If callouts influence follower trading, we would expect to observe sharp, discontinuous increases in trading activity immediately following the publication of a callout.

We test this prediction by constructing standardized abnormal trading measures around each callout. Specifically, for each callout we compute *Standardized Abnormal Retail Volume*, defined as retail volume in minute *t* less the average retail volume from minutes *t-16* to *t-30* (the benchmark period), scaled by the standard deviation of minute-level retail volume during the same benchmark window. We also compute analogous measures based on total option trading volume (*Standardized Abnormal Total Volume*). To ensure reliable estimation of benchmark trading activity, we require at least 10 valid pre-callout contract minute observations in the benchmark window. In addition, we exclude callouts where the benchmark-period standard deviation of trading volume is below 5 contracts. This filter removes illiquid options with near-zero pre-event trading activity, where even small changes in trading would generate very large standardized values.[5]

Figure 1 presents minute-level event-time patterns in option trading around callouts. The plot shows *Standardized Abnormal Retail Volume* and *Standardized Abnormal Total Volume* from minutes [-30, +30], where time 0 denotes the first post-publication interval. The pattern shows gradually increasing trading activity in the minutes leading up to the callout. The observed pre-callout trading activity is potentially consistent with several different mechanisms, including the callout's author reacting to contemporaneous information or price momentum, as well as some subscribers learning about and trading on recommendations prior to their posting. While these interpretations have very different implications, the competing explanations cannot be cleanly distinguished using anonymous transaction-level data.

[5] These filters exclude 6,122 callouts issued within 10 minutes of the market open, where insufficient pre-event observations are available to estimate benchmark trading activity, and an additional 1,307 callouts with negligible variation in benchmark-period trading volume. The final sample consists of 13,348 callouts.

Trading volume increases immediately following the publication of a callout. Retail trading volume rises from 8.3 to 16.2 standard deviations above baseline, while total volume rises to 18.2 standard deviations.[6] The sharp discontinuity in trading activity around the callout timestamp strongly suggests that these recommendations play an important role in directing retail option trading activity. Total trading volume exhibits a nearly identical pattern, indicating that the increase in retail trading is sufficiently large to materially affect overall option market activity in the recommended contracts.

3.1.2. Directional Trading Around Callouts

While the previous analysis shows that callouts are associated with sharp increases in overall trading activity, it does not indicate whether investors predominantly trade in the direction of the recommendation. Because the callouts in our sample recommend purchasing option contracts rather than writing them, directional follower trading should manifest as positive signed trading volume. To examine this issue, we next analyze *Signed Trading Volume*, defined as buyer-initiated trading volume minus seller-initiated trading volume, where trades are signed using the approach outlined in Grauer, Schuster, and Uhrig-Homburg (2026).

Figure 2 presents event-time patterns for *Standardized Abnormal Signed Retail Volume* and *Standardized Signed Abnormal Total Volume*. The patterns are similar to the unsigned trading measures documented in Figure 1. Specifically, signed retail and total trading increase gradually in the minutes leading up to the callout, and rise sharply immediately following the publication of the callout. Signed retail trading rises from approximately 3.1 standard deviations above baseline

[6] Figure IA1 in the Internet Appendix reports analogous event-time plots using the cross-sectional median standardized abnormal trading measures. Although the magnitudes are smaller, the qualitative patterns remain nearly identical, with sharp increases in both retail and total trading immediately following callouts. Overall, the results indicate that the observed trading responses are broad-based rather than driven by a small number of extreme observations.

one minute prior to the callout to 5.5 standard deviations above baseline in the first post-callout minute. Total signed trading volume exhibits a similar pattern. These findings indicate that callouts are associated not only with elevated trading activity, but also with directional order flow consistent with followers purchasing the recommended contracts.

3.1.3. Second-Level Trading Responses

The minute-level analysis in Figures 1 and 2 show that callouts are associated with sharp increases in retail trading activity. However, because Discord recommendations are issued in near real time, minute-level intervals may still mask important information about the precise timing of investor reactions. To more precisely examine the immediacy of trading responses, we next conduct an event study using 15-second trading intervals centered around the callout timestamp.

Following the minute-level analysis, we aggregate trading activity into 15-second bins while maintaining the same benchmark window, sample restrictions, and standardization procedures. Figures 3a and 3b present event-time patterns for second-level retail trading volume and signed retail trading volume, respectively, where time 0 denotes the first 15 seconds after the callout is published. Both trading volume and signed trading volume increase sharply in the first 15 seconds after the publication of the callout. Retail trading volume peaks approximately 30-45 seconds after the callout at more than 7 standard deviations above baseline trading activity, while signed retail trading peaks at approximately 2.5 standard deviations above baseline. The rapid increase in signed trading is consistent with followers purchasing the recommended contracts within seconds of publication.

3.1.4. Formal Event-Window Tests

Table 3 quantifies the event-time trading patterns illustrated in Figures 1–3. For each event window, we report average standardized abnormal trading activity relative to the benchmark period from minutes [−30,−16] and formally test whether these estimates are statistically different from zero using standard errors double clustered by ticker and callout date. Consistent with the graphical evidence, trading activity increases sharply immediately following callouts. Retail trading volume rises to approximately 14.5 standard deviations above benchmark levels during the [0,1] minute window, while total trading volume increases to more than 16 standard deviations. Signed retail trading volume also rises more than 4 standard deviations above baseline. All of these estimates are statistically significant, with *t*-statistics typically exceeding 40 during the immediate post-callout window. Trading activity gradually declines following the initial spike but remains elevated for at least 30 minutes after the callout.

3.2. Trading around Trim and Exit Recommendations

The previous analysis demonstrates that retail investors increase directional trading activity following callouts. We next examine whether retail investors also respond to subsequent trade-management recommendations, including both trim and exit recommendations. Unlike initial callouts, these recommendations provide guidance on managing existing positions. If followers actively monitor and implement these recommendations, we would expect to observe directional selling pressure following their publication.

Figures 4A and 4B report standardized abnormal signed volume measures for retail and total trading around trim and exit recommendations, respectively. Panels A and B of Table 4 report formal event-window tests analogous to those in Table 3. The central finding is that signed trading volume becomes significantly negative immediately following both message types, consistent with followers reducing existing option positions after the publication of the trim or exit recommendation.

The plots reveal that net buying drops sharply in the minute prior to trim and exit announcements, with larger drops prior to exits. The selling responses after trim recommendations is similar in magnitude to that following exits, with signed retail trading volume being 0.4 standard deviations below the benchmark period in the minute after both trims and exits. Followers thus appear to treat trims as meaningful selling signals, even if the recommendation does not call for full liquidation.

The evidence suggests that followers respond not only to initial entry recommendations, but also to ongoing trade-management guidance throughout the life cycle of recommended trades. More generally, the reversal in the direction of order flow following trim and exit postings is useful for distinguishing the follower-response interpretation from alternative explanations based on broader market conditions. Initial callouts are followed by net buying, whereas trim and exit messages are followed by net selling. This contrast bolsters the interpretation that messages affect retail trading rather than merely coinciding with unrelated trading shocks.

4. Returns to Following Trade Recommendations

The previous section demonstrates that callouts are associated with sharp increases in retail trading activity and directional order flow consistent with followers purchasing the recommended contracts. An important unanswered question, however, is whether these recommendations can be implemented profitably. In this section, we examine the returns available to investors following callouts under a range of execution assumptions. Section 4.1 analyzes option return dynamics around callouts using both minute-level and second-level event studies. Section 4.2 examines the average returns earned by subscribers under alternative entry speeds and exit strategies.

4.1 Return Dynamics Around Callouts

Figure 5 plots average option cumulative returns around callouts using one-minute intervals. Throughout this section, we focus on return horizons extending up to 120 minutes following the publication of a callout. This horizon is motivated by the short holding periods of the recommendations.[7] At the same time, a two-hour window is long enough to evaluate whether the initial price increases following callouts persist or reverse, while avoiding the substantial noise associated with longer-horizon option returns.

Figure 5 examines three return measures, using prices at the callout publication time (to the second) as the entry point. The first uses midpoint prices at both entry and exit and therefore abstracts from transaction costs. The second assumes investors purchase the option at the prevailing ask price and subsequently liquidate at the bid price, thereby incorporating the full bid-ask spread. The third assumes investors enter at the ask price but exit at the midpoint price. This measure reflects the idea that subscribers likely seek to execute quickly following the publication of a callout and therefore face the ask price when establishing positions, while positions may be unwound more patiently over the holding period closer to the midpoint.

Several findings emerge from the figure. First, option prices rise sharply immediately following the publication of a callout. Measured using midpoint prices, options increase by approximately 3% within the first minute after the recommendation. This finding is consistent with the trading results in Section 3, which show an immediate increase in retail buying pressure following callouts. Second, the price increases are largely temporary. Midpoint returns steadily decline and become -1.07% by the end of the two hours. The gradual reversal suggests that the

[7] For example, Table 1 reports that, among callouts with a trim recommendation, the median time to first trim is 11.84 minutes. Among callouts with an exit recommendation, the median time to exit is 21.20 minutes, with a 75th percentile of 68.55 minutes and a 90th percentile of 184.37 minutes.

initial price impact reflects temporary demand pressure rather than the incorporation of permanent information.

Third, returns are substantially worse once transaction costs are incorporated. Investors who purchase at the prevailing ask price and subsequently liquidate at the midpoint earn average returns of approximately -4% over the following two hours. When the full bid-ask spread is incorporated, average returns fall to approximately -7%. These findings indicate that although Discord callouts generate a short-lived increase in option prices, the typical subscriber is unlikely to profit from following them once realistic trading costs are incorporated.

Figure 6 provides a more granular view of return dynamics by plotting average midpoint returns in 15-second intervals from 5 minutes before to 5 minutes after the publication of a callout. Unlike Figure 5, which reports cumulative returns, Figure 6 reports interval-by-interval returns and therefore allows us to more precisely identify when price movements occur. Consistent with the trading results in Section 3, option prices begin rising prior to publication.

Figure 6 also reveals an immediate price response following publication. The largest return occurs during the first 15-second interval after the recommendation, with prices increasing by approximately 1.6%. Return magnitudes decline rapidly thereafter and largely disappear within the first minute. Combined with the trading evidence in Section 3, these findings indicate that Discord callouts generate a sharp but short-lived increase in option prices concentrated within seconds of publication. The concentration of returns following publication highlights the importance of execution speed, suggesting that even modest delays in implementing recommendations can materially reduce subscriber performance.

4.2 Measuring Performance to Following Callouts

Figures 5 and 6 characterize the evolution of option prices following callouts. We next translate these return dynamics into performance measures by examining callout profitability under alternative entry and exit assumptions. To capture differences in execution speed, we consider entry intervals ranging from one minute before the callout to five minutes after publication. While entry prior to publication is generally not feasible for ordinary subscribers, these pre-callout benchmarks provide a useful measure of the profits potentially available to investors able to trade ahead of a recommendation. Such profits may arise from early access to the recommendation or other pre-publication information diffusion.

We also examine holding periods ranging from one minute to 120 minutes following entry. Motivated by the evidence in Figure 4 and Table 4 that retail traders respond to subsequent trim and exit recommendations, we also consider two dynamic exit strategies that reduce the position by 50% following the first trim recommendation, close the remaining position following an exit recommendation, and otherwise default to 60- or 120-minute holding periods. Table 5 reports two return measures. Panel A reports midpoint returns, using the average midpoint quote over the entry interval and midpoint quotes at exit. Panel B reports realized execution returns, using the retail purchase VWAP during the entry interval as the entry price and exit midpoint prices adjusted for estimated execution costs. For each entry and exit strategy, we report average returns and test whether they differ from zero using standard errors clustered by date.

Panel A of Table 5 reports midpoint returns. Investors who enter before publication earn large positive returns, consistent with the pre-callout price appreciation shown in Figure 6. For example, entering during the minute before publication and holding for five minutes earns an average midpoint return of 5.97%. These pre-publication returns are not generally feasible for ordinary subscribers, but they highlight the price movement that occurs before or around the time a recommendation is posted.

Once entry is restricted to post-publication intervals, midpoint performance deteriorates sharply with delay. Under the dynamic 60-minute strategy, midpoint returns decline from 1.00% for investors entering over the first 15 seconds after publication to -0.19% for those entering over the first minute and -2.19% for those entering over the first five minutes. Fixed-horizon returns show a similar pattern at longer horizons; for example, 120-minute midpoint returns decline from -1.92% for the first-15-second entry interval to -4.13% for the first-five-minute entry interval. Thus, even before implementation costs, the return advantage from entering immediately after a callout is short-lived and turns negative as execution is delayed. This finding stands in sharp contrast to the large gains frequently highlighted in Discord marketing materials and suggests that the average subscriber experience differs substantially from the performance implied by promotional claims.

Panel B reports realized execution returns. Under the dynamic 60-minute strategy, realized execution returns are negative for all post-publication entry intervals, falling from -1.96% for entry during the first 15 seconds to -2.88% for entry during the first minute and -4.88% for entry during the first five minutes. These estimates show that realistic execution prices and liquidation costs materially worsen subscriber performance relative to midpoint returns.

To gauge the economic magnitude of these return effects, we combine abnormal trading volume following each callout with the returns earned by investors entering at the corresponding time. Specifically, we compute abnormal dollar volume in each minute relative to the benchmark window [-30,-16] and multiply this volume by corresponding VWAP-based realized execution return under the dynamic 60-minute exit strategy. Summing across the callouts in our sample yields estimated losses of approximately $58 million.

The estimate is likely conservative for two reasons. First, the calculation attributes losses only to abnormal retail during the first five minutes following publication, while our trading results suggest that elevated trading persists over longer periods, as evidenced in Figure 1 and Table 3.[8] Second, our analysis is limited to 15 large Discord servers. Given that Discord hosts hundreds of investment-related servers, the broader economic impact of Discord-based trading recommendations may be substantially larger than the estimates reported here.

5. Subscriber Demand, Investment Performance, and Service Incentives

The previous sections show that callouts generate substantial retail trading, yet investors implementing these recommendations earn negative returns after accounting for execution timing and trading costs. These findings initially appear difficult to reconcile. In a competitive market for investment advice, one would expect recommendation services with persistently poor investment performance to lose subscribers as investors gravitate toward services that deliver superior returns. However, behavioral theories suggest that retail investors may prefer speculative, lottery-like recommendations that are especially salient and attention-grabbing.[9] If so, recommendation services may be able to attract and retain subscribers by emphasizing speculative trades even if they produce poor subscriber returns.

We focus on two contract characteristics that may shape subscriber demand and investment performance through different channels. The first is contract speculativeness, which captures low-

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[8] For example, extending the calculation to the first 30 minutes increases the estimate to $725 million.

[9] Subscribers need not value these services because they facilitate speculative trading per se. Rather, they may believe server administrators possess superior ability to identify attractive speculative trading opportunities. Such beliefs may also be reinforced by selective highlighting of especially successful recommendations.

premium, short-dated, highly levered recommendations written on smaller, lower-priced firms. Prior evidence suggests that retail investors are attracted to speculative, lottery-like securities, even though they tend to deliver poor subsequent returns (Barberis and Huang, 2008; Kumar, 2009; Bali, Cakici, and Whitelaw, 2011; Boyer and Vorkink, 2014; Byun and Kim, 2016). If callout subscribers exhibit similar preferences, speculative recommendations should attract stronger retail trading despite producing weaker investment performance. The second characteristic is the contract's bid-ask spread, which captures the cost of implementing a recommendation. Wider spreads directly reduce realized returns and, in a market where subscribers primarily reward investment performance, should discourage demand. Evidence that subscribers do not discount high-spread recommendations would therefore be inconsistent with the view that these services compete primarily on realized subscriber returns.

Our empirical analysis proceeds in three steps. Section 5.1 examines whether more speculative and costlier to trade recommendations attract stronger retail trading. Section 5.2 asks whether those same characteristics are associated with subscriber investment performance. Finally, Section 5.3 examines whether servers differ systematically in the speculativeness and bid-ask spreads of their recommendations, and whether those differences are associated with subscriber demand and investment performance.

5.1 Subscriber Demand for Speculative and Costly-to-Trade Recommendations

We begin by examining whether contract speculativeness and implementation costs predict subscriber demand. Table 6 reports the results. Panel A reports regressions of Standardized Abnormal Retail Volume over the [0,1] minute window following the callout. Retail trading is strongly increasing in speculativeness. In Column 1, a one-standard-deviation increase in the Speculative Index is associated with an 8.18 increase in Standardized Abnormal Retail Volume.[10] The estimate remains large after controlling for bid-ask spreads and including time and server fixed effects, with a coefficient of 7.22 in Column 4. Panel B yields similar results using Standardized Abnormal Signed Retail Volume as the dependent variable, indicating that the relation reflects directional retail buying rather than elevated two-sided trading.

Bid-ask spreads also robustly predict retail trading. A one-standard-deviation increase in the spread is associated with a 4.99 increase in retail volume in Column 2 and a 2.27 increase after controlling for speculativeness and including time and server fixed effects in Column 4. Estimates in Panel B using Standardized Signed Retail Volume are similar. Thus, rather than discounting recommendations with higher implementation costs, subscribers are systematically more likely to trade them, contrary to what one would expect if recommendation services competed primarily on expected net investment performance.

5.2 Subscriber Returns for Speculative and Costly-to-Trade Recommendations

We next examine whether the same characteristics that attract retail trading are associated with subscriber performance. Table 7 reports the results using three alternative return measures that isolate the effects of execution timing and transaction costs. Panel A reports realized execution returns, assuming subscribers begin purchasing within the first five minutes following the callout and subsequently implement the dynamic 60-minute exit strategy. Panel B uses the same dynamic

[10] To examine the contribution of the individual components, Figure IA2 in the Internet Appendix repeats the univariate specification in Column 1 after replacing the Speculative Index with each of its five underlying characteristics individually. Among the individual components, lower option premiums, smaller underlying firms, and lower underlying stock prices exhibit the strongest associations with retail demand, whereas leverage and time to expiration play a more modest role.

exit strategy but assumes subscribers purchase immediately following the callout, thereby removing execution delay while retaining transaction costs. Finally, Panel C reports midpoint returns under the same immediate-entry assumption, abstracting from both execution delay and transaction costs.

Across all return measures and model specifications, contract speculativeness is associated with significantly poorer subscriber investment performance. In Panel A, a one-standard-deviation increase in the Speculative Index is associated with a 3.16 percentage point reduction in realized execution returns in Column 1 and a 2.65 percentage point reduction after controlling for bid-ask spreads and including time and server fixed effects in Column 4. Panels B and C produce qualitatively similar results, indicating that speculative recommendations underperform regardless of whether returns incorporate execution delays or implementation costs.

Bid-ask spreads display a similar relation with subscriber investment performance. In Panel A, a one-standard-deviation increase in the bid-ask spread is associated with a 2.65 percentage point reduction in realized execution returns in Column 2 and a 1.40 percentage point reduction after controlling for contract speculativeness and including time and server fixed effects in Column 4. Panel B produces similar estimates after removing execution delays while continuing to account for transaction costs. In contrast, the relation largely disappears in Panel C, where returns are measured using midpoint prices that abstract from transaction costs. This pattern suggests that wider spreads reduce subscriber investment performance primarily through higher implementation costs rather than poorer underlying option performance.

Overall, Table 7 shows that the more speculative callouts and callouts with wider bid-ask spreads attract greater retail buying also generate poorer realized subscriber returns. These findings point to an engagement-performance tradeoff at the recommendation level: the contracts that generate the strongest follower response are systematically associated with the weakest realized investment outcomes.

5.3 Persistent Recommendation Styles and the Engagement-Performance Tradeoff

The results in Sections 5.1 and 5.2 suggest an engagement-performance tradeoff. If subscriber growth and retention depend more on engagement than investment performance, services may have incentives to emphasize the recommendation characteristics that attract trading. Table 8 examines whether some servers systematically specialize in recommendation styles that generate stronger subscriber engagement despite poorer subscriber outcomes. For each server-day, we measure a server's recent style using the average Speculative Index or bid-ask spread of its previous 50 callouts, excluding same-day callouts, and then sort server-days into quintiles based on the lagged measure.

Server recommendation styles are persistent. Servers with more speculative recent callouts continue to feature more speculative recommendations, while those with wider-spread recent callouts continue to recommend higher-spread contracts. These styles also generate substantially different retail responses and subscriber outcomes. In Panel A, average standardized retail volume rises from 10.72 in the lowest-speculativeness quintile to 26.59 in the highest-speculativeness quintile. Over the same range, dynamic 60-minute realized execution returns decline from 0.18% to -5.36% when entry is measured over the first 15 seconds after publication and from -2.60% to -7.68% when entry is measured over the first five minutes.

Panel B shows a similar pattern when server-days are sorted on lagged bid-ask spreads. Retail volume rises from 9.99 in the lowest-spread quintile to 24.20 in the highest-spread quintile, while realized execution returns fall from -1.73% to -4.42% for the first-15-second entry interval and from -3.77% to -7.11% for the first-five-minute entry interval. The evidence indicates that persistent recommendation styles associated with stronger subscriber engagement are also associated with weaker realized subscriber performance.

Taken together, the findings suggest that the engagement-performance tradeoff documented at the recommendation level extends to the server level. Servers that consistently emphasize more speculative or higher-spread recommendations are associated with stronger subscriber participation but systematically weaker realized subscriber returns. The persistent differences in recommendation style are consistent with service incentives that reward subscriber engagement more strongly than subscriber investment performance.

6. Conclusions

Retail investors increasingly encounter investment advice through social media and paid online communities. Understanding the consequences of this advice in option markets is especially important because contracts are short-lived, highly levered, and costly to trade. This paper studies subscription-based trading services on Discord that provide real-time option recommendations. We examine the contracts recommended through these services, how retail traders respond to them, whether subscribers can profitably implement them, and whether the trades that attract the strongest engagement also deliver better investor outcomes.

Discord option callouts are concentrated in highly speculative contracts, and retail traders respond strongly and quickly to these recommendations. Retail buying begins within seconds of publication and reverses following subsequent trim and exit messages, indicating that subscribers closely follow both entry and trade-management guidance. Although option prices initially rise following callouts, these gains are short-lived. After accounting for realistic execution timing and transaction costs, subscriber returns are significantly negative under economically plausible trading strategies. Under our dynamic 60-minute exit strategy, estimated realized losses from abnormal retail trading in the first five minutes after callouts are approximately $58 million.

The cross-sectional results point to an engagement-performance tradeoff. More speculative recommendations and recommendations with wider bid-ask spreads attract substantially greater retail participation, yet both are associated with weaker realized subscriber returns. Moreover, these patterns extend beyond individual recommendations. Servers on Discord exhibit persistent recommendation styles, and those that consistently feature more speculative or higher-spread contracts attract stronger subscriber engagement but deliver poorer realized investment outcomes.

These findings have implications for ongoing discussions about transparency in subscription-based investment services. Our results suggest that finfluencers may have incentives to emphasize highly speculative recommendations that generate subscriber engagement because of their potential for large short-term gains, even when those recommendations produce poor average subscriber outcomes. Finfluencers can selectively highlight successful trades, whereas subscriber performance depends on the full distribution of recommendations, execution timing, and transaction costs. As a result, investors may have difficulty evaluating the true quality of these services. More comprehensive performance disclosure, with feasible assumptions about entry prices, exit prices, and trading costs, could help investors better assess subscriber outcomes.

Appendix A: Variable Definition

A1. Option Characteristics:

- *Signed Moneyness:* (Spot − Strike)/Strike × *Sign*, where sign equals one for call options and negative one for put options. Positive values indicate in-the-money contracts, and negative values indicate out-of-the-money contracts.
- *Days to Expiration:* the number of calendar days between callout recommendation date and contract expiration.
- *0DTE:* an indicator equal to one if the contract has zero days to expiration, and zero otherwise.
- *Call Indicator*: an indicator variable equal to one if the callout recommends a call option and zero if the callout recommends a put option.
- *Bid-Ask Spread:* (ask-bid)/midpoint, based on the prevailing bid and ask quotes at the time of callout.
- *Premium:* midpoint of the prevailing bid and ask quote at the time of the callout.
- *Leverage*: a measure of the option elasticity with respect to the underlying stock price, computed as Delta × Spot Price/Premium, where Delta is computed using the Black-Scholes model.
- *Underlying Market Capitalization:* the equity market capitalization (price × shares outstanding) of the underlying firm from CRSP, as of the close of the prior day.
- *Underlying Price:* the stock price of the underlying firm at the time of the trade.
- *Speculative Index:* A standardized composite measure equal to standardized leverage minus standardized log option premium, standardized log underlying stock price, standardized log underlying market capitalization, and standardized log option maturity. Higher values correspond to option contracts that are more levered, lower priced, shorter dated, and written on smaller and lower-priced underlying firms.

A2. Position Management Variables

- *Number of Trims:* the number of trim recommendations associated with the position. The identification of trims is described in Internet Appendix B.
- *Any Trim*: an indicator equal to one if the number of trims is greater than zero.
- *Any Exit:* an indicator equal to one if the server administrator recommends exiting the position. The identification of exits is described in Internet Appendix B.
- *Minutes to Trim*: the number of minutes between callout and first trim recommendation. This value is set equal to missing for observations without any trims.
- *Minutes to Exit:* the number of minutes between callout and exit recommendation. This value is set equal to missing for observations without any exits.

A3. Trading Activity Measures

- *Total Volume:* total dollar trading volume in the option contract during a given minute.
- *Signed Volume:* Buy volume minus sell volume during a given minute, where trade direction is assigned using the approach of Grauer, Schuster, and Uhrig-Homburg (2026).

- *SLIM Retail Trade*: Option trade classified as retail under the Single-Leg Price Improvement Mechanism (SLIM) methodology of Bryzgalova, Pavlova, and Sikorskaya (2023).
- *Retail Volume:* dollar trading volume associated with SLIM-classified retail trades during a given minute.
- *Signed Retail Volume:* retail buy volume minus retail sell volume during a given minute, where retail trades are identified using the SLIM methodology and signed based on the approach of Grauer, Schuster, and Uhrig-Homburg (2026).
- *Standardized Abnormal Volume:* dollar trading volume in a given minute minus the average dollar trading volume during the benchmark period [-30,-16], scaled by the standard deviation of dollar trading volume during the benchmark period.
    - *Standardized Abnormal Retail Volume*, *Standardized Abnormal Signed Volume*, and *Standardized Abnormal Signed Retail Volume* are defined analogously using *Retail Volume*, *Signed Volume*, and *Signed Retail Volume*, respectively.
- *Lag Retail Volume Quartile:* the quartile rank of the server's average standardized abnormal retail volume during the prior calendar month. Average retail volume is computed across all callouts posted in the server using the [0,1] event window, and server-months are sorted into quartiles within calendar month.
    - *Lag Signed Retail Volume* is defined analogously using *Signed Retail Volume*.

A4. Option Return Measures:

- *Entry Interval:* The interval over which the subscriber is assumed to establish the position, measured relative to the callout publication time. Entry intervals in the return tables are measured in seconds. For example, ([0,15]) denotes the first 15 seconds after publication, and ([0,300]) denotes the first five minutes after publication.
- *Return Window [x,y]***:** *x* denotes the entry period in seconds or minutes relative to the callout timestamp and *y* denotes the holding period. Event period 0 corresponds to the callout timestamp.
- *Midpoint Return [x,y]:* Return from purchasing the option at the midpoint quote in minute *x* and selling the option at the midpoint quote *y* minutes later.
- *Ask-to-Bid Returns [x,y]:* Return from purchasing the option at the ask quote in minute *x* and selling the option at the bid quote *y* minutes later.
- *Ask-to-Midpoint Returns [x,y]:* The return to buying an option at the ask price in minute *x* (entry point) and selling the option at the midpoint in minute *y* (exit point).
- *Retail Purchase VWAP:* The volume-weighted average purchase price of SLIM-classified retail buy trades during the relevant entry interval.
- *Realized Execution Return:* The return from purchasing the option at the Retail Purchase VWAP during the entry interval and liquidating the position at midpoint quotes adjusted for estimated exit costs. The exit price equals the midpoint quote multiplied by one minus the median bid-ask spread estimated from retail purchases during the entry interval. When the entry-interval spread is unavailable, the sample median bid-ask spread is used.
- *Dynamic Returns [x,y]*: Return from purchasing the option at the midpoint quote in minute *x* and subsequently following the server administrator's trade-management recommendations.

Positions are reduced by 50% following the first trim recommendation and fully liquidated upon the first exit recommendation. If no exit recommendation is observed, the remaining position is liquidated *y* minutes after entry.

- *Dynamic 60 Return:* The return from entering the recommended option over the specified entry interval and then following the server administrator's subsequent trade-management recommendations. One-half of the position is liquidated at the first trim recommendation. Any remaining position is liquidated at the first exit recommendation or, if no exit recommendation is observed, 60 minutes after the end of the entry interval.
- *Dynamic 120 Return:* Defined analogously to Dynamic 60 Return, except that positions without an exit recommendation are liquidated 120 minutes after the end of the entry interval.
- *Pre-Callout Return [-5,-1]:* the option return from five minutes before the callout to one minute before the callout, computed using midpoint quotes.
- *Pre-Callout Return [-1, 0]:* the option return from one minute before the callout to the callout minute, computed using midpoint quotes.

A5. Server Recommendation Style Measures

- *Lagged Server Speculative Index:* For each server-day, the average Speculative Index across the server's previous 50 callouts, excluding callouts issued on the current day.
- *Lagged Server Bid-Ask Spread:* For each server-day, the average Bid-Ask Spread across the server's previous 50 callouts, excluding callouts issued on the current day.
- *Server-Style Quintiles:* Quintile portfolios formed by independently sorting server-days by event date on either Lagged Server Speculative Index or Lagged Server Bid-Ask Spread. Quintile 1 contains server-days with the lowest lagged values of the sorting characteristic, and Quintile 5 contains server-days with the highest lagged values.
- *Callout Value:* The contemporaneous value of the sorting characteristic for the callouts issued on the server-day after the lagged server-style measure is formed.

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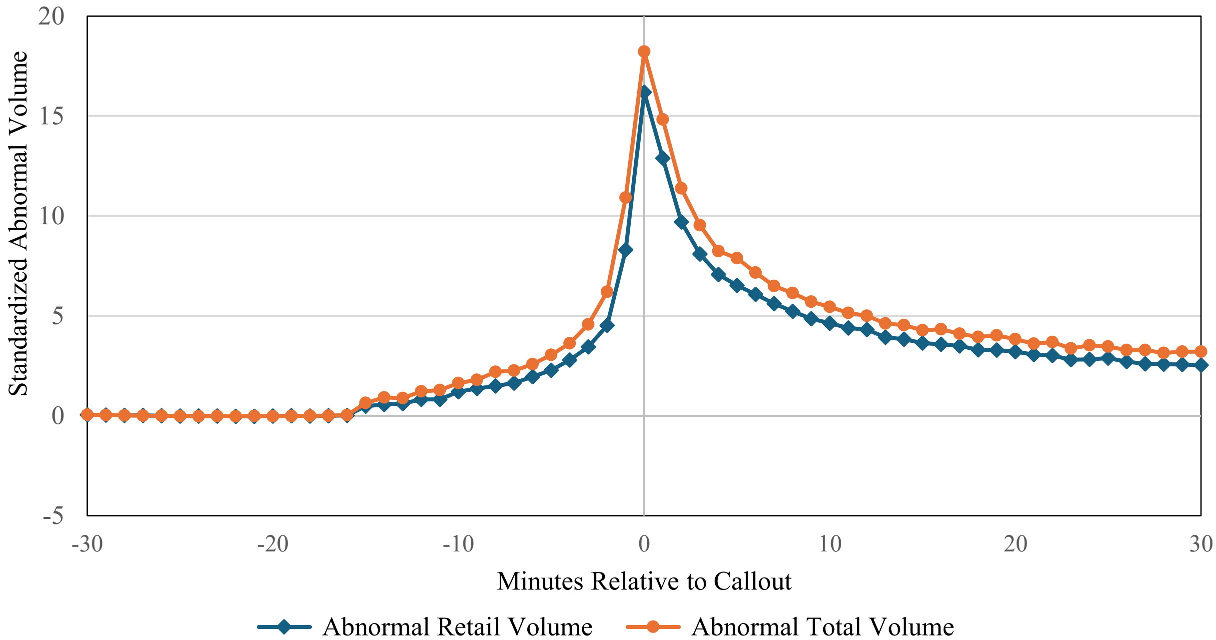

Figure 1: Abnormal Trading Volume around Callouts

This figure plots the average standardized abnormal retail and total option trading volume around callouts. Retail trading volume is identified using SLIM trades following Bryzgalova, Pavlova, and Sikorskaya (2023), while total trading volume includes all option transactions. For each callout, abnormal trading volume is measured as dollar trading volume in a given minute minus the average dollar trading volume during the benchmark period [-30,-16]. Standardized abnormal volume is computed by dividing abnormal volume by the standard deviation of dollar trading volume during the benchmark period. The figure reports average standardized abnormal volume across callouts for each minute relative to publication, where time 0 denotes the first post-publication interval.

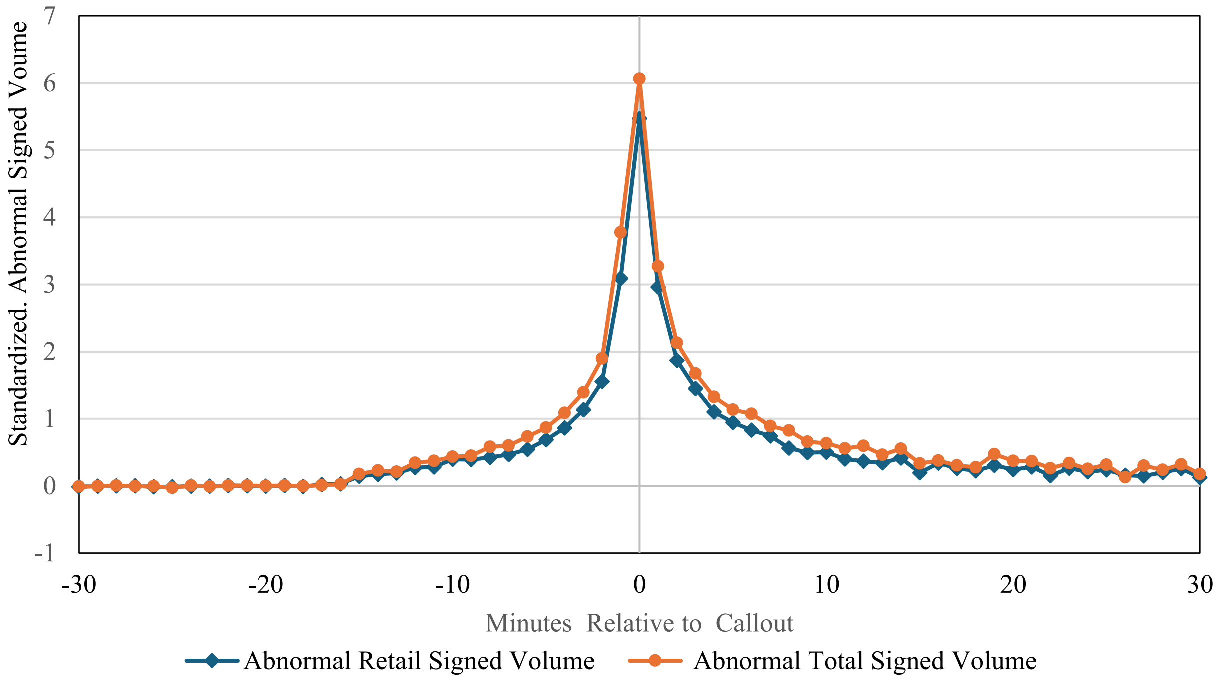

Figure 2: Abnormal Signed Trading Volume around Callouts

This figure is analogous to Figure 1 but examines signed trading volume. For each callout, signed trading volume is measured as buyer-initiated dollar volume minus seller-initiated dollar volume, where trades are classified as buyer- or seller-initiated based on the approach of Grauer, Schuster, and Uhrig-Homburg (2026). Abnormal signed trading volume is computed relative to the benchmark period [-30,-16], and standardized abnormal signed volume is obtained by dividing abnormal signed volume by the standard deviation of signed trading volume during the benchmark period. The figure reports the mean standardized abnormal signed volume across callouts for each minute relative to publication, where time 0 denotes the first post-publication interval.

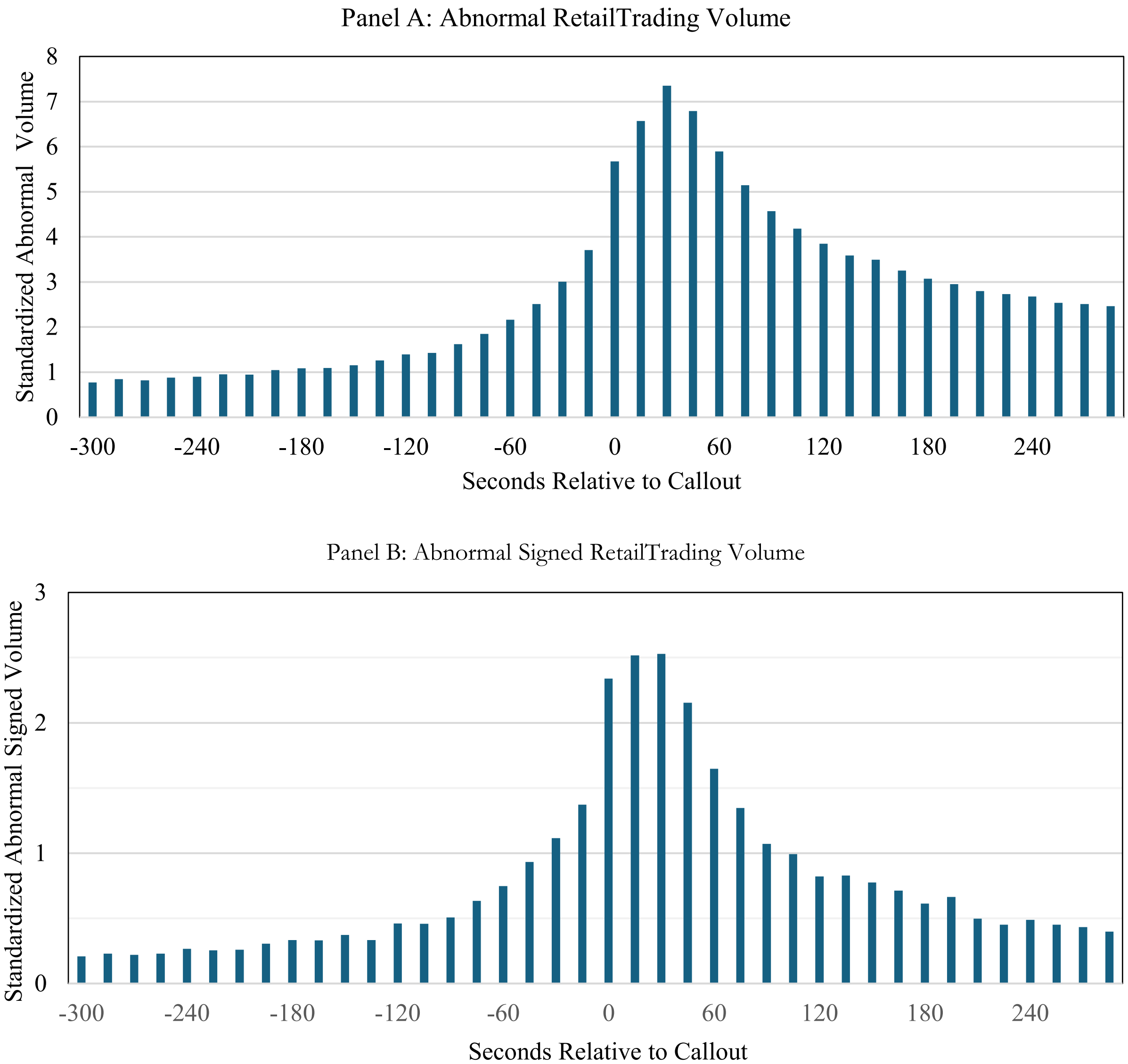

Figure 3: Abnormal Retail Trading around Callouts at the Second Level

This figure examines retail trading activity around callouts using 15-second intervals. Panel A reports standardized abnormal retail trading volume, while Panel B reports standardized abnormal signed retail trading volume. Retail trading volume is identified using SLIM trades following Bryzgalova, Pavlova, and Sikorskaya (2023) and signed using the method of Grauer, Schuster, and Uhrig-Homburg (2026). Abnormal trading measures are computed relative to the benchmark period [-30, -16] minutes and standardized using the standard deviation of trading activity during the benchmark period. The figure reports the mean standardized trading activity across callouts for each 15-second interval relative to publication, where time 0 denotes the first post-publication interval.

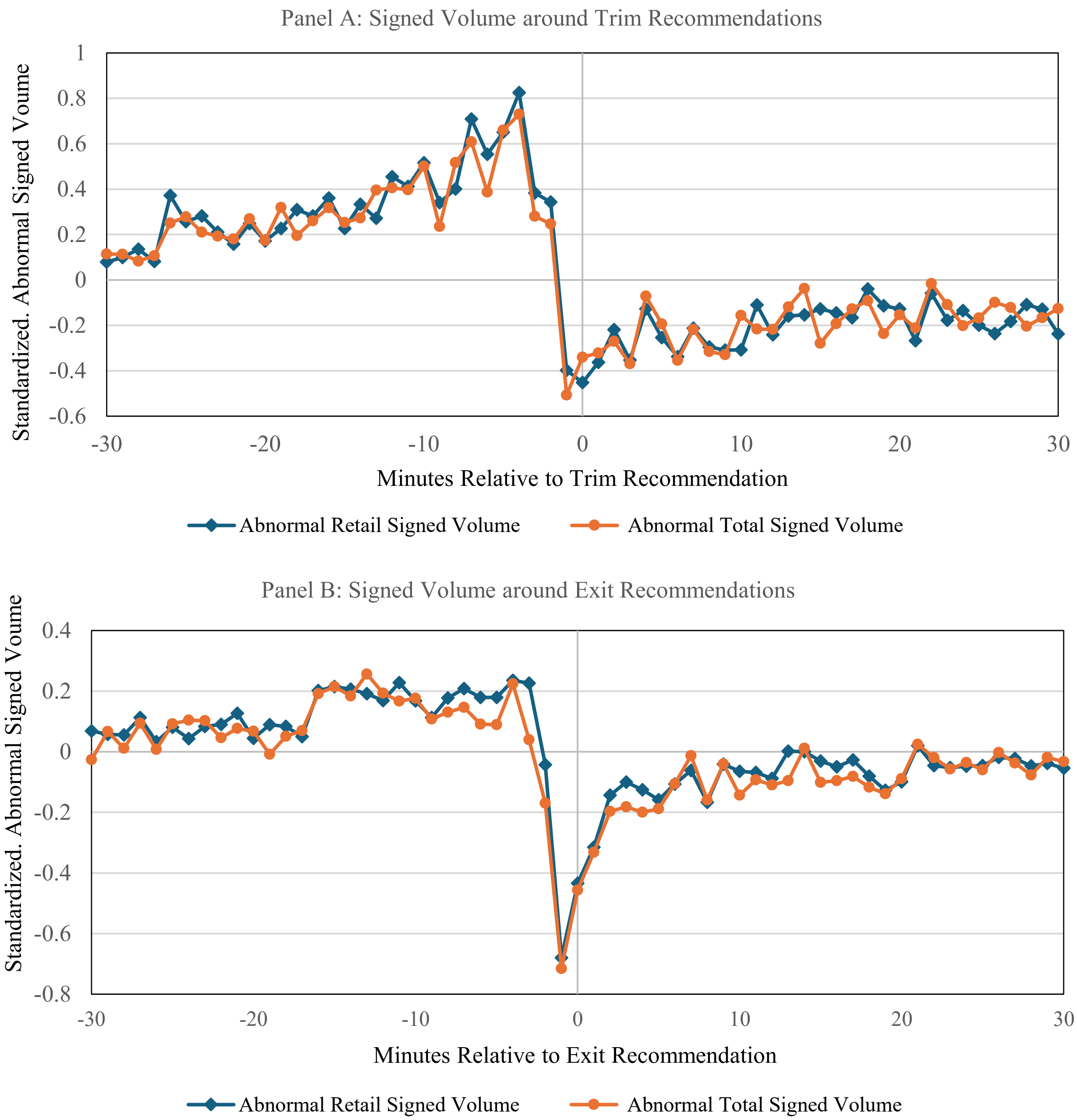

Figure 4: Abnormal Signed Trading Volume around Trim and Exit Recommendations
This figure examines signed retail or total trading volume around trim and exit recommendations. Retail trading volume is identified using SLIM trades following Bryzgalova, Pavlova, and Sikorskaya (2023), while total trading volume includes all option transactions. Panel A reports standardized abnormal signed trading volume around trim recommendations, while Panel B reports standardized abnormal signed trading volume around exit recommendations. For each recommendation, signed trading volume is measured as buyer-initiated dollar volume minus seller-initiated dollar volume, where trades are classified as buyer- or seller-initiated based on the approach of Grauer, Schuster, and Uhrig-Homburg (2026). Abnormal signed trading volume is computed relative to the benchmark period [-30,-16] surrounding the original callout recommendation and standardized by the standard deviation of signed trading volume during this benchmark period. The figure reports the mean standardized abnormal signed trading volume across recommendations for each minute relative to the publication of the trim or exit recommendation, where time 0 denotes the first post-publication interval.

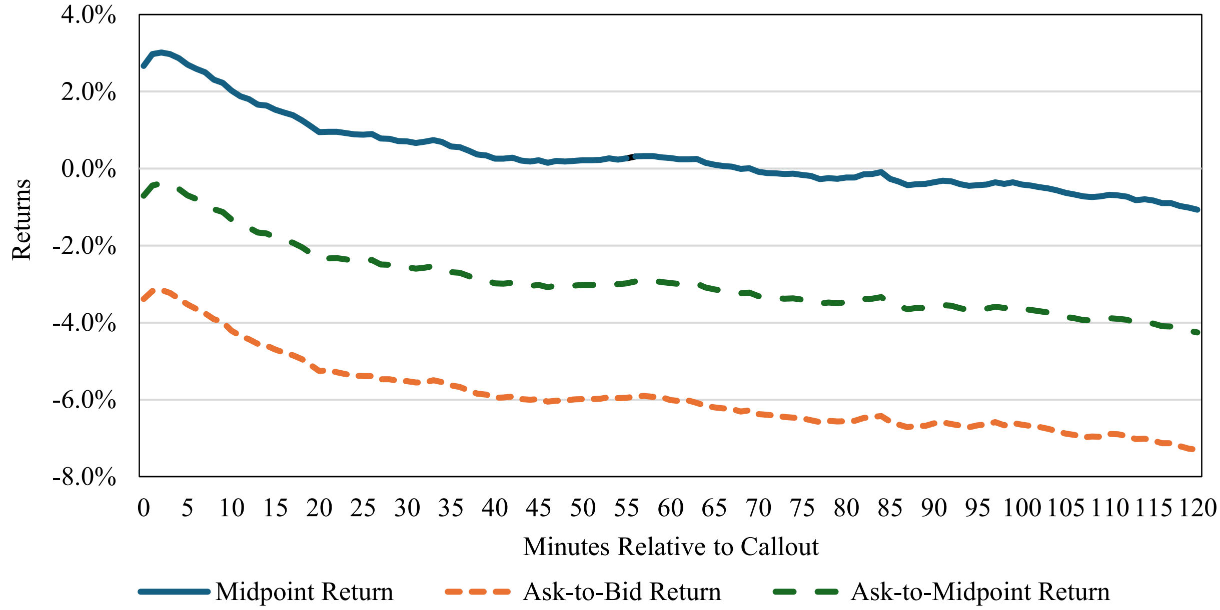

Figure 5: Returns Following Callouts

This figure plots average cumulative option returns following callouts over the first 120 minutes following the publication of the callout. The blue line reports midpoint-to-midpoint returns (no transaction costs), the orange line reports ask-to-bid returns (full transaction costs), and the gray line reports ask-to-midpoint returns (partial transaction costs). Returns are measured relative to the option price at the time of publication and averaged across callouts.

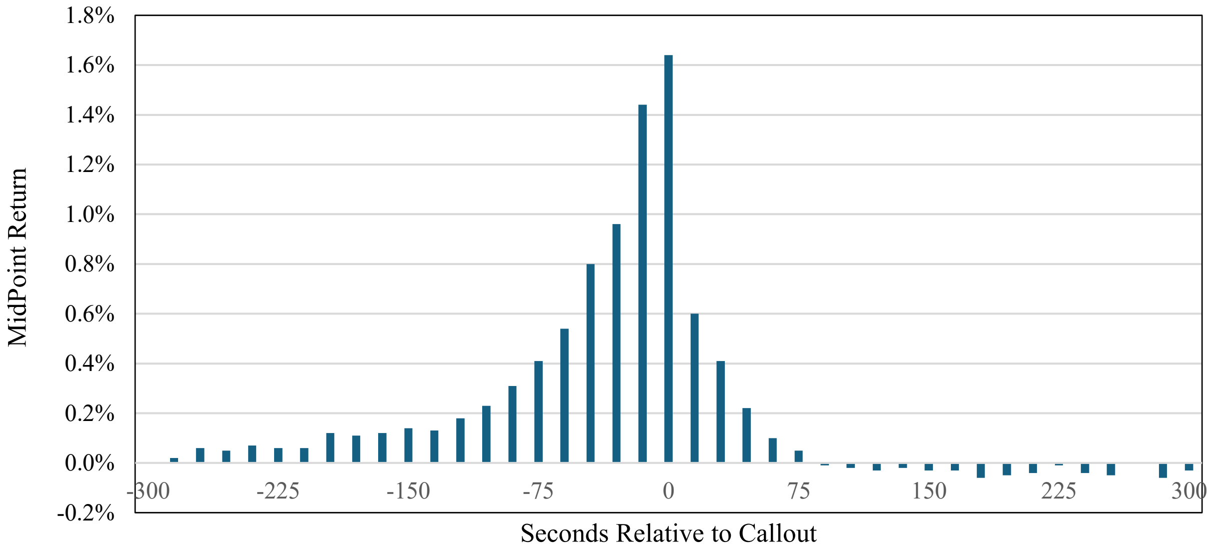

Figure 6: Option Returns around Callouts
This figure plots average midpoint returns around callouts by 15-second intervals. Returns are measured relative to the midpoint immediately prior to the interval and averaged across callouts. The horizontal axis reports time relative to publication, where time 0 denotes the first post-publication interval.

Table 1. Summary Statistics

Table 1 reports summary statistics for the Discord callout sample. The table reports summary statistics for individual callouts. All indicator variables are reported as percentages. The sample consists of 20,793 option callouts posted between January 2020 and December 2025. Detailed variable definitions are provided in Appendix A.

	N	Mean	Std Dev	10th	25th	50th	75th	90th
Signed Moneyness	20,792	-0.04	0.05	-0.11	-0.05	-0.02	-0.01	0.00
Days to Expiration	20,793	7.63	16.04	0.00	1.00	3.00	7.00	17.00
0DTE (Indicator)	20,793	10.76	30.99	0.00	0.00	0.00	0.00	100.00
Call (Indicator)	20,793	81.67	38.69	0.00	100.00	100.00	100.00	100.00
Bid-Ask Spread (%)	20,793	7.07	10.71	1.21	2.05	4.08	8.00	14.81
Option Premium ($)	20,040	2.17	3.61	0.21	0.50	1.25	2.45	4.30
Leverage	20,040	39.91	54.66	8.16	16.61	29.58	49.62	78.31
Speculative Index	20,038	0.00	1.00	-1.18	-0.71	-0.12	0.69	1.33
Number of Trims	20,793	0.50	1.34	0.00	0.00	0.00	0.00	2.00
Any Trim (Indicator)	20,793	22.60	41.82	0.00	0.00	0.00	0.00	100.00
Any Exit (Indicator)	20,793	40.73	49.14	0.00	0.00	0.00	100.00	100.00
Time to Exit (minutes)	8,470	57.51	81.44	2.75	6.76	21.20	68.55	184.37
Time to First Trim (minutes)	4,699	37.88	62.09	1.69	3.59	11.84	39.00	112.78
Underlying Price	20,793	$207.32	$344.09	$19.26	$44.22	$124.56	$235.99	$424.61
Underlying Market Cap ($B)	20,793	$584.92	$937.25	$4.84	$18.46	$118.60	$724.71	$2,196.22

Table 2: Comparison of Callout Contracts And Option Trading Activity

This table compares the characteristics of option contracts recommended through Discord trading servers with the composition of retail option trading. Column (1) reports summary statistics for the callout contracts in our sample. Columns (2)–(5) report the characteristics of option contracts weighted by their share of retail (SLIM) and non-retail trading using both trade counts and dollar volume. Columns (6)–(7) report the difference between callout contracts and the SLIM trade-share distribution together and t-tests of the difference, computed from standard errors clustered by event date and firm. Panel A reports time-to-expiration categories, Panel B reports moneyness categories, and Panel C reports additional option and underlying-stock characteristics. Additional variable definitions are provided in Appendix A.

		Slim Trades		Non-Slim Trades		Callout - Slim Trade Share	
	Callout Options	Trade Share	Volume Share	Trade Share	Volume Share	Estimate	t-stat
	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Panel A: Time to Expiration							
0 DTE	11.26%	7.93%	3.48%	7.57%	2.46%	3.33%	(6.11)
1-7 Days	67.55%	39.61%	27.74%	33.53%	18.15%	27.94%	(15.38)
2-4 Weeks	15.28%	25.98%	22.18%	28.16%	22.74%	-11.00%	(-16.88)
>1 Month	5.92%	26.47%	46.60%	30.73%	56.65%	-21.00%	(-13.06)
Ave Days to Expiration	7.56	45.13	101.48	49.81	114.78	-37.57	(-15.37)
Panel B: Moneyness							
Deep OTM (Moneyness <-0.10)	4.54%	15.50%	15.80%	18.30%	13.50%	-10.96%	(-10.56)
OTM [-0.10, -0.02)	48.96%	46.10%	23.20%	46.80%	14.10%	2.86%	(1.57)
ATM [-0.02, 0.02]	45.50%	23.20%	22.10%	16.80%	9.80%	22.30%	(10.65)
ITM (0.02, 0.10]	0.65%	6.50%	12.20%	7.40%	9.20%	-5.85%	(-36.19)
Deep ITM (> 0.10)	0.36%	8.70%	26.70%	10.60%	53.40%	-8.34%	(-17.73)
Average Signed Moneyness	-0.03	-0.04	-0.02	-0.05	-0.01	1.30%	(-3.09)
Panel C: Other Characteristics							
%Call	81.59%	66.43%	67.15%	59.65%	51.85%	15.16%	(13.77)
Bid-Ask Spread	6.17%	8.08%	3.76%	9.73%	3.77%	-1.91%	(-4.84)
Option Premium	$2.93	$7.65	$53.58	$9.89	$89.70	-$4.72	(-6.40)
Leverage	23.51	7.94	1.96	4.97	4.88	15.57	(15.83)
Underlying Price	$207.76	$228.38	$536.80	$226.64	$411.34	-$20.62	(-1.06)
Underlying Size ($Bil)	$583.67	$522.52	$751.47	$506.56	$670.89	$61.15	(1.11)
Speculative Index	0.36	0	-0.99	-0.07	-1.11	0.36	(11.92)

Table 3. Abnormal Volume Around Callouts

This table reports average standardized abnormal trading volume around callouts. Columns [1] and [2] report retail trading volume and signed retail trading volume, respectively, where retail trading is identified using SLIM trades following Bryzgalova, Pavlova, and Sikorskaya (2023) and signed using the method of Grauer, Schuster, and Uhrig-Homburg (2026). Columns [3] and [4] report total trading volume and signed total trading volume. The reported intervals denote event windows relative to callout publication. For example, [-15,-6] measures average trading activity from 15 minutes before publication through 6 minutes before publication, while [0,1] measures average trading activity during the publication minute and the subsequent minute. For each callout, abnormal trading volume is measured relative to the benchmark period [-30,-16], and standardized by the standard deviation of trading activity during the benchmark period. The table reports average standardized abnormal trading volume across callouts for the indicated event windows relative to publication. Standard errors are clustered by event date, and *t*-statistics are reported in parentheses.

	Retail Volume	*Signed Retail Volume*	*Total Volume*	*Signed Total Volume*
	[1]	[2]	[3]	[4]
[-15, -6]	1.10	0.33	1.55	0.42
	(23.00)	(18.19)	(24.28)	(18.77)
[-5, -1]	4.26	1.46	5.68	1.81
	(34.63)	(32.75)	(34.15)	(32.15)
[0,1]	14.54	4.22	16.55	4.67
	(48.77)	(42.28)	(43.88)	(38.59)
[2,5]	7.85	1.34	9.28	1.57
	(40.52)	(25.18)	(37.11)	(24.67)
[6, 30]	3.69	0.34	4.41	0.45
	(33.14)	(15.17)	(31.10)	(16.16)
[0, 30]	5.06	0.77	5.98	0.94
	(39.55)	(27.61)	(36.44)	(26.74)

Table 4. Abnormal Volume Around Trim and Exit Recommendations

This table reports average standardized abnormal trading volume around exit and trim recommendations. Columns [1] and [2] report retail trading volume and signed retail trading volume, respectively, where retail trading is identified using SLIM trades following Bryzgalova, Pavlova, and Sikorskaya (2023) and signed using the method of Grauer, Schuster, and Uhrig-Homburg (2026). Columns [3] and [4] report total trading volume and signed total trading volume. Panel A reports results around trim recommendations, while Panel B reports results around exit recommendations. The reported intervals denote event windows relative to the publication of the trim or exit recommendation. Abnormal trading volume is computed relative to the benchmark period [-30,-16] surrounding the original callout recommendation and standardized by the standard deviation of trading activity during this benchmark period. The table reports average standardized abnormal trading volume across recommendations for each event window. Standard errors are clustered by event date, and *t*-statistics are reported in parentheses.

Panel A: Trading around Trims

	Retail Volume	*Signed Retail Volume*	*Total Volume*	*Signed Total Volume*
	[1]	*[2]*	*[3]*	*[4]*
[-15,-6]	2.75	0.42	3.07	0.40
	(19.25)	(11.77)	(18.12)	(9.95)
[-5,-1]	5.20	0.36	5.23	0.28
	(24.87)	(6.60)	(22.55)	(4.85)
[0,1]	4.91	-0.41	4.85	-0.33
	(22.17)	(-5.17)	(19.30)	(-3.88)
[2,5]	3.47	-0.25	3.76	-0.23
	(20.05)	(-4.85)	(18.74)	(-4.46)
[6,30]	2.20	-0.19	2.32	-0.19
	(17.04)	(-8.30)	(16.87)	(-7.78)
[0,30]	2.62	-0.22	2.73	-0.20
	(19.19)	(-8.99)	(18.52)	(-8.49)

Panel B: Trading around Exits

	Retail Volume	*Signed Retail Volume*	*Total Volume*	*Signed Total Volume*
	[1]	[2]	[3]	[4]
[-15,-6]	2.32	0.19	2.46	0.17
	(22.00)	(8.43)	(21.39)	(7.08)
[-5,-1]	4.06	-0.02	4.12	-0.11
	(27.73)	(-0.46)	(25.07)	(-2.67)
[0,1]	3.81	-0.38	3.71	-0.40
	(25.55)	(-7.49)	(23.07)	(-7.52)
[2,5]	2.46	-0.13	2.56	-0.19
	(21.70)	(-4.21)	(20.83)	(-5.79)
[6,30]	1.59	-0.08	1.71	-0.09
	(18.01)	(-4.43)	(18.64)	(-4.68)
[0,30]	1.96	-0.10	2.07	-0.12
	(20.23)	(-5.39)	(20.27)	(-5.96)

Table 5. Returns of Callouts by Entry and Exit Assumptions

This table reports average returns to option callouts under alternative assumptions regarding subscriber entry timing and trade execution. Panel A reports midpoint returns, where the entry price equals the average midpoint quote over the indicated entry interval and the exit price equals the midpoint quote at the indicated holding horizon. Panel B reports realized execution returns, where the entry price equals the volume-weighted average purchase price (VWAP) of retail buy orders executed during the indicated entry interval and the exit price equals the midpoint quote adjusted for estimated execution costs by multiplying the midpoint by (1 − median bid-ask spread). The bid-ask spread is estimated from retail purchases during the entry interval and, when unavailable, is imputed using the sample median. Holding periods are measured relative to the last second of the entry interval. Dynamic exit strategies reduce positions by 50% following the first trim recommendation, close the position following an exit recommendation, and otherwise default to the 60- or 120-minute holding period. Returns are reported in percent. Standard errors are clustered by event date, and t-statistics are reported below the coefficient estimates.

	Fixed Holding Periods					**Dynamic Holding Periods**	
Entry Point	1 Minute [1]	5 Minutes [2]	15 Minutes [3]	60 Minutes [4]	120 Minutes [5]	60 Minute Strategy [6]	120 Minute Strategy [7]
Panel A: Option Price Response (Midpoint Returns)							
[-60, -1]	5.77	5.97	4.75	3.48	2.20	5.07	5.01
.	(50.25)	(35.26)	(18.06)	(5.53)	(2.49)	(11.24)	(8.02)
[0,15]	2.13	1.88	0.71	-0.56	-1.92	1.00	0.78
	(22.37)	(12.80)	(3.13)	(-0.95)	(-2.26)	(2.39)	(1.32)
[0, 30]	1.68	1.44	0.27	-0.99	-2.37	0.54	0.30
.	(18.77)	(10.05)	(1.22)	(-1.70)	(-2.81)	(1.30)	(0.50)
[0,60]	1.04	0.80	-0.36	-1.63	-3.02	-0.19	-0.45
	(13.30)	(5.87)	(-1.66)	(-2.87)	(-3.69)	(-0.47)	(-0.78)
[0,120]	0.46	0.08	-1.04	-2.28	-3.63	-1.11	-1.37
	(6.34)	(0.58)	(-4.82)	(-4.13)	(-4.51)	(-2.75)	(-2.38)
[0,300]	-0.43	-0.86	-1.96	-3.01	-4.13	-2.19	-2.41
	(-4.88)	(-6.18)	(-9.07)	(-5.34)	(-5.15)	(-5.17)	(-3.95)
Panel B: Realized Execution Returns							
[-60, -1]	1.82	2.00	0.86	-0.33	-1.58	1.20	1.14
.	(18.12)	(12.98)	(3.47)	(-0.55)	(-1.91)	(2.84)	(1.95)
[0,15]	-0.96	-1.20	-2.30	-3.48	-4.78	-1.96	-2.12
	(-10.42)	(-8.31)	(-10.27)	(-6.15)	(-5.97)	(-4.87)	(-3.73)
[0, 30]	-1.26	-1.49	-2.59	-3.77	-5.09	-2.30	-2.48
.	(-14.14)	(-10.51)	(-11.75)	(-6.77)	(-6.40)	(-5.80)	(-4.42)
[0,60]	-1.75	-1.98	-3.07	-4.28	-5.60	-2.88	-3.08
	(-21.59)	(-14.54)	(-14.25)	(-7.95)	(-7.27)	(-7.52)	(-5.67)
[0,120]	-2.18	-2.57	-3.62	-4.81	-6.07	-3.66	-3.87
	(-25.88)	(-18.64)	(-16.81)	(-9.08)	(-7.96)	(-9.53)	(-7.04)
[0,300]	-3.21	-3.62	-4.68	-5.69	-6.78	-4.88	-5.06
	(-31.63)	(-24.67)	(-21.59)	(-10.65)	(-8.97)	(-11.98)	(-8.72)

Table 6: Retail Demand for Speculative and High-Transaction-Cost Options

This table reports regressions examining the relation between retail trading and option characteristics following callouts. The dependent variable in Panels A and B are Standardized Abnormal Retail Volume and Standardized Abnormal Signed Retail Volume, respectively. Speculative Index is a standardized composite measure constructed as the sum of standardized leverage minus standardized log(option premium), log(underlying stock price), log(underlying market capitalization), and log(option maturity). Higher values therefore correspond to more speculative option contracts. Bid-Ask Spread is defined as (Ask – Bid)/Midpoint using the prevailing bid and ask quotes at the time of the callout. All continuous explanatory variables are standardized to have mean zero and unit standard deviation. Columns (4) include time and server fixed effects. Standard errors are clustered by event date, and t-statistics are reported in parentheses.

Panel A: Retail Vol

	[1]	[2]	[3]	[4]
Speculative Index	8.18		7.32	7.12
	(25.04)		(21.85)	(20.13)
Bid-Ask Spread		4.99	2.57	2.17
		(15.08)	(8.11)	(6.51)
Observations	13,348	13,348	13,348	13,348
R-squared	9.36%	3.49%	10.21%	28.49
Time FE	No	No	No	Yes
Server FE	No	No	No	Yes
Mean Dependent Variable	14.54	14.54	14.54	14.54

Panel B: Signed Retail Volume

	[1]	[2]	[3]	[4]
Speculative Index	2.37		2.07	1.90
	(21.31)		(18.87)	(15.33)
Bid-Ask Spread		1.30	0.61	0.49
		(11.81)	(5.74)	(4.29)
Observations	13,323	13,323	13,323	13,323
R-squared	5.89%	1.94%	6.31%	22.17
Time FE	No	No	No	Yes
Server FE	No	No	No	Yes
Mean Dependent Variable	4.22	4.22	4.22	4.22

Table 7. Subscriber Returns for Speculative and High-Transaction-Cost Options

This table reports regressions examining the relation between subscriber returns and option characteristics following callouts. Panel A reports realized execution returns, where the entry price equals the retail purchase volume-weighted average price (VWAP) over the interval from 0 to 300 seconds following the callout and the exit price is based on the Dynamic 60 exit strategy using midpoint prices adjusted for estimated execution costs. Panel B reports realized execution returns using the same exit strategy, but where the entry price equals the retail purchase VWAP over the interval from 0 to 15 seconds following the callout. Panel C reports midpoint returns, where the entry price equals the average midpoint quote over the interval from 0 to 15 seconds following the callout and the exit price is based on the Dynamic 60 exit strategy using midpoint prices, as defined in Table 5. The Speculative Index is a standardized composite measure constructed as the sum of standardized leverage minus standardized log(option premium), log(underlying stock price), log(underlying market capitalization), and log(option maturity). Higher values therefore correspond to more speculative option contracts. Bid-Ask Spread is defined as (Ask − Bid)/Midpoint using the prevailing bid and ask quotes at the time of the callout. All continuous explanatory variables are standardized to have mean zero and unit standard deviation. Columns (4) include time and server fixed effects. Standard errors are clustered by event date, and t-statistics are reported in parentheses.

Panel A: Realized Execution Returns - Entry = [0, 300], Dynamic 60 Exit Strategy				
	[1]	[2]	[3]	[4]
Speculative Index	-3.16		-2.58	-2.65
	(-7.68)		(-4.56)	(-5.75)
Bid-Ask Spread		-2.65	-1.79	-1.40
		(-5.79)	(-3.45)	(-2.73)
Observations	11,884	11,884	11,884	11,884
R-squared	0.85%	0.58%	1.09%	15.54%
Time FE	No	No	No	Yes
Server FE	No	No	No	Yes
Panel B: Realized Execution Returns Entry = [0, 15], Dynamic 60 Exit Strategy				
	[1]	[2]	[3]	[4]
Speculative Index	-2.12		-1.53	-1.51
	(-4.98)		(-3.15)	(-3.40)
Bid-Ask Spread		-2.33	-1.82	-1.62
		(-4.56)	(-3.17)	(-2.93)
Observations	11,956	11,956	11,956	11,956
R-squared	0.37%	0.43%	0.60%	15.16%
Time FE	No	No	No	Yes
Server FE	No	No	No	Yes
Panel C: Midpoint Returns - Entry = [0, 15], Dynamic 60 Exit Strategy				
	[1]	[2]	[3]	[4]
Speculative Index	-0.88		-1.19	-1.29
	(-1.96)		(-2.31)	(-2.80)
Bid-Ask Spread		0.56	0.96	1.02
		(1.02)	(1.55)	(1.73)
Observations	11,884	11,884	11,884	11,884
R-squared	0.06%	0.02%	0.61%	14.72%
Time FE	No	No	No	Yes
Server FE	No	No	No	Yes

Table 8. Server Recommendation Styles, Retail Engagement, and Subscriber Returns

This table examines whether servers whose callouts consistently involve more speculative or higher-transaction-cost option contracts generate greater retail engagement and different subscriber outcomes. For each server-day, the sorting characteristic is computed as the average value of the corresponding characteristic over the server's previous 50 callouts, excluding callouts issued on the current day. Servers are sorted into quintiles by event date based on this lagged measure. Columns (1) and (2) report the average sorting characteristic during the estimation and subsequent periods, respectively. Column (3) reports standardized abnormal retail trading volume. Columns (4)–(6) report subscriber returns using the Dynamic 60 exit strategy. Midpoint returns are computed using the average midpoint quote over the interval from 0 to 15 seconds as the entry price and midpoint quotes for exit prices. Realized execution returns use the retail purchase volume-weighted average price (VWAP) over the indicated entry interval as the entry price and midpoint prices adjusted for estimated execution costs as exit prices. The High–Low row reports the difference between Quintile 5 and Quintile 1. Standard errors are clustered by event date, and t-statistics are reported below the coefficient estimates.

Quintile	Pre-Callout Ave	Callout Value	Retail Volume	Dynamic 60 Midpoint Ret. Entry = [0,15]	Dynamic 60 Realized Ret. Entry = [0,15]	Dynamic 60 Realized Ret. Entry = [0,300]
	[1]	[2]	[3]	[4]	[5]	[6]
Panel A: Sort on Speculative Index						
1	-0.46	-0.39	10.72	2.02%	0.18%	-2.60%
				(1.90)	(0.17)	(-2.86)
2	-0.31	-0.27	9.96	-0.08%	-2.21%	-3.75%
				(-0.11)	(-3.18)	(-5.22)
3	-0.15	-0.16	11.11	2.09%	-0.40%	-2.68%
				(2.96)	(-0.60)	(-4.18)
4	0.44	0.42	20.21	0.02%	-3.54%	-5.82%
				(0.02)	(-3.68)	(-6.49)
5	0.62	0.57	26.59	-1.74%	-5.36%	-7.68%
				(-1.77)	(-5.60)	(-8.02)
High - Low	1.08	0.97	15.88	-3.76%	-5.54%	-5.08%
		(22.89)	(12.56)	(-2.63)	(-4.01)	(-3.93)
Panel B: Sort on Server Bid-Ask Spread						
1	3.63	4.07	9.99	-0.03%	-1.73%	-3.77%
				(-0.03)	(-1.71)	(-3.78)
2	4.48	4.82	10.54	0.33%	-1.75%	-3.63%
				(0.40)	(-2.16)	(-4.80)
3	5.66	5.63	11.38	1.50%	-1.09%	-3.16%
				(2.28)	(-1.77)	(-5.20)
4	7.35	7.19	20.64	0.98%	-2.51%	-4.95%
				(0.99)	(-2.60)	(-5.48)
5	9.00	8.31	24.20	-0.74%	-4.42%	-7.11%
				(-0.72)	(-4.44)	(-7.26)
High - Low	5.37	4.23	14.20	-0.71%	-2.70%	-3.34%
		(13.81)	(11.46)	(-0.50)	(-1.96)	(-2.44)

Speculation by Subscription:

Finfluencers and Retail Option Trading on Discord

Internet Appendix

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Internet Appendix A. Discord Trading Service Legal and Regulatory Setting

Private, subscription-based option recommendation services occupy a gray area between social media commentary and paid trading services. Many services describe their content as educational, informational, or entertainment-oriented, and often state that their administrators are not financial advisors, investment advisers, broker-dealers, or fiduciaries. However, regulators are likely to focus less on the label than on the underlying conduct. Relevant factors include whether subscribers pay for access, whether administrators identify specific securities to buy or sell, whether trade alerts are time-sensitive, whether administrators have undisclosed trading conflicts, and whether marketing materials give a misleading impression of likely subscriber outcomes.

Our setting does not permit conclusions regarding whether the conduct of any service or administrator in our sample violates securities law. In this section, we describe two concerns that may be relevant in the finfluencer Discord setting: trading around one's own recommendations and misleading performance advertising. We also discuss relevant enforcement examples.

A.1. Scalping

The most direct conflict-of-interest concern is scalping. In the finfluencer context, scalping refers to a person buying or holding a security before recommending it to followers, and then selling after the recommendation generates follower demand or a price increase. If an administrator already owns an option before issuing a callout, subscriber buying after the callout may improve the administrator's exit price. In this setting, even a small timing advantage can matter. The administrator may benefit from the immediate buying pressure, while subscribers may enter after prices have already moved and may later bear the reversal. The most clearly problematic pattern is where an administrator buys before the alert, encourages subscribers to buy, and then sells into the resulting demand without clearly disclosing this conflict.

Trading services may attempt to mitigate culpability through broad conflict-of-interest disclaimers. For example, a service might state that its employees or affiliates may trade in the securities discussed through the service at any time without notice, and that their positions may differ from what is implied by its content. Such disclosures may reduce the likelihood that regulators view subscribers as unaware of the general conflict. However, they do not legitimize scalping. The key issue is not whether the administrator reserves the right to trade, but whether subscribers understand the economically important conflict at the moment of the recommendation.

Our data do not allow us to observe administrator trading, so we do not test whether scalping occurs. The relevance of our evidence is instead that callouts on Discord generate the kind of immediate trading response that would make scalping economically valuable if an administrator were trading ahead of subscribers.

A.2. Misleading Performance Claims

A second concern is how trading services advertise performance. Many paid trading communities market themselves using screenshots of successful trades or win rates. These materials can be misleading if they give an incomplete picture of the returns that ordinary subscribers are likely to earn. For example, a promotional post may report returns based on the administrator's own entry price, while subscribers could enter only after the callout was posted. These omissions are important because subscriber profitability depends heavily on execution timing and trading costs. Material gaps between advertised trade performance and feasible subscriber performance are a relevant regulatory concern. Securities antifraud rules apply to materially false or misleading statements made in connection with securities transactions, and general consumer-protection rules prohibit deceptive advertising practices.

Finfluencers often attempt to mitigate exposure to false-advertising claims arising statements such as “96% success rate” using a variety of disclosures. For example, they may frame performance claims as internally calculated rather than as independently verified. In particular, a finfluencer may disclose that the performance figures are based on the finfluencer’s own accounting, selected historical periods, and internally defined criteria for what counts as a “win” or “success.” Disclaimers may include wording that states that alternative assumptions about trade timing or transaction costs could materially change the reported results. However, these disclosures are unlikely to eliminate liability if the overall marketing message misrepresents likely performance, especially where advertised success rates exclude losing positions or fail to reflect realistic market conditions. We do not evaluate whether any specific performance claim is false or misleading, but we do examine how subscriber performance is sensitive to assumptions about timing and transaction costs.

A.3. Relevant Enforcement Examples

Tokyo Joe. SEC v. Park in 2020, involved Yun Soo Oh Park, known as “Tokyo Joe,” and his paid online stock recommendation service. The SEC alleged that Park charged subscribers for daily stock picks, email alerts, members-only webpages, and chat-room access, and that he recommended stocks he already owned while selling into subscriber demand without disclosing his trading. The SEC also alleged that Park used testimonials and false or misleading performance results to persuade investors to follow his recommendations.[11] Park settled for $750K without admitting or denying the allegations, with a link to the court order posted to the home page of the Tokyo Joe web site for a period of 30 days.[12] The case shows that courts may look past labels such

[11] https://law.justia.com/cases/federal/district-courts/FSupp2/99/889/2290926/
[12] https://www.sec.gov/news/press/2001-26.txt

as "publication" or "investment commentary" when an online service provides paid, time-sensitive recommendations and allegedly conflicted trading advice.

Titan. A 2023 performance-advertising example is the SEC's administrative proceeding against Titan Global Capital Management, a registered FinTech investment adviser that offered investment strategies to retail investors through a mobile app. The SEC charged Titan with using misleading hypothetical performance claims, including advertising annualized performance for its crypto strategy as high as 2,700% without clearly disclosing that the figure was based on a purely hypothetical account and extrapolated from the strategy's first three weeks of performance. The SEC also emphasized that some assumptions and risks were available only through embedded links and were not as clear and prominent as the headline performance claim, which the SEC found did not present the hypothetical projection in a fair and balanced way. Titan settled without admitting or denying the findings and agreed to a cease-and-desist order and an $850,000 civil penalty.[13] The case illustrates that regulators may treat prominent performance claims as misleading when the assumptions or risks are not well presented.

Atlas Trading. In 2022, the SEC brought charges against several social-media traders associated with Atlas Trading, alleging that they used Twitter, Discord, and podcasts to promote stocks while secretly selling into the demand generated by their recommendations, describing the behavior as a "$100 million stock manipulation scheme."[14] The district court dismissed the indictment before trial, reasoning that the government had alleged that followers received misleading information, but had not adequately alleged that the scheme deprived them of money or property. In 2025, the Fifth Circuit reversed, holding that the indictment alleged more than a loss of information because it alleged that followers were induced, through misrepresentations, to

[13] https://www.sec.gov/newsroom/press-releases/2023-153
[14] https://www.sec.gov/newsroom/press-releases/2022-221

buy securities with their own money.[15] The case remains pending and shows that regulators view undisclosed trading around social-media recommendations as an important enforcement concern, but it also shows that courts may require a clear link between the alleged deception and investors' trading decisions and performance.

[15] https://clsbluesky.law.columbia.edu/2025/10/16/quinn-emanuel-discusses-fifth-circuit-decision-reinstating-securities-fraud-indictment/

Internet Appendix B. Data Collection and Message Classification

This appendix reports the Whop search queries and the fixed word lists used to identify callouts and reconstruct position lifecycles in the main text. All terms are matched against the standardized, lowercased message text.

B.1 Whop search queries. To assemble the set of candidate services, we query the Whop marketplace with the terms below and retain results that mention live trading or real-time alerts: *"option," "options," "trading," "option trading," "daytrading," "day trading," "stock alerts," "trade alerts," "option alerts," "stock signals," "live trading," "stock education," "learn from traders," "learn to trade," "trading discord," "master trading," "copy trading," "copy trades.*

B.2 Directional-language lexicons.
We classify the directional content of each message against five fixed word lists. Profit and return updates (e.g., "+50%", "20% here") are captured separately by a numeric-percentage pattern rather than by a word list.

Watch or consider (non-entry). Terms that mark a message as monitoring a setup rather than entering it: *"considering," "eyeing," "eying," "load," "loading," "looking," "watch," "watching."*

Entry. Terms that signal a new position:
"added," "adding," "back in," "bot," "bto," "bought," "buy," "enter," "filled," "going long," "in @," "in at," "lotto," "open," "starter," "sto," "swing," "swinging."
The word "in" appears only as "in @" and "in at" so that it is not matched in ordinary conversational text.

Trim or manage. Terms that signal a partial exit or active management of an open position: *"absis", "bag secured", "banked", "be careful", "banger", "cash out", "cashed out", "cut", "cut it", "cut loss", "derisking", "derisk", "don't hold", "dont hold", "half out", "hit my target", "hit target", "in runners", "let it ride", "lock in", "lock profits", "locking in", "move stop", "move your stop", "partial", "protect gains", "protect profits", "raise stop", "reducing", "ride free", "runner", "runners", "runners free", "running free", "scale out", "scaled out", "scaling out", "scaled", "scaling", "secure profits", "sell more", "set stop", "sell at will", "sell at your", "take profit", "take profits", "take some", "taking off", "taking profits", "taking some", "tighten stop", "took some", "trail stop", "trailing stop", "trim", "trimmed", "trimming", "up big".*

Close (full exit). Terms that signal a full exit:
"all out", "btc", "closed", "closing", "done with", "exit", "exited", "exiting", "expired", "expired worthless", "flat now", "fully out", "get out", "got stopped", "no longer in", "not holding", "out of this", "out", "sell", "selling", "sl be", "sold", "stc", "stop hit", "stop loss hit", "stopped", "stopped out", "took loss", "took the loss", "took win", "took the win".

B.3 Ticker handling.
Three constants govern how candidate tickers are validated and matched to options data.

Excluded tokens.
An unprefixed candidate matching any token below is never treated as a ticker. These fall into single letters and other short ambiguous tokens:
A, AN, B, C, D, I, L, M, O, P, R, S, T, U, W, X, Y.
The month abbreviations:
JAN, FEB, MAR, APR, MAY, JUN, JUL, AUG, SEP, OCT, NOV, DEC.
Common slang and trading jargon:
YALL, LFG, IMO, DD, PT, BTO, STC, PM, ITM, OTM, ATH, CPI, EOD, FOMO

Table IA1. Representative Discord Messages by Server and Message Type

This table reports representative examples of Discord messages classified as initial callouts, trims, and exits. Initial callouts announce new positions, trims indicate partial profit-taking or position management, and exits indicate full liquidation or stop-out language. In the messages, BTO generally stands for buy to open, and STC stands for sell to close.

Initial Callout	Trim	Exit
BTO F 23c @0.21	TWTR @0.73 will trim 2/3	NFLX OUT LAST @4.45
BTO BP 6/18 28c @ .38	First trim on ROKU @ 2.54	Out TSLA @ 2.66
Bought - $NVAX 9 Call @ $29	Trimmed 40% $LULU	all out $BIDU 155C @ 2.25
BTO V 315C 12/20 @ 2.55	ASTS cut here -10% or ride	stc 3 ebay 65c 1/17/25 @ 1.82
$GOOG 182.5C june / 13 1.88	Trimming some profits here on $PFE for a 10% gain	ALL OUT OF $U CALLS HERE @ +85%
92P @ .10 $XOM	22% - first trim $UBER swing	Fully out $RIVN
$FANG 160 call 11/10 @.73	ENPH now 3.95 (+61%) banger!! Secure most	None
RBLX 70C 2/14 0.85	UAL 80% trim	Out of $BMY
ALERT BOUGHT $SHOP 130c at 1.30	alert trim 1/2 - nvda 123c 3/28 @ 1.7	ALERT ALL OUT $OKLO 55c at 1.85
BTO MRVL 110C 12/19 @ 1.25	trim AMD @ 1.65	TSM closing, small is still good
[Buy] GM 3/15 $40 Put @ .54	[TRIM] GOOGL 3/15 $137 Puts for 20% profit!	[Sell] AMZN calls here for +40% Profit! ALL OUT!!
BTO X 26.5c @0.26	$DLTR @.40 | +35% SOLD MOST , LEFT RUNNERS!!!	$COP @.35 | +75% SOLD ALL
BOUGHT | AVGO DEC 13 240C $5.00	SOLD | MSTR DEC 13 420C $10.00 1/2 POS , SCALING A BIT HERE	MSFT DEC 13 445C $5.20 ALL OUT
$JNJ 165c aug 1 @1.99	30% on $ASTS trimming some here	closing $XOM here in profits
$META 460 CALL 5/10 @ 5.00 🚨	None	None

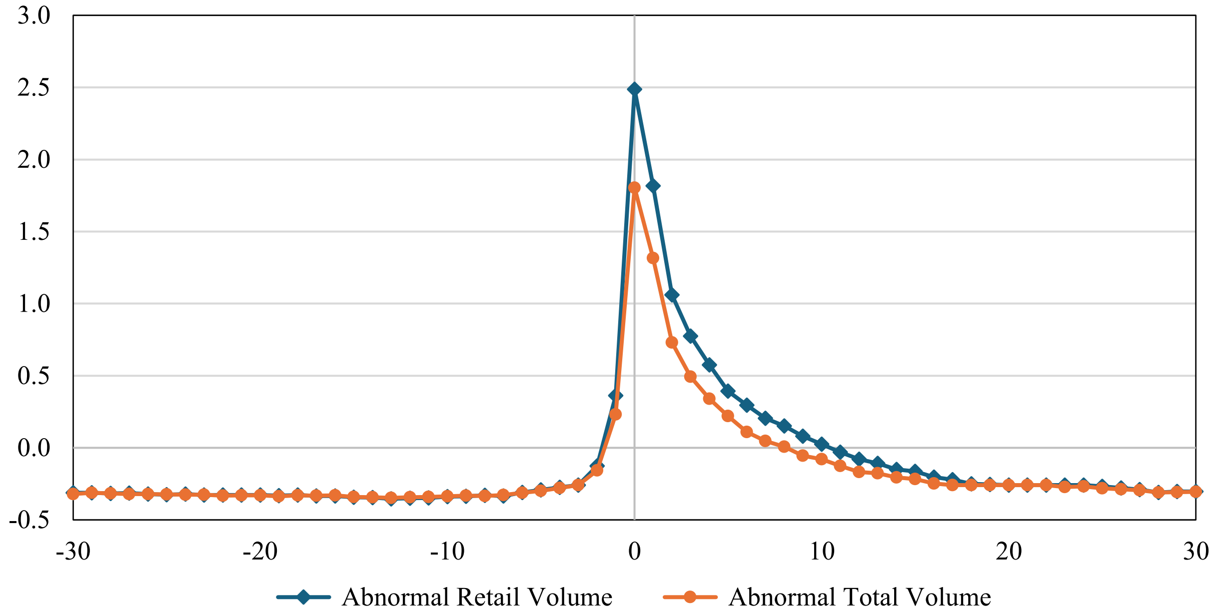

Figure IA.1: Median Abnormal Trading Volume around Callouts
This figure replicates Figure 1 using median standardized abnormal retail and total option trading volume across callouts. All variable definitions and estimation procedures are identical to those used in Figure 1.

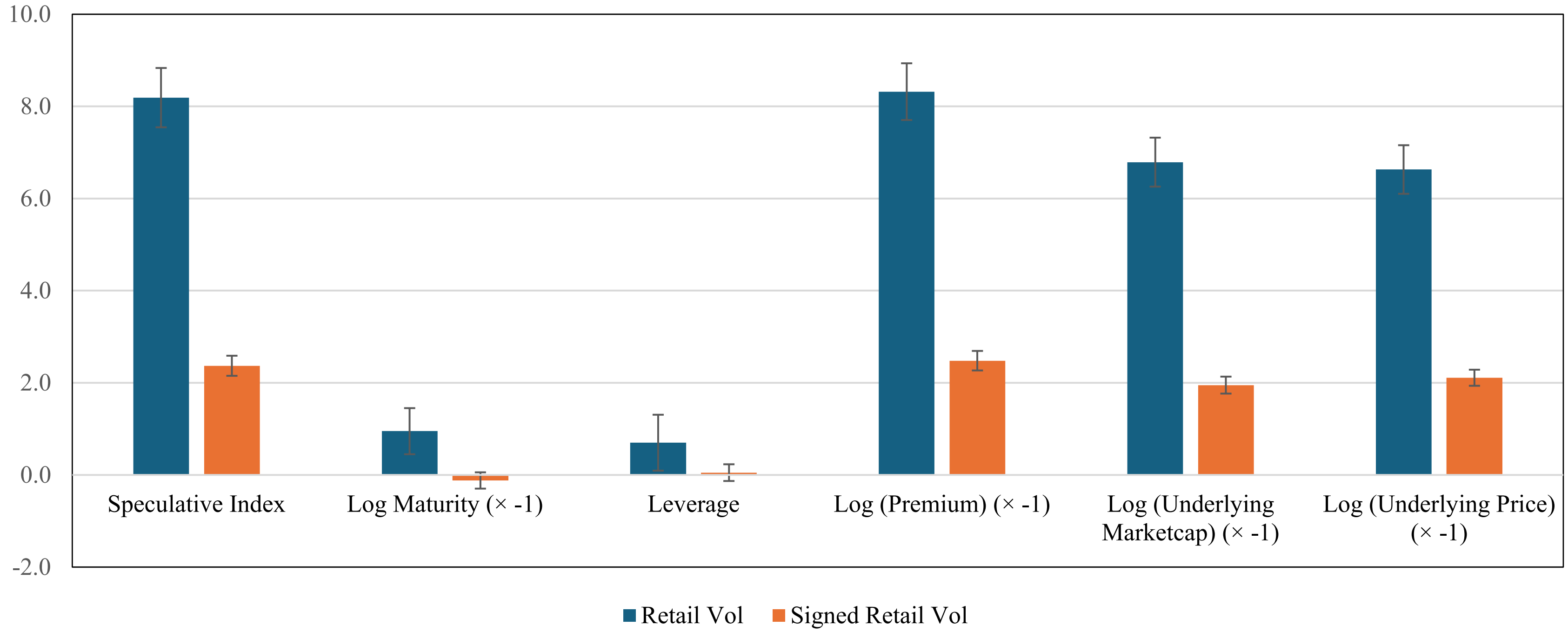

Figure IA2. Retail Demand and the Individual Components of the Speculative Index
This figure reports coefficient estimates and 95% confidence intervals from regressions analogous to the univariate specification in Table 6, Panel A, Column 1 (Retail Volume) and Panel B, Column 1 (Signed Retail Volume). In each regression, the Speculative Index is replaced with one of its five standardized components: option maturity, leverage, option premium, underlying firm market capitalization, and underlying stock price. Variables are signed so that larger values correspond to greater speculativeness and are standardized to have unit variance.