In the Money? Low-Leverage in the time of Option Betting

Edna Lopez Avila *

ABSTRACT

I examine the role of In-The-Money (ITM) options, an underexplored yet economically significant segment of the options market. Using one of the most comprehensive equity options databases, I find ITM options capture a larger share of dollar volume. This volume is particularly concentrated in large-cap stocks, short-maturity contracts, and significantly correlated to retail investor activity on social media. Despite their low leverage, ITM options attract investors seeking higher probabilities of payoffs and consistent, smaller returns compared to lottery-like Out-of-the-Money options. However, ITM options investors often underperform by trading during periods of high stock volatility and elevated retail attention in social media, deviating from a model's optimal short-term strategy.

Keywords: options, leverage, retail investors, gambling, social networks.

*Thank you to Charles Martineau, Chay Ornthanalai, Mariana Khapko, Ing-Haw Cheng, Redouane Elkamhi, Claire Celerier, Alexandre Corhay, Steven Riddiough and Jincheng Tong. I am grateful for financial support from the Canadian Securities Institute, the Canadian Derivatives Institute, the TD Management Data and Analytics Lab and The Financial Innovation Lab at Rotman School of Management. Lopez Avila: Rotman School of Management, University of Toronto, 105 St-George, Toronto ON, Canada, M5S 3E6 (edna.lopez.avila@rotman.utoronto.ca).

1. Introduction

What are the motives of investors to trade in equity options? Options appeal to investors primarily for their leverage benefits. Black (1975) argues that leverage is the key variable considered by informed investors when choosing the options market over the stock market. Options leverage allow investors to have larger positions in the underlying asset with less capital, amplifying potential returns compared to the direct ownership of the stock. High-leverage options not only offer higher expected returns (Coval and Shumway, 2001), but also provide opportunities for hedging (Goldstein, Li, and Yang, 2014) and exhibit lottery-like payoffs, which attract investors with gambling preferences (Boyer and Vorkink, 2014). Consequently, Out-of-The-Money (OTM) options, which provide the highest leverage, have taken the focus of much of the academic research.

In contrast, In-The-Money (ITM) options, which offer the lowest leverage, have received relatively less attention in the literature. This paper addresses this gap by presenting several stylized facts that underscore the economic significance of ITM options and offer new insights into the motives driving investors' decisions to trade options beyond the appeal of high leverage. I explore both the economic and behavioral factors influencing investor preferences for these low-leverage instruments, particularly their growing attraction to retail investors. Despite the lower leverage, ITM options attract retail investors due to their perceived higher probability of payoff and the potential for consistent, albeit smaller, returns. By examining ITM options, this paper enhances our understanding of retail trading behavior and performance in the options market, addressing key concerns about the underperformance and gambling tendencies often associated with retail traders in options.

For this analysis, I constructed one of the most comprehensive open-close option databases. It covers approximately 70% of the entire equity options market, and it allows for precise identification of the direction of trading volumes and the type of investor involved in each option contract. To my knowledge, this dataset stands as one of the most comprehensive and exhaustive Open-Close option database utilized in academic research. While previous studies typically relied on open-close option data from only one or two exchanges, my analysis integrates data from six exchanges —CBOE, CBOE-C2, ISE, PHLX, NOM, and GEMX. I focus on options traded by "end users", which includes "professional customers", "proprietary trading firms", and "customers" classification. I further refine my analysis by conditioning on trade size within the "customers" category, paying particular attention to "small trades" involving fewer than 100 contracts per trade, which are referred to as "small customers" throughout the paper. This granular approach offers deeper insights into the trading behaviors of distinct market participants.

Among the stylized facts, I observe that while OTM options have the highest trading volumes, ITM options capture a significantly larger share of the dollar trading volume. Despite their lower trade frequency, ITM options contribute significantly more in dollar terms to the overall options market, highlighting their economic significance. This pattern is particularly pronounced in options traded by "small customers". On average, ITM options account for approximately 40% of the total dollar volume traded by small customers in equity options, compared to 35% for OTM options and 25% for At-the-Money (ATM) options. By contrast, ITM options account for only 33% of the dollar volume of option trades made by professionals and firms. The high dollar volume of ITM options among small customers is primarily driven by call options, particularly those with short maturities of less than one week. Since 2018, the dollar volume of ITM call options with maturities under seven days has surged, surpassing that of longer-term contracts, including those with maturities of 7 to 30 days, 31 to 90 days, and over 91 days. For small customers trading OTM options, however, contracts with maturities longer than 91 days dominate in dollar volume across all maturity buckets. When examining the cross-sectional variation in ITM option dollar volumes across underlying stocks, the concentration is evident in large-cap stocks, particularly in the technology sector. A comparison of ITM and OTM call options for the same underlying stocks shows that the top 25 stocks with the largest average dollar volume difference favoring ITM options are mostly in the highest market capitalization quantile. In contrast, stocks where OTM call options dominate are generally smaller-cap, higher-risk names, including meme stocks like GameStop (GME) and AMC. This highlights the distinct role ITM options play in the strategies of small customers, particularly in large-cap stocks, while OTM options remain popular for speculative trades in riskier, smaller-cap stocks.

While the increase in ITM options dollar volume is largely driven by trades from small customers, and my findings align with broader studies on retail investor behavior in options trading[1], I cannot definitively attribute the recent popularity of ITM options to retail investors. As noted by Bogousslavsky and Muravyev (2024), the “customer” category in the open-close option data may also include other participants besides retail traders, such as professional hedge funds. To address this limitation and gain a deeper understanding of the relationship between options trading and retail investor behavior, I incorporate data produced by retail investors in the social media platform Stocktwits. Although previous studies have explored retail trading patterns on StockTwits, this paper is, to my knowledge, the first to specifically examine its role in retail options trading. StockTwits, the largest investor-focused social media platform, averages more than one million monthly posts covering most stocks. This extensive dataset allows for a deeper exploration of retail investor behavior, helping to clarify the drivers behind the recent surge in ITM options trading.

When retail investor attention to a specific stock increases on StockTwits, I observe a significant increase in the options dollar volume for that stock, particularly among small customers. Notably, the dollar volume of ITM options, especially call options, sees a more pronounced rise compared to OTM options. This effect is particularly pronounced for ITM call options with short maturities, particularly in cases where the underlying stocks have

[1] Bryzgalova, Pavlova, and Sikorskaya (2022) found that retail investors favor call options over puts, with 50% of retail trades involving short-term options expiring within a week. Bogousslavsky and Muravyev (2024) noted a decrease in the median maturity of retail options, falling from four days in 2020 to just one day by 2022, with retail trading heavily focused on high-priced technology stocks.

larger market capitalizations. Importantly, this relationship holds even after controlling for past stock returns, stock volatility, and abnormal news volume from traditional news sources. In contrast, this increase is not observed in options traded by professionals and firms. Moreover, I show that when retail attention is driven by posts containing keywords related to options trading, the rise in ITM call option dollar volume for small customers becomes even more pronounced.

Overall, my findings suggest that ITM call options play a crucial role in retail investors' trading activities in the options market. Although retail investors are commonly associated with favoring OTM options for their lottery-like payoffs and positive skewness (Filippou, Garcia-Ares, and Zapatero (2018), Han and Kumar (2013)), the evidence drawn from Stocktwits posts reveals a distinct motivation when it comes to ITM options. These unsophisticated investors are attracted toward ITM options, driven by the perceived higher likelihood of payoff. OTM call options, though cheaper and capable of delivering higher expected returns due to their skewed payoff structure, they have lower probability of exercise. This makes ITM options more attractive to investors seeking consistent, albeit smaller returns. Indeed, I find evidence of this perception when I analyze the distribution of average daily returns for call options with less than seven days to maturity. OTM options exhibit a left-skewed distribution with fatter tails. In contrast, ITM options show a more symmetric return distribution with lower kurtosis. Interestingly, for options with longer maturities (more than 90 days), the difference in the daily average return distribution between ITM and OTM options is less pronounced, suggesting that short-term options highlight the more distinct trading motives between these two types of contracts.

The growing interest in ITM options, motivated by the perceived higher likelihood of consistent returns, inevitably raises a crucial question: how do these investors actually perform when trading ITM options? To explore this, I examine both dollar performance and daily percentage returns, calculated using net dollar open interest for each option contract and daily option prices. The results reveal a significant negative relationship between the daily average returns of options by stock and the corresponding abnormal retail investor activity on StockTwits. This relationship persists across all option types but is particularly more pronounced for ITM call options compared to OTM call options. in fact, ITM call options underperform the most during periods of heightened retail attention.

To explain this underperformance, I use a theoretical framework based on the Kelly Criterion, a well-established approach for determining the optimal size of investments or bets to maximize the long-term growth of wealth. Interestingly, I find evidence that this model is been discussed by retail investors on Stocktwits where investors actively discuss strategies related to position sizing. Adapting this framework to the options market, the model predicts an optimal allocation for short-maturity ITM options, particularly in low-volatility stocks. However, while ITM investors empirically favor short-maturity options, they often fail to account for events marked by heightened stock volatility. This miscalculation contributes to their underperformance, highlighting the sensitivity of ITM options to volatility fluctuations, particularly during periods of increased retail participation. This simple model offers interesting avenues for future research, especially in understanding the preferences of gambling-motivated investors who trade options for reasons beyond their lottery-like payoffs. It also prompts further exploration into the role of social media in influencing the performance of equity options, particularly those favored by retail investors.

1.1. Related literature and contributions

My research contributes to several areas within the existing literature. It adds to the understanding of why investors are drawn to trading options and the distinctive features that options offer. Sanghvi, Sharma, and Chandani (2024) provide a comprehensive review of literature elucidating the motives of individual investors to engage in equity derivatives trading, categorizing these motives as "hedging and speculation" (Lakonishok, Lee, Pearson, and

Poteshman (2007), Goldstein, Li, and Yang (2014), "returns versus risk" (Bernard, Boyle, and Gornall, 2011), and "gambling" (Bauer, Cosemans, and Eichholtz, 2009). My paper aligns with the "gambling" motives. Specifically, it extends the literature that has shifted focus toward the asset pricing implications of models that depart from the conventional representative agent/expected utility framework to explain individual trading behavior in the options market. For instance, Boyer and Vorkink (2014) argue that the lottery-like features of options, implicit in their leverage and nonlinear payoff structures, appeal to investors with a preference for skewness. Additionally, recent research by Filippou, Garcia-Ares, and Zapatero (2018) suggests that OTM options serve as the primary securities with lottery characteristics for skewness-seeking investors, particularly among retail investors. However, my paper introduces another dimension to the motives beyond high leverage. ITM options characterized by their low leverage, attract investors due to their perceived higher probability of payoff and consistent smaller returns, thereby expanding the conversation around the motivations behind options trading.

Second, this paper contributes to the growing literature on retail options trading. Recent studies, such as Bryzgalova, Pavlova, and Sikorskaya (2022) and Bogousslavsky and Muravyev (2024), show that retail trading concentrates in short-maturity call options, particularly in large-cap and meme stocks. My findings extend this by highlighting leverage's crucial role in shaping retail strategies. ITM options, with lower leverage, dominate in large-cap stocks, while OTM options, offering higher leverage and lottery-like payoffs, are popular in smaller-cap, riskier stocks. These studies, along with de Silva, Smith, and So (2023), find limited evidence of leverage or skewness-seeking preferences. My paper addresses this by highlighting the growing interest in ITM options and its correlation with retail attention in social media.

Third, this paper extends the literature on social media's influence in financial markets. Cookson, Mullins, and Niessner (2024) offers a detailed review of the role social media plays in shaping retail investor behavior. Studies like Cookson and Niessner (2020), Cookson, Fos, and Niessner (2021), and Cookson, Lu, Mullins, and Niessner (2022) focus on Stocktwits and its impact on retail trading in equity markets. However, this paper takes a novel approach by analyzing Stocktwits data within the context of retail options trading, providing new insights into how social media activity correlates with retail trading strategies and performance in the options market.

Fourth, my research contributes to the growing literature on retail trading attention. Studies such as Barber and Odean (2000) and Barber, Lin, and Odean (2023) have shown that retail investors tend to be uninformed and often make systematic mistakes when selecting stocks, frequently chasing attention-grabbing stocks without regard to fundamentals. My findings align with this body of work, revealing that retail investors are similarly prone to suboptimal trading behaviors in the options market. Specifically, I find that retail investors exhibit heightened activity in ITM options during periods of increased attention on social media, but this often coincides with underperformance due to increased stock volatility.

Lastly, my paper also extends the literature on money management by exploring the Kelly Criterion (Kelly, 1956) as an alternative approach to Markowitz's framework. Initially utilized by Edward Thorp for blackjack betting in Las Vegas casinos (Thorp, 1966), the Kelly Criterion was later adapted as a portfolio optimization method (Thorp, 1975). Subsequently, numerous researchers have scrutinized the Kelly Criterion, highlighting its benefits and drawbacks, and it has been adopted by hedge fund managers in their asset allocation strategies. Specifically, my research aligns with recent papers that have studied the application of the Kelly Criterion in option portfolios, like Carta and Conversano (2020), and Wu and Hung (2018).

2. Data and Main Variables

2.1. Option data and variables

To construct the primary dataset, I aggregated daily Open-Close records of option trading volume from January 2014 to December 2022 across the following eight exchanges:

1. CBOE: Open-Close Chicago Board Options Exchange C1 and C2 exchanges: CBOE, CBOE-C2, CBOE-BZX, CBOE-EDGX.

2. NOTO: Nasdaq Options Trade Outline.

3. PHOTO: PHLX Options Trade Outline.

4. ISE: International Securities Exchange Open/Close Trade Profile.

5. GEMX: GEMX Open/Close Trade Profile.

To my knowledge, this dataset is one of the most comprehensive and granular Open-Close datasets used in academic research on options markets, as it covers approximately 70% of the total options trading volume as reported by OptionMetrics. Figure 3 provides a detailed breakdown of data coverage across the exchanges, as each has varying inclusion periods in the analysis. The dataset covers all the option contracts of stocks with share code 10 or 11 from the Center for Research in Security Prices (CRSP) at the contract-day level.

Aggregating data from all 8 exchanges for each option contract results in a big and comprehensive database. Overall, the database covers 3,000 unique stocks, 3 million option contracts, and up to 200 million observations, on average per year, as detailed in Table 1. Each option contract recorded on OptionMetrics of all stocks considered in this analysis is merged with its corresponding open-close volume data across all exchanges. The variables of Optionmetrics include the daily option price, forward price, implied volatility, and delta. This linkage is established by matching key parameters, including the ticker symbol, root, trade date, expiration date, option type (put or call), strike price, and settlement time (AM or PM). This matching process relies on the SecId-PERMNO crosswalk provided by WRDS.

Each option contract is identified as a put or a call, by its strike price, by time of execution, and by time of expiration. Furthermore, each option is accompanied by its directional trading data, encompassing both its trading volume and the number of trades recorded at the close of each trading day, divided into four specific categories: opening buys, opening sells, closing buys, and closing sells. Opening buys refer to new trades that initiate a long position on the underlying, and closing buys to trades that close an existing short position. Conversely, opening sells refer to new trades that initiate a short position on the underlying, and closing sells to trades that close an existing long position.

The option volume is also categorized according to which investor classes initiate the trades: customers, professional customers, market makers, proprietary trading firms, and broker-dealers. These four types of investors collectively constitute the trading data for all non-market makers. Precisely, a "Professional Customer" is defined as an individual or entity that (i) is not a broker or dealer in securities, and (ii) places more than 390 orders in listed options per day on average during a calendar month for its own beneficial accounts. On the other hand, "Customers" also engage in trading on their own accounts, but their trading activity does not reach the threshold required to qualify them as "Professional Customers". Furthermore, the trading activity of "Customers" is broken down into trade size buckets: less than 100 contracts, 100-199 contracts, and greater than 199 contracts. This granular breakdown of trade size is an important feature for my analysis, as my primary variable of interest will be "Customers" trades with the smallest size, i.e., less than 100 contracts, referred to as "small customers" throughout the paper.

I calculate the Trade Volume and Dollar Volume for every option contract by aggregating all opening buys, opening sells, closing buys, and closing sells. Unlike Trade Volume, which measures the number of contracts traded, Dollar Volume reflects the value of investor capital committed to the options market, denominated in US dollars. While Trade Volume is the simplest and most commonly used metric in the literature, Dollar Volume, which indirectly accounts for leverage using the price of the option contract, provides a more comprehensive representation of the wealth invested in the options market. Trade Volume $Volume(j,t)$ and Dollar Volume $DollarVolume(i,j,t)$ of option contract i, stock j, at day t, are calculated as follows:

$$Volume(i,j,t) = OpenBuy_{i,j,t} + CloseBuy_{i,j,t} + OpenSell_{i,j,t} + CloseSell_{i,j,t}$$

$$DollarVolume(i,j,t) = OptionPrice_{i,j,t} \cdot Volume(i,j,t) \tag{1}$$

Where $OpenBuy, CloseBuy, OpenSell, CloseSell$ represents the trading volume in number of contracts of option contract i, stock j, at day t.

To account for the direction of each option trade, it is important to note that $OpenBuy$ and $CloseBuy$ account for buy volume, while $OpenSell$ and $CloseSell$ account for sell volume. Therefore to compute the buy-minus-sell volume, I calculate the Order Imbalance $OIB(i,j,t)$ of option contract i, stock j, at day t, as follows:

$$OIB(i,j,t) = OpenBuy_{i,j,t} + CloseBuy_{i,j,t} - OpenSell_{i,j,t} - CloseSell_{i,j,t}$$

In dollar terms the Dollar Order Imbalance is calculated:

$$DollarOIB(i,j,t) = Price_{i,j,t} \cdot OIB(i,j,t) \tag{2}$$

Where $Price_{i,j,t}$ is the price of the option contract i, of stock j, at day t. Order Imbalance measures the directional volume of options contracts traded on a given day but does not account for positions from previously traded contracts that remain open or unexercised. To address this, I calculate the Net Open Interest (NOI) using Order Imbalance, which captures the current outstanding net exposure for each contract as follows:

$$NOI(i,j,t) = \sum_{s=0} OIB(i,j,t-s) \tag{3}$$

Where s is the day of inception of the option contract i, of stock j, on day t. The calculation of $NOI(i, j, t)$ is complex as it requires accumulating the daily order imbalance since the inception of the option contract, considering all trades from all exchanges where the option contract is traded, and using balanced panel data. Given that my database covers approximately 70% of the option trading volume exchanges, it serves as a reliable proxy for the net open interest of each option contract.

This paper examines the performance of every option contract using the previously defined Net Open Interest, $NOI(i, j, t)$. Performance is calculated both in dollar terms and as a percentage return. Specifically, the dollar performance of each option contract is calculated as follows:

$$\$PerfNOI_{i,j,t:t+1} = NOI_{i,j,t} \times 100 \times (Price_{i,j,t+1} - Price_{i,j,t})$$

While the performance in percentage of every option contract is computed:

$$\%PerfNOI_{j,t:t+1} = Direction_{NOI_{i,j,t}} \times \frac{Price_{j,t+1} - Price_{j,t}}{Price_{j,t}}$$

Where $Price_{i,j,t}$ and $Price_{i,j,t+1}$ are the prices of option contract i, of stock j on day t and $t+1$, respectively, and $Direction_{NOI_{i,j,t}}$ is the sign of the net open interest of option contract i, of stock j on day t. Using the net open interest to calculate the performance of the option contract, allows me to consider all contracts that are open at every time t and not only the contracts that are traded that day. As a result, both $PerfNOI_{i,j,t:t+1}$ and $\%PerfNOI_{i,j,t:t+1}$ are robust measures of peformance.

While I calculate all variables for each option contract i, for my main analysis I aggregate these variables at the stock-day level. This aggregation considers different payoff types (Call or Put), time to maturity (τ), types of moneyness (F/K), and type of investor (Small Customers, Professionals, and Firms). Regarding the maturity of the options, I consider four different buckets: less than 7 days, 8 to 30 days, 30 to 90 days, and over 91 days. Moneyness is classified into three types: In-the-Money (ITM), Out-of-the-Money (OTM), and At-the-Money (ATM). To determine the level of moneyness of an option, I calculate the ratio (F/K) between the Forward Price of the Stock (F) and the Strike Price of the Option Contract (K). For call options, if $F/K < 0.975$, the contract is considered to be OTM, while if $F/K > 1.025$, it is ITM. Conversely, for put options, if $F/K < 0.975$, the contract is ITM, and if $F/K > 1.025$, it is OTM.

2.2. Social Media, News and Stock data

For my analysis, I obtained data from one of the most popular social media platforms among retail investors: Stocktwits, from January 2014 to December 2022. This data was accessed via RapidAPI. Similar to Twitter, users can post on Stocktwtis "tweets" or messages on the platform about stocks adding a $ Cashtag symbol followed by the stock ticker symbol. I retrieve all posts whose $ Cashtag symbolx are tickers of stocks with share code 10 or 11 from CRSP. I aggregate the number of posts related to each ticker on a daily basis. Figure 5 in Panel A shows the aggregate monthly number of posts that include at least one ticker from my sample.

Additionally, I consider firm-level news data from RavenPack for the same stock sample, aggregating the number of news articles by stock on a daily basis. From CRSP, I also obtained daily stock returns and market capitalization for every firm. Finally, I merged the StockTwits data, RavenPack news, and stock data with the options data using ticker symbols and dates.

3. Stylized facts of ITM options

OTM equity options have been the focus of much of academic research. In contrast, ITM options have received less attention, given they offer the lowest leverage. In this section, I present several stylized facts that underscore the economic significance of ITM options and offer new insights into the motives driving investors' decisions to trade options beyond the appeal of high leverage.

In summary, I find that ITM options account for a substantial share of dollar trading volume, suggesting that a significant portion of overall market wealth is allocated to these instruments. This pattern is particularly pronounced in trades by small customers, primarily in short-maturity call options on large-cap stocks. I explore these trends further, contrasting the behaviors of different investor groups, such as professionals and firms.

Fact 1: *The average dollar volume of ITM options exceeds that of OTM options for trades made by small customers. This trend is less pronounced for options traded by professionals and firms.*

I begin by calculating the trade volume and dollar volume for all option contracts, aggregating the data by stock, date, and moneyness. Moneyness is defined as the ratio F/K rounded to two decimals, where F is the forward price of the underlying stock, and K is the option's strike price. In Figure 2, Panel A shows the average trade volume (number of trades), while Panel B displays the average dollar volume, both by different level of moneyness for options traded by small customers.

It is evident that OTM options dominate in terms of trade volume for both call and put options. However, this trend reverses when dollar volume is considered. On an average day, for an average stock, ITM options surpass other types, particularly OTM options, in dollar volume, reflecting a greater level of investment in ITM options. A similar, though less pronounced, trend is observed for options traded by professionals and firms, as shown in Figure AA1.

I further aggregate the dollar volume, this time by type of moneyness instead, and report the summary statistics on Table 2 for call (Panel A) and put (Panel B) options by investor. For call options, if $F/K < 0.975$, the contract is considered to be OTM, while if $F/K > 1.025$, it is ITM. Conversely, for put options, if $F/K < 0.975$, the contract is ITM, and if $F/K > 1.025$, it is OTM. For an average day and for the average stock, the dollar volume of ITM options traded by small customers surpasses that of OTM and ATM options for both call and put options. Specifically, in Panel A for call options, aggregating the dollar volume across the entire sample period shows that ITM options account for 42% of the total, compared to 29% for OTM options and 29% for ATM options. This trend is reversed for professionals and firms, where the average dollar volume of ITM call options is lower than that of OTM and ATM call options, representing only 21% and 23% of the total dollar volume, respectively. A similar trend is observed for put options in Panel B, though the average dollar volume of ITM call options is significantly higher than that of ITM put options.

Overall, these results highlight the strong preference of small customers for investing in ITM options, particularly for call options, though to a lesser extent for puts. ITM options account for a significant portion of the total dollar volume traded by small customers. In contrast, professionals and firms tend to favor OTM and ATM options, revealing distinct trading patterns between different type of investors.

Fact 2: *The dollar volume of ITM options traded by Small Customers is higher for maturities of less than 7 days.*

Next, I examine the distribution of dollar volume in equity options across different maturities. I calculate the daily average dollar volume for options within five maturity categories: 0 to 7 days, 7 to 30 days, 30 to 90 days, and over 90 days. The results are presented in Table 13, with Panel A showing data for call options and Panel B for put options. Panels C and D illustrate the percentage distribution of the aggregate dollar volume through the entire period of analysis.

For ITM options, the dollar volume is predominantly higher in options with maturities of less than 7 days. Notably, the daily average dollar volume for short-term call options is higher than that for put options when maturities are less than 7 days. Approximately 46%

of the stock-daily average dollar volume for ITM call options and 48% for ITM put options is concentrated in contracts with less than a week to maturity. This pattern contrasts with the behavior of professionals and firms, who direct most of their dollar trading toward options with maturities longer than 90 days.

Fact 3: *The dollar volume of ITM call options traded by Small Customers is predominantly concentrated in large-cap technology stocks.*

I then analyze the distribution of dollar volume in equity options based on the size of the underlying stocks. Table 14 presents a breakdown across NYSE market capitalization quantiles. The data, shown in Panel A for call options and Panel B for put options, indicate that the average dollar volume is higher for options on stocks with larger market capitalizations, particularly those in the highest quantile. Panels C and D further demonstrate that for large-cap stocks, the average dollar volume accounts for approximately 56% of call options and 49% of put options.

To deepen the analysis, I calculate for every ticker the daily average of the difference in dollar volume of ITM minus OTM options. Table 5 displays the top 25 underlying stocks with the highest daily average difference and the 25 stocks with the lowest. It stands out that for call options, in Panel A, the top 25 stocks where ITM options are most actively traded relative to OTM are predominantly technology companies. In contrast, the bottom 25, where OTM options dominate, are mostly small-cap high-risk investments including Gamestop (GME) and AMC meme stocks.

For put options, this pattern is less pronounced. Notably, meme stocks like GME and AMC do not appear in either the top or bottom 25 lists of stocks with the largest ITM-OTM dollar volume differences, as they do for call options.

4. ITM options and Retail Attention

The findings from the previous section highlight that ITM options are predominantly traded by small customers, aligning with recent studies on retail options trading. For instance, Bryzgalova, Pavlova, and Sikorskaya (2022) found that 50% of retail trades are in ultra short-term options, typically expiring in less than a week. Similarly, Bogousslavsky and Muravyev (2024) reported a shift in median option maturity for retail traders, dropping from four days in 2020 to just one day by 2022, with trading heavily focused on large technology stocks and riskier assets like GameStop (GME).

Although I focus on customers trading fewer than 100 contracts per transaction, which may suggest retail participation in ITM options, this assumption is not definitive. As Bogousslavsky and Muravyev (2024) noted, the "customer" category in daily signed volume data from open-close options may also include professional hedge funds and other participants, making it difficult to isolate pure retail trading activity.

To overcome this limitation, I examine the relationship between StockTwits activity and option trading to better identify retail investor behavior. While several studies have leveraged StockTwits data to explore retail trading dynamics, this paper is the first to specifically examine its role in retail options trading, providing novel insights into how social media drives retail engagement in this segment of the market.

The results reveal a significant and robust correlation between the dollar trading volume of options by small customers and retail investor activity on StockTwits. Importantly, this correlation is more pronounce for ITM call options of stocks of market capitalization. Which suggest that the recent increase of ITM options, discussed in the previous section, is driven by retail traders. This further reinforces the idea that retail traders, are actively engaging in trading of short-maturity ITM options, contributing to the broader trends observed in the options market.

4.1. Dollar volume of Options traded by Small Customers and Abnormal Retail Attention

I start by analyzing the abnormal dollar volume of options with different levels of moneyness around days with abnormal StockTwits activity. Days with abnormal activity are defined as those where the number of posts exceeds the stock's historical average number of posts by more than three standard deviations. Figure 6 plots the abnormal dollar volume of ITM, OTM, and ATM options. The abnormal dollar volume is calculated as the difference in the log dollar volume (in millions) from the average during the benchmark period $t = [-20, -10]$, where $t = 0$ represents the day of abnormal StockTwits activity. The figure shows the event average as a solid line, with shaded areas representing the 95% confidence intervals.

The figure reveals a significant increase in abnormal dollar volume across all types of moneyness, for both call and put options. However, the rise is more pronounced for ITM call options, suggesting a strong correlation between heightened retail investor attention on social media and a rise in ITM option trading, particularly for call options. This finding indicates that retail investors, likely influenced by social media activity, favor short-term ITM call options when abnormal attention spikes around certain stocks.

To explore this preference for ITM call options over ITM put options in greater detail, I calculate the ratio of call option dollar volume to total option dollar volume around days of abnormal StockTwits activity. This ratio allows me to further assess whether retail investors exhibit a stronger bias towards call options, especially ITM call options, during periods of heightened social media activity. For each stock j at time t during these events, the call option ratio is defined as follows:

$$Call(j,t)_{Ratio} = \frac{DollarVolume(j,t)^{CALL}}{DollarVolume(j,t)^{CALL} + DollarVolume(j,t)^{PUT}}$$

Figure 7 plots the average of this ratio for ITM options, comparing it to the corresponding ratios for OTM and ATM options, along with their respective confidence intervals. For all types of options, the ratio exceeds 0.50, indicating that the dollar volume of call options consistently surpasses that of put options on any given day t during the event window. However, for ITM options, there is a notable increase in the ratio leading up to day t, the day of abnormal StockTwits activity, a trend not observed for OTM or ATM options. This finding suggests that retail investors show a clear and significant preference for trading ITM call options over ITM put options, in periods of abnormal retail attention in social media.

Building on the observation that the abnormal dollar volume of ITM options increases more than that of OTM options around periods of abnormal retail attention, particularly for call options. I extend the analysis in a regression framework using the full time series to ensure the economic significance of these results. Specifically, I calculate the number of abnormal posts as the difference between the average number of posts in the previous five days $[t-5, t-1]$ and the average number during a benchmark period $[t-60, t-6]$ for each stock. I compute the abnormal dollar volume of options as the difference between the dollar volume on day t and the average dollar volume over the previous 60 days, for every stock. I then regress the abnormal dollar volume of options, categorized by different types of moneyness, on the abnormal number of StockTwits posts for each underlying stock in my database. The regression model is as follows:

$$\begin{aligned} AbnVolume(j)_t^M =& AbnPost(j,\tau)_{t-1} + AbnNews(j,\tau)_{t-1} + |Ret(j)_{[t-5,t-1]} \\ =& + |Ret(j)_{[t-60,t-5]}| + Vol(j)_{[t-60,t-1]} + \alpha_j + \alpha_t + \varepsilon_{j,t} \end{aligned} \tag{4}$$

Where $AbnVolume(j)_t^M$ represents the abnormal change in option dollar volume for stock j at time t compared to its average dollar volume over the period $[t-60, t-6]$, for different types of moneyness $M = ITM, OTM, ATM$, specifically for options traded by small customers. $AbnPost(j,\tau)_{t-1}$ is the abnormal number of StockTwits posts related to stock j, calculated as the difference between the average number of posts over the period $\tau = [t-5, t-1]$ and the average over $[t-60, t-6]$. A similar calculation is applied to $AbnNews(j,\tau)_{t-1}$, which represents the abnormal number of RavenPack news mentions for stock j during the period $\tau = [t-5, t-1]$, relative to the average over $[t-60, t-6]$. $Ret(j)_{[t-5,t-1]}$ and $Ret(j)_{[t-60,t-5]}$ capture the average stock returns of j over the periods $[t-5, t-1]$ and $[t-60, t-5]$, respectively. Lastly, $Vol(j)_{[t-60,t-1]}$ is the standard deviation of stock j returns over the period $[t-60, t-1]$. The model also incorporates stock-specific and time-specific fixed effects, α_j and α_t, respectively.

The results, presented in Table 6, show a significant positive relationship between abnormal dollar volume and the abnormal number of StockTwits posts for both call options (columns 1 to 3) and put options (columns 4 to 6), across all types of moneyness. As expected for skewness-seeking retail investors there is a strong relatioship for OTM options. But notably, there is also a strong relationship for ITM options. In fact for call options, the coefficient is greater for ITM than for OTM options, suggesting a greater responsiveness of ITM options demand by retail investors in dollar terms. This correlation remains robust even after controlling for variables such as abnormal news volume, past stock returns, and stock volatility. Importantly, these findings suggest that retail investors are not exclusively drawn to options with lottery-like payoffs, such as OTM options. Instead, a segment of retail investors demonstrates a preference for ITM options, rather than solely seeking skewed returns.

4.2. ITM vs OTM Options traded by different investors

To further assess the statistical difference between the coefficients of ITM and OTM options shown in Table 6. I refine the analysis by isolating the specific impact of ITM options relative to OTM options. This approach enables a more precise comparison of trading activity, offering a clearer perspective on the distinct abnormal volume dynamics across these two categories. Specifically, I compute the abnormal dollar volume difference between ITM and OTM options, denoted as $AbnVolume(j)_t^{ITM-OTM}$. First, I calculate the difference in daily dollar volume between ITM and OTM options at the daily-stock level, then compute the change of this variable for stock j at day t from its average dollar volume over the period $[t-60, t-6]$.

The results, presented in Table 7, indicate that the difference in dollar volume between ITM and OTM call options is both positive and statistically significant, as shown in column (1). This suggests that small customers exhibit a stronger preference for ITM call options, particularly following periods of abnormal retail attention on StockTwits. In contrast, column (4) reflects a more modest, yet still positive, relationship for put options.

When extending the analysis to options traded by professionals and firms, a distinct pattern emerges. The negative and significant coefficient for call options reveals in colums (2) and (3) that institutional participants tend to favor OTM over ITM call options. For put options, the coefficients in columns (5) and (6) are positive, yet much smaller for institutional investors compared to small customers. This suggests that while both retail and professional investors increase their option trading periods of abnormal retail attention on social media, the reaction of institutional investors is far more subdued.

Overall, these findings challenge the notion that retail investors are exclusively drawn to options with lottery-like payoffs, such as OTM options. Instead, a significant segment of retail investors shows a preference for ITM options, suggesting that their trading behavior is not solely driven by a desire for skewed returns. Furthermore this results highlight the divergent responses between retail and professional investors: retail traders, gravitate toward ITM options, whereas institutional investors display a more measured preference for OTM options

4.3. ITM vs OTM Options for short maturities and large cap stocks

Having established the strong and significant correlation between abnormal dollar volume of ITM options and heightened retail attention on social media, I now turn to validating the findings from the previous section. Specifically, I test whether the increased interest in short-maturity ITM call options, particularly in large-cap stocks, is indeed closely linked to surges in retail investor attention driven by social media activity.

To examine this in detail, I apply the regression model from Equation 4, using $AbnVolume(j)_t^{ITM-OTM}$ as the dependent variable, segmented into different maturity buckets: less than 7 days, 8 to 30 days, 31 to 90 days, and more than 91 days. The results, presented in Table 8 on Panel A confirm that the effect is most pronounced for options with shorter maturities, particularly those under 7 days for small customers. This indicates that retail investors, influenced by spikes in social media attention, are more inclined to engage in speculative trading with short-term ITM options. The heightened sensitivity of these options to underlying stock movements, coupled with the immediacy of their expiration, makes them an attractive instrument for retail traders seeking quick returns. For profesionals and firms, the results depicted in Table **??** of the Appendix, reveal a more measured response.

Next, I explore the cross-sectional variation in ITM option dollar volumes based on the size of the underlying stocks by estimating the following regression:

$$
\begin{aligned}
AbnVolume_{j,t}^{ITM-OTM} =& AbnPost(\tau)_{j,t-1} + \mathbb{1}^{\text{Small Size}} + \mathbb{1}^{\text{Big Size}} + AbnPost(\tau)_{j,t-1} \times \mathbb{1}^{\text{Small Size}} \\
&+ AbnPost(\tau)_{j,t-1} \times \mathbb{1}^{\text{Big Size}} + C + \alpha_j + \alpha_t + \varepsilon_{j,t}
\end{aligned}
$$

Where $\mathbb{1}^{\text{Big Size}}$ is a dummy variable set to one if the underlying stock of the option belongs to the top size quantile according to its market capitalization. $\mathbb{1}^{\text{Small Size}}$ is a dummy variable set to one if the underlying stock of the option belongs to the bottom size quantile according to its market capitalization. On Table 9 the results on Panel A shows that correlation of abnormal attention of retail investors and abnormal dollar volume of ITM over OTM options traded by small customers is stronger for big-size stocks. In contrast for small-size stocks the coefficient is negative and significant, suggesting that there is a higher dollar volume of OTM over ITM options. Notably, for call options traded by professionals and firms, the interaction coefficient for large-cap stocks and abnormal retail attention is also negative and significant, indicating a preference for OTM over ITM options. However, the magnitude of this coefficient remains smaller than that observed for small customers, further emphasizing the differing responses between retail and institutional investors. While small customers, particularly in large-cap stocks, tend to favor ITM options when influenced by abnormal social media attention, professionals and firms lean toward OTM options, but their reaction is more subdued compared to the more speculative behavior of retail traders.

Overall this confirm the recent increase of ITM options of short maturity and large-caps are related to the recent activity of retai attention in social media, which suggests that retail investors are favouring ITM options, for short term strategies and for stocks with market capitalization stocks. In fact, Bogousslavsky and Muravyev (2024) suggests that retail investors are primarily drawn to options trading as a means of gaining exposure to high-priced underlying assets. This supports my findings, indicating that retail investors are strategically leveraging ITM options to capitalize on short-term movements in large-cap stocks, while still pursuing lottery-like payoffs from OTM options. This dual approach reflects a more nuanced understanding of how retail traders balance risk and reward in their option trading strategies.

4.4. Robustness check

In this section, I perform a test to ensure the robustness of my results. Specifically, I refine the variable $AbnPost(j, \tau)_{t-1}$, which accounts for all posts related to stock j. While this metric captures general retail attention, not all posts necessarily pertain to option trading. To address this, I perform a robustness check by filtering posts specifically related to option trading. Using text analysis, I extract keywords from each post that are commonly associated with option trading, such as "derivatives", "calls", "puts", "call spread", "put spread", "itm", "in the money", "in-the-money", "otm", "out of the money", "out-of-the-money", "at-the-money", "at the money". This filtering ensures that the analysis focuses solely on posts relevant to options, providing a more targeted measure of retail attention in the options market. The volume of option-related posts has surged since 2018, aligning with the introduction of commission-free options trading for retail investors by platforms like Robinhood.

The number of posts specifically related to option trading is significantly lower than the total number of posts on StockTwits. Figure 5 illustrates this distinction by showing the total number of posts aggregated by month. Panel A presents all posts, while Panel B shows the subset of posts containing at least one of the aforementioned option-trading-related keywords.

I then estimate the following the regression:

$$
\begin{aligned}
AbnVolume^{ITM-OTM}_{j,t} =& AbnPost(j,\tau)_{t-1} + \mathbb{1}^{\text{Option}}_{j,t-1} + AbnPosts(\tau)_{t-1} \times \mathbb{1}^{\text{Option}}_{j,t-1} + AbnNews(j,\tau)_{t-1} \\
&+ |Ret(j)_{[t-5,t-1]}| + |Ret(j)_{[t-60,t-1]|} + Vol(j)_{[t-60,t-1]} + \alpha_j + \alpha_t + \varepsilon_{j,t}
\end{aligned}
$$

where $AbnVolume(j, M)_t$, $AbnPost(j, \tau)_{t-1}$, $AbnNews(j, \tau)_{t-1}$, $|Ret(j)_{[t-5,t-1]}|$, $|Ret(j)_{[t-60,t-1]}|$ and $Vol(j)_{[t-60,t-1]}$ are defined in Equation 4. $\mathbb{1}^{\text{Option}}_{j}$ is a dummy variable set to one if a stock j has at least 60 posts related to option trading in the 60 preceding days. The results, displayed in Table 10, show that for both call and put options, the interaction term between abnormal StockTwits posts and option-related content is positive and statistically significant. This effect is particularly pronounced for ITM and OTM options, and remains robust even after controlling for other variables. These results reveal that social media attention of retail investors, particularly posts related to option trading, have a greater impact on the options trading behavior of small customers.

5. Trading motives and performance of ITM options

5.1. Motives

Although retail investors are commonly associated with favoring OTM options for their lottery-like payoffs and positive skewness, the evidence drawn from Stocktwits posts reveals a distinct motivation when it comes to ITM options. Some examples of these posts are depicted in Figure AA2 on the Appendix. These unsophisticated investors arappear to be attracted toward ITM options, driven by the perceived higher likelihood of payoff. OTM call options, though cheaper and capable of delivering higher expected returns due to their skewed payoff structure, they have lower probability of exercise.

If true, I should see that returns on ITM call options are more consistent and less volatile compared to OTM options, reflecting the higher likelihood of positive returns, particularly for options with short maturity. To test this, I calculate the daily returns of all call option contracts and compute the average for each underlying stock, distinguishing between ITM and OTM options, as well as between short and long-maturity options. The distribution of these call option returns is presented in Figure 8. In Panel A, the distribution of daily returns for call options with less than 7 days to expiration clearly shows that ITM options exhibit a narrower and more centered distribution, in contrast to the wider and more left-skewed distribution of OTM options. This suggests that ITM options deliver more stable returns, reinforcing the notion that retail investors are drawn to their higher probability of a positive return in short-term strategies. In Panel B, the distribution of daily returns for call options with more than 90 days to expiration reflects a less pronounced difference between the daily average return distributions of ITM and OTM options.

5.2. Performance

This raises the question of whether ITM invesotors actually outperform? To answer this, I calculate the performance of each option contract using its daily net open interest and price, as explained in the Section 2. I further calculate the cummulative performance, for each option contract at different horizons $h = 5, 10, 30$ days as the sum of the performane in h days $CumPerf(j, M)_{t,h} = \sum_{t-h}^{t}$ in millions of dollars, and in returns(%) $\%CumPerf(j, M)_{t,h} = \sum_{t-h}^{t} \%PerfNOI_j$. Next, I analyze the contemporaneous correlation of the cummulative performance aggregate by stock for options at different types of moneyness and the abnormal activity of that stock in Stocktwits categorized in deciles, by calcuting the following regression:

$$\$CumPerf_{j,t,h} = \mathbb{1}_d^{\text{AbnPost}} + \alpha_j + \alpha_t + \varepsilon_{j,t} \tag{5}$$

Where $\mathbb{1}_d^{\text{AbnPost}}$ is dummy variable equal to one if the abnormal attention of that stock in Stocktwits belong to the d decile of the distribution of abnormal attention for all stocks in day t. The abnormal attention is calculated as the number of posts related to stock j over the horizon of h days $[t-h, t]$, minus the average on $[t-60, t-h]$. α_s and α_t correspond to stock and day fixed effects, respectively. The results, depicted in Table 11, reveal a significant negative relationship between cumulative performance in dollar terms and dummy decile variables of abnormal retail investor activity on StockTwits, considering the horizon of 5 days. Particularly, the coefficients of the abnormal rettail attention variable that belong to the lowest decile, is related to a positive cumulative performance in dollar terms. This coefficient decreases for abnormal retail attention variables that belong to higher deciles. For the abnormal retail attention variables that belong to the highest attention decile, the performance of ITM options is significantly negative, and in fact, underperform any other options for that same decile. Notably, this negative relationship is more pronounced for ITM call options compared to OTM call options.

I further repeat this analysis for the cumulative performance in percentage return, by regressing:

$$\%CumPerf(j, M)_{t,h} = AbnPost(j, \tau)_{t,h} + \alpha_j + \alpha_t + \varepsilon_{j,t}$$

Where $\%CumPerf(j, M)_{t,h}$ is the cummulative sum of percentage returns from $t - h$ to t for each option contract. The results on the entire sample, from 2014 to 2022 are depicted in Table 12. As with the dollar performance analysis, I find that the coefficient for ITM call options is the most negative for a 5-day horizon. However, as the horizon length increases, the returns for OTM call options become more negative and surpass those of ITM options for a 30-day horizon. When splitting the period into before and after 2018, as detailed in Table **??**, the coefficient for both ITM and OTM call options becomes significantly more negative after 2018. This trend confirms that retail trading's impact is more pronounced post-2018, with ITM call options showing the most substantial negative performance.

Given that previous results indicate retail investors significantly trade ITM options, it is important to examine the consequences of this behavior, particularly regarding the performance of these low-leverage options. The literature on retail trading has highlighted concerns about the poor performance of unsophisticated investors in the options markets (Bryzgalova, Pavlova, and Sikorskaya, 2022, de Silva, Smith, and So (2023)). Therefore, in this section, I analyze the impact of trading ITM options on the wealth of small customers

Overall, these results reveal a significant negative correlation between cumulative performance (both in dollar terms and percentage returns) of ITM options and abnormal retail activity on StockTwits. This negative relationship is particularly pronounced for ITM call options, suggesting that these low-leverage options underperform more severely when retail investor attention increases. This highglights the impact of retail trading on the performance of ITM options, indicating that these options are particularly vulnerable to poor performance when retail trading volumes increase.

6. Optimal strategy for trading ITM options

In the previous section, I demonstrated that ITM options underperform the most during periods of increased retail trading. This raises an important question: why do ITM investors underperform? To answer this, I propose in this paper an optimal strategy to trade ITM options based a toy model that adapts the Kelly Criterion to the options market.

While much of the existing literature has linked the gambling motives of unsophisticated investors to trading options with positive skewness, such as deep OTM options with lottery-like payoffs, this paper takes a different approach. It explores the possibility that these investors use low-leverage ITM options as a form of betting. The motivation for using the Kelly Criterion lies in its origins in gambling, particularly in sports betting and casino games like blackjack Thorp (1966). Over time, its application extended to financial markets, as noted by Thorp (1975).

Interestingly, there is evidence that investors on StockTwits mention the Kelly Criterion in their trading strategies. By scraping posts that include the terms "Kelly Criterion" or "Kelly Criteria," I identified 143 posts between 2014 and 2022, with a noticeable increase in recent years. Figure AA3 highlights 10 examples of such posts. Many of these posts discuss how investors use the Kelly Criterion to determine position sizing, often viewing their trades as bets. Notably, most of the posts referencing the Kelly Criterion are connected to betting or gambling strategies. In fact, one of these posts, of User X6 in Figure AA3 suggests the idea that some retail investors approach low-leverage options like ITM calls through a gambling perspective, using the Kelly Criterion.

In this section, I provide a detailed overview of the Kelly Criterion and its application in determining the optimal fraction of wealth to invest in both ITM and OTM options. By conducting a comparative statistical analysis that accounts for the volatility of the underlying stock at the option's maturity, I find that the optimal allocation when trading ITM options favors contracts with short maturity and underlying stocks with low volatility.

While ITM investors tend to gravitate toward short-maturity options, they often fail to adjust their trading strategies around events characterized by heightened stock volatility. This misstep contributes to their underperformance, as ITM options are particularly sensitive to fluctuations in volatility. This sensitivity becomes even more pronounced during periods of increased retail participation, when stock volatility tends to spike, exacerbating the challenges faced by ITM investors in generating consistent returns.

6.1. Kelly Criterion

The Kelly Criterion, introduced by Kelly in 1956 Kelly (1956), serves as a method to determine the optimal fraction or size of wealth to invest in a bet or a favorable investment opportunity, aiming to maximize the exponential growth rate.

In contrast with conventional portfolio optimization methods like mean-variance analysis, which seek to maximize a portfolio's expected returns, the Kelly Criterion pursues the maximization of the expected value of the logarithm of wealth, essentially optimizing expected logarithmic utility. The key idea behind the Kelly Criterion is to allocate more capital to opportunities with higher expected returns and favorable odds, while also considering the possibility of losses.

The Kelly criterion corresponds to the following Bayesian decision problem under binary uncertainty that optimizes the bidding fraction of total assets. Consider a sequence of i.i.d. bets where the probabilities of events are known and independent, where p is the probatility of a win, $q = 1 - p$ is the probability of a loss, and f $(0 < f < 1)$ is the bidding fraction of the total assets at each turn.

6.2. Kelly Criterion with Asymmetric Payoffs

Given the initial capital X_0 and after W number of wins and L number of losses ($W+L=n$), the capital X_n at the n-th trial is:

$$X_T = X_0\left((1+bf)^W(1-f)^L\right)$$

The quantity that measures the exponential rate of increase per trial is the growth rate of wealth:

$$G_n(f) = log\left[\frac{X_n}{X_0}\right]^{1/n} = \frac{W}{n}log(1+bf) + \frac{L}{n}log(1-f)$$

Kelly chose to maximize the expected value of growth rate coefficient as follows:

$$g_n(f) = E\left(log\left[\frac{X_n}{X_0}\right]^{1/n}\right) = plog(1+bf) + (1-p)log(1-f)$$

$$g'(f) = \frac{pb}{1+bf} - \frac{1-p}{1-f} = 0$$

The optimal betting fraction, f^*, is:

$$f^* = \frac{p(1+b)-1}{b}$$

Assuming Black and Scholes, we can implement these framework in the context of options. The bet size will be determined by the price paid for the option. In the case of call options, this will be $C(S_0, T)$, where S_0 is the stock price at time $t=0$ and T is the maturity of the option. The gain per unit bet is the profit earned when the option is exercised, for Call options is $F_T - K$, where $F_T = S_0 \exp^{rT}$ is forward stock price maturing at $t=T$ assuming a risk free r, and K is the strike price of the option. Therefore for Call options b will be:

$$b = \frac{F_T - K}{C(S_0, T)}$$

Furtheremore, the probability of winning the bet p, for options can be interpreted as the probability of exercising the option, which is captured by the Delta of the option Δ and it is defined as $\Delta = N(d_1)$. Thus, plugging all numbers in f^*:

$$f^* = \frac{\Delta\left(1 + \frac{F_T - K}{C(S_0,T)}\right) - 1}{\frac{F_T - K}{C(S_0,T)}} = \frac{N(d_1)\left(1 + \frac{F_T - K}{C(S_0,T)}\right) - 1}{\frac{F_T - K}{C(S_0,T)}} = N(d_1) - (1 - N(d_1))\frac{C(S_0,T)}{F_T - K}$$

Where:

$$F_T = S_0 \exp^{rT}$$
$$d_1 = \frac{log\left(\frac{S_0}{K}\right) + (r + \sigma^2/2)T}{\sigma\sqrt{T}}$$
$$d_2 = d_1 - \sigma\sqrt{T}$$
$$C(S_0,T) = S_0 N(d_1) - \exp^{-rT} K N(d_2)$$

Note that since $F_T = S_0 \exp^{rT}$, then $b = \frac{S_0 \exp^{rT} - K}{S_0 N(d_1) - \exp^{-rT} K N(d_2)}$. Therefore for every level of moneyness α such that $K = \alpha S_0$, then b does not depend of the stock price S_0 at time $t = 0$ since $b = \frac{S_0 \exp^{rT} - \alpha S_0}{S_0 N(d_1) - \exp^{-rT} \alpha S_0 N(d_2)} = \frac{\exp^{rT} - \alpha}{N(d_1) - \exp^{-rT} \alpha N(d_2)}$. In other words, changes in the stock price will not change the value of b on every period of investment.

6.3. Comparative Statics

This section offers comparative statics results on the changes in the optimal investment fraction, denoted as f^* according to the Kelly Criterion, in response to variations in the maturity (T) and volatility (σ) of options, considering both ITM and OTM options. The findings unveil two crucial observations: 1) a negative correlation between the optimal fraction invested in ITM options and the option's maturity, and 2) a negative correlation between the optimal fraction invested in ITM options and the historical volatility of the underlying stock. The following four propositions offer a more detailed exploration of these relationships.

6.3.1. Maturity

Proposition 1 *For ITM options, when $F_T - K > 0$, then $\frac{\partial f^*}{\partial T} < 0$ for all strike prices $K < S_0 \exp^{-(r+\sigma^2/2)T}$. That is, there is a negative relationship between the optimal fraction of investment and the maturity of ITM options.*

Proof: See Appendix

6.3.2. Volatility

Proposition 2 *For ITM options, when $F_T - K > 0$, then $\frac{\partial f^*}{\partial \sigma} > 0$, for all strike prices $K < S \exp^{(r-\sigma^2/2)T}$ and $\sigma^2/2 > r$. That is, there is a negative relationship between the optimal fraction of investment and the volatiity of the stock for ITM options.*

Proof: See Appendix

Proposition 3 *For OTM options, when $F_T - K > 0$, then $\frac{\partial f^*}{\partial \sigma} > 0$, for all strike prices $K > C(S_0, T) + F_T$ and $\sigma^2/2 > r$. That is, there is a positive relationship between the optimal fraction of investment and the volatility of OTM options.*

Proof: See Appendix

In Figure 9, I illustrate these findings. Panel A depicts the optimal investment fraction f^* and its variations across different maturity levels. Specifically, subplots (a) and (b) respectively depict this relation for OTM and ITM options, considering different moneyness levels. Similarly, Panel B presents the optimal investment fraction f^* across varying levels of historical stock volatility. Subplots (c) and (d) represent this relationship for OTM and ITM options, accounting for different moneyness levels as well.

Overall, these findings explain why small customers underperform when trading ITM options during periods of heightened retail activity. While these retail investors may follow the Kelly Criterion's guidance of focusing on low-volatility stocks, they fail to trade around events of increased stock volatility. Consequently, ITM options, which may seem like sound investments under stable market conditions, are prone to underperformance in volatile environments driven by surges in retail trading. This underscores the significant role ITM options play within the broader landscape of the options market and the need for investors to consider volatility dynamics when trading these low leverage options as a form of betting or gambling.

7. Conclusion

The motives driving investors to trade in equity options have long been centered around leverage. Options allow investors to control larger positions in the underlying asset with less capital, amplifying potential returns compared to direct ownership. This leverage, particularly in OTM options, has been the focus of much academic research, offering both higher expected returns and the allure of lottery-like payoffs. However, this paper shifts the focus to ITM options, which offer lower leverage but have been largely underexplored.

This study fills the gap by highlighting the economic significance of ITM options and examining the behavioral and economic factors that influence investor preferences for these lower-leverage instruments. ITM options, particularly those with short maturities, have become increasingly popular with retail investors due to their perceived higher probability of payoff and the potential for consistent, albeit smaller, returns. By constructing one of the most comprehensive open-close option databases, covering 70% of the equity options market, I provide new insights into the trading behaviors of small customers, who drive much of the ITM options activity.

Among the findings, I observe that ITM options capture a significantly larger share of the dollar volume traded by small customers, especially in large-cap stocks and short-term contracts. Retail investors, as evidenced by social media data from StockTwits, are particularly drawn to ITM call options during periods of heightened retail attention, often focusing on high-priced technology stocks. This trend persists even when controlling for stock returns, volatility, and news volume, suggesting that social media plays a critical role in shaping retail trading behavior.

However, despite their popularity, ITM options tend to underperform, particularly during periods of elevated retail attention. Using the Kelly Criterion as a theoretical framework, I demonstrate that retail investors may fail to follow this strategy, favoring short-term ITM options without fully accounting for stock volatility. The findings open avenues for future research into the gambling tendencies of retail investors and the motives of investors to trade options beyond leverage.

References

Barber, Brad M, Shengle Lin, and Terrance Odean, 2023, Resolving a paradox: Retail trades positively predict returns but are not profitable, *Journal of Financial and Quantitative Analysis* pp. 1–35.

Barber, Brad M, and Terrance Odean, 2000, Trading is hazardous to your wealth: The common stock investment performance of individual investors, *The journal of Finance* 55, 773–806.

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

Bernard, Carole, Phelim P Boyle, and Will Gornall, 2011, Locally-capped investment products and the retail investor, *Journal of Derivatives* 18, 72–88.

Black, Fischer, 1975, Fact and fantasy in the use of options, *Financial Analysts Journal* 31, 36–41.

Bogousslavsky, Vincent, and Dmitriy Muravyev, 2024, An anatomy of retail option trading, *Available at SSRN*.

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

Bryzgalova, Svetlana, Anna Pavlova, and Taisiya Sikorskaya, 2022, Retail trading in options and the rise of the big three wholesalers, *Available at SSRN*.

Carta, Andrea, and Claudio Conversano, 2020, Practical implementation of the kelly criterion: Optimal growth rate, number of trades, and rebalancing frequency for equity portfolios, *Frontiers in Applied Mathematics and Statistics* 6, 577050.

Cookson, J. Anthony, Vyacheslav Fos, and Marina Niessner, 2021, Does disagreement facilitate informed trading? evidence from activist investors, *Working paper* p. 45.

Cookson, J. Anthony, Runjing Lu, William Mullins, and Marina Niessner, 2022, The social signal, *Journal of Financial Economics, forthcoming*.

Cookson, J Anthony, William Mullins, and Marina Niessner, 2024, Social media and finance, *Available at SSRN 4806692*.

Cookson, J. Anthony, and Marina Niessner, 2020, Why don't we agree? Evidence from a social network of investors, *Journal of Finance* 75, 173–228.

Coval, Joshua D, and Tyler Shumway, 2001, Expected option returns, *The journal of Finance* 56, 983–1009.

de Silva, Tim, Kevin Smith, and Eric C So, 2023, Losing is optional: Retail option trading and expected announcement volatility, *Available at SSRN 4050165*.

Filippou, Ilias, Pedro Angel Garcia-Ares, and Fernando Zapatero, 2018, Demand for lotteries: The choice between stocks and options, *Available at SSRN 3016462*.

Goldstein, Itay, Yan Li, and Liyan Yang, 2014, Speculation and hedging in segmented markets, *The Review of Financial Studies* 27, 881–922.

Han, Bing, and Alok Kumar, 2013, Speculative retail trading and asset prices, *Journal of Financial and Quantitative Analysis* 48, 377–404.

Kelly, John L, 1956, A new interpretation of information rate, *the bell system technical journal* 35, 917–926.

Lakonishok, Josef, Inmoo Lee, Neil D Pearson, and Allen M Poteshman, 2007, Option market activity, *The Review of Financial Studies* 20, 813–857.

Sanghvi, Manisha J, Pankaj Sharma, and Arti Chandani, 2024, Why do investors trade in equity derivatives? a literature review, *Vision* p. 09722629241226447.

Thorp, Edward O, 1966, *Beat the dealer: A winning strategy for the game of twenty-one* . vol. 310 (Vintage).

——— , 1975, Portfolio choice and the kelly criterion, in *Stochastic optimization models in finance* . pp. 599–619 (Elsevier).

Wu, Mu-En, and Pang-Jen Hung, 2018, A framework of option buy-side strategy with simple index futures trading based on kelly criterion, in *2018 5th international conference on behavioral, economic, and socio-cultural computing (BESC)* pp. 210–212. IEEE.

Figure 1. Exchange Volume Coverage

This figure shows the monthly aggregated volume of options of stocks with share code 10 or 11 from CRSP at the contract-day level, as percentage of the total volume reported on Optionmetrics. The sample period is from January 1, 2012, to December 31, 2022.

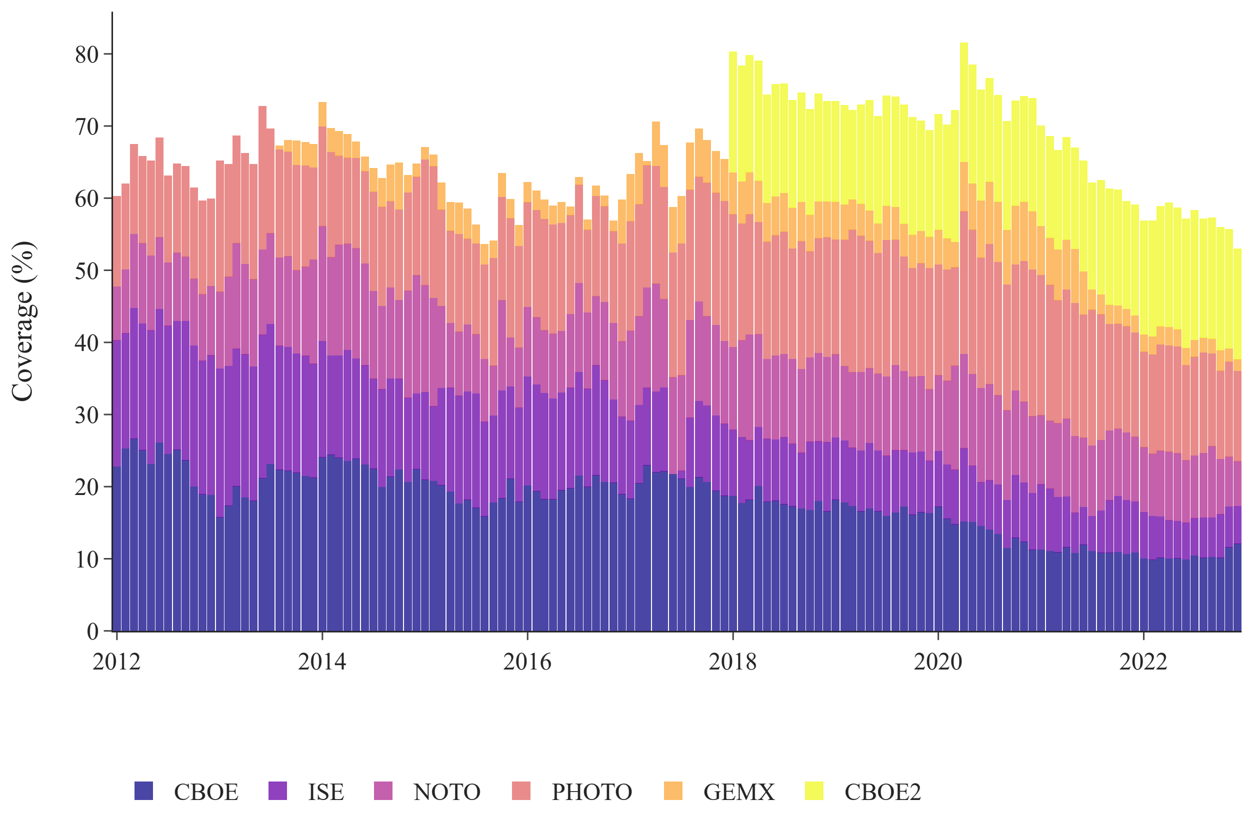
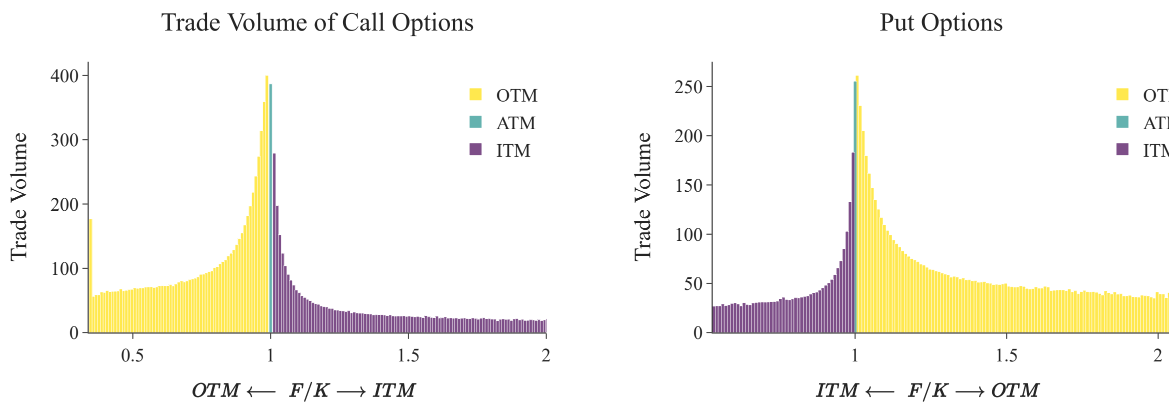


Figure 2. Average Trade and Dollar Volume of options traded by Small Customers

This figure displays the average stock-daily trade volume in Panel A and the average stock-daily dollar volume in Panel B, segmented by different levels of moneyness for call and put options traded by small customers. The level of moneyeness F/K is calculated as the ratio between the Forward Price of the Stock (F) and the Strike Price of the Option Contract (K). The sample period January 2014 to December 2022 for options of all stocks considered in the analysis.

Panel A: Trade Volume of Small Customers



Panel B: Dollar Volume of Small Customers

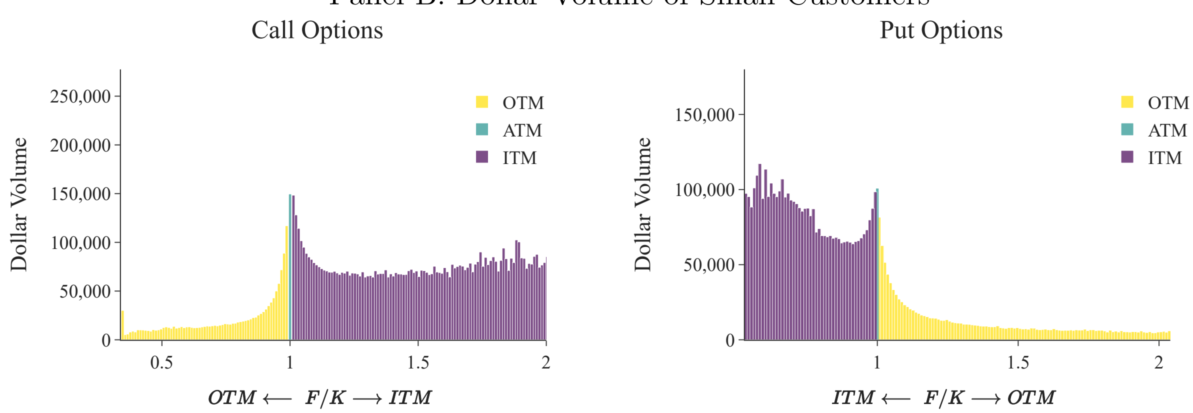
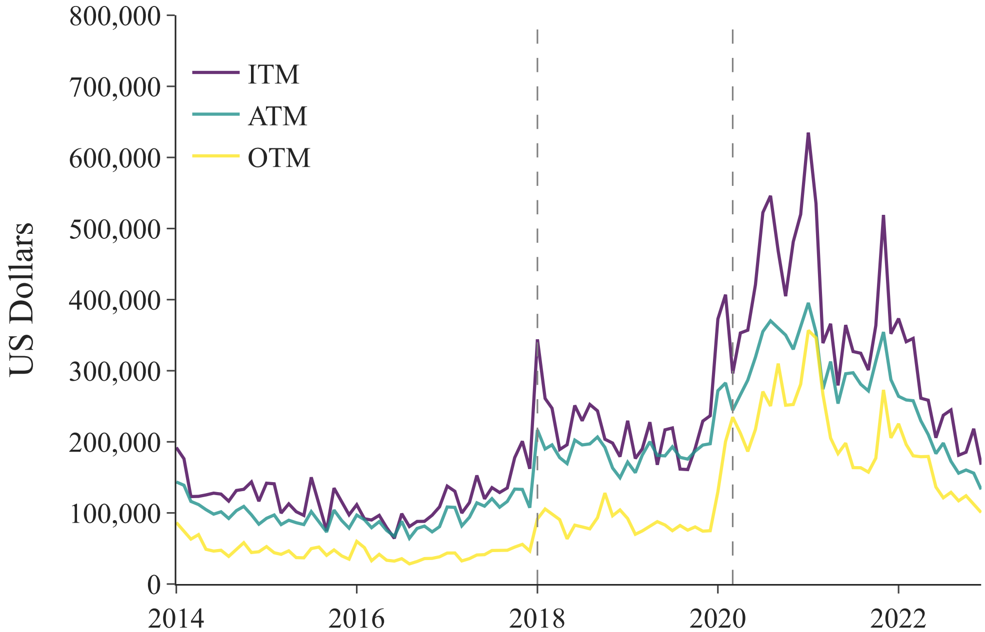


Figure 3. Dollar Volume

This figure shows the daily average dollar volume at the stock-daily level for different level of moneyness: ITM, OTM and ATM. Moneyness of an option is calculated the ratio (F/K) between the Forward Price of the Stock (F) and the Strike Price of the Option Contract (K). For call options, if $F/K < 0.975$, the contract is considered to be OTM, while if $F/K > 1.025$, it is ITM. Conversely, for put options, if $F/K < 0.975$, the contract is ITM, and if $F/K > 1.025$, it is OTM.

Panel A: Call Options



Panel C: Put Options

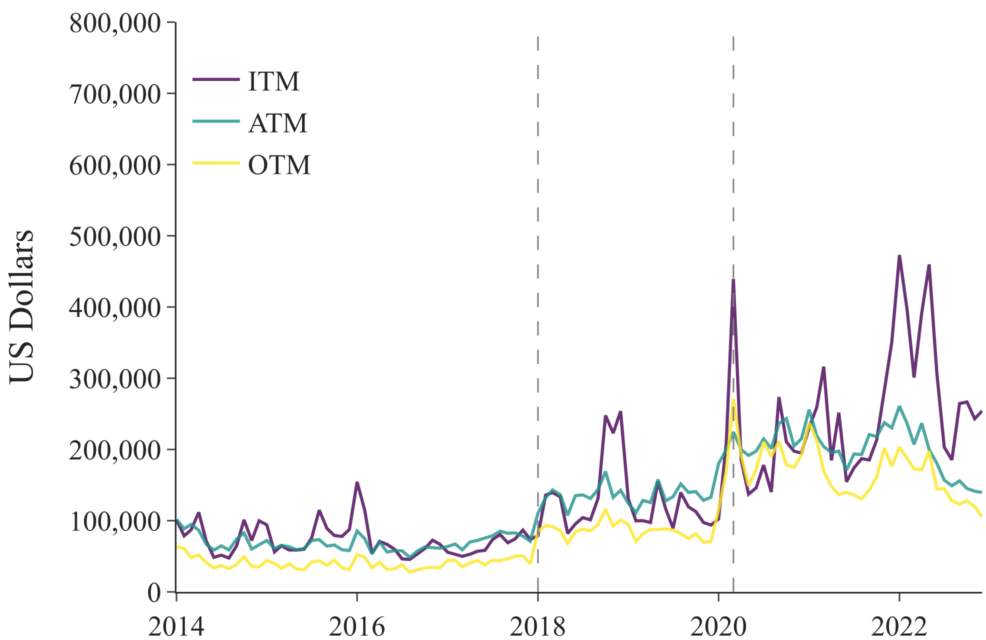
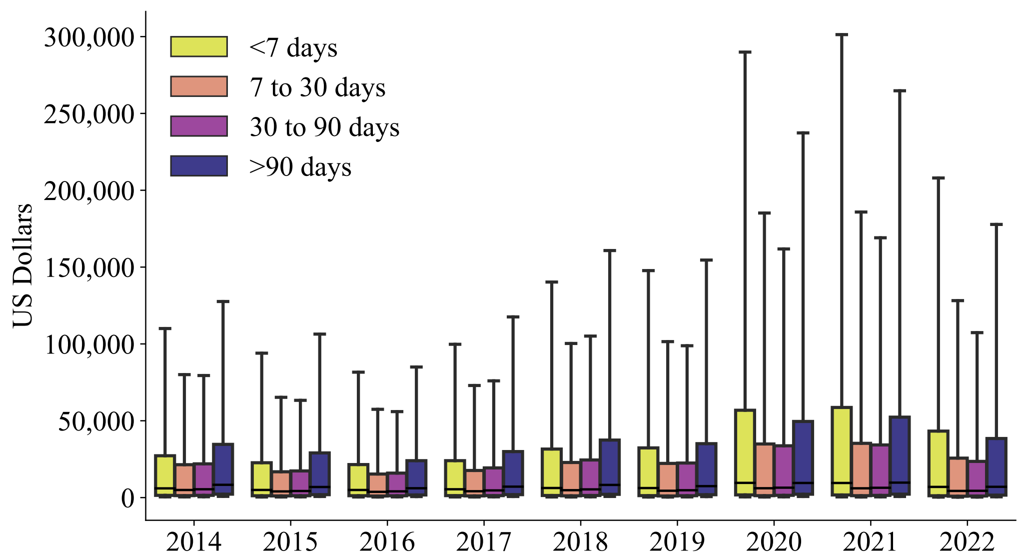


Figure 4. Dollar Volume by Maturity

This figure shows box plot of the stock-daily dollar volume for ITM Call (Panel A) and OTM Call (Panel B) options with different levels of maturity. The arms of the box plot represent the 10th and 90th percentile of the distribution. The sample period January 2014 to December 2022 for options of all stocks considered in the analysis.

Panel A: ITM Call Options



Panel B: OTM Call Options

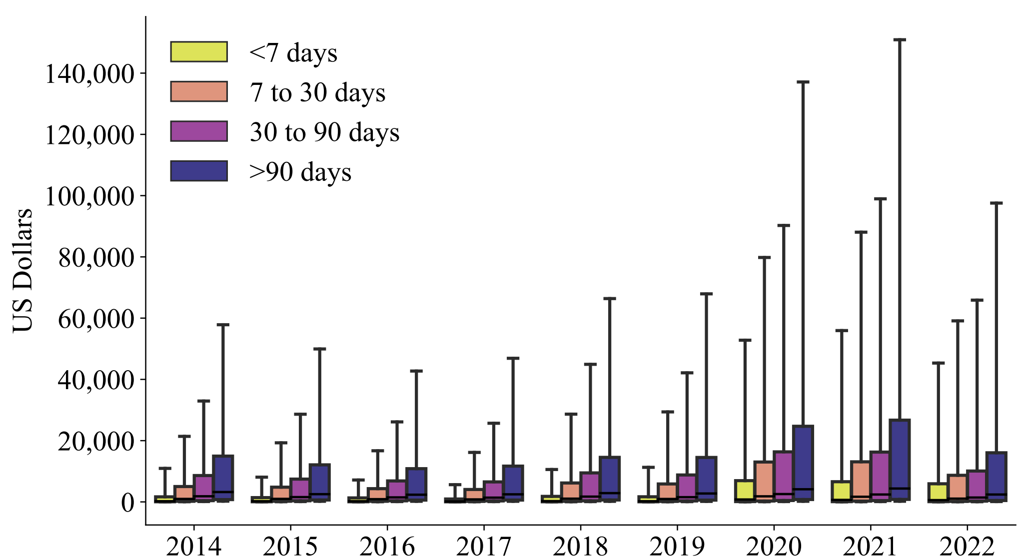
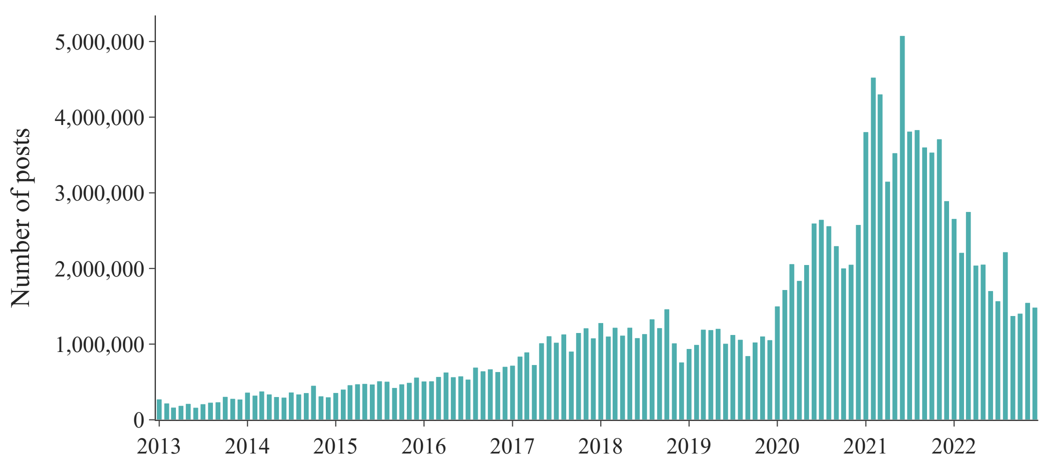


Figure 5. Information production on Stocktwits

This figure shows the monthly number of stock-specific posts on StockTwits on Panel A. The monthly number of stock-specific posts related to option trading on Stockstwtis on Panel B. The sample period is from January 1, 20134, to December 31, 2022.

Panel A: Number of stock-specific posts on StockTwits



Panel B: Number of stock-specific posts on StockTwits related to option trading

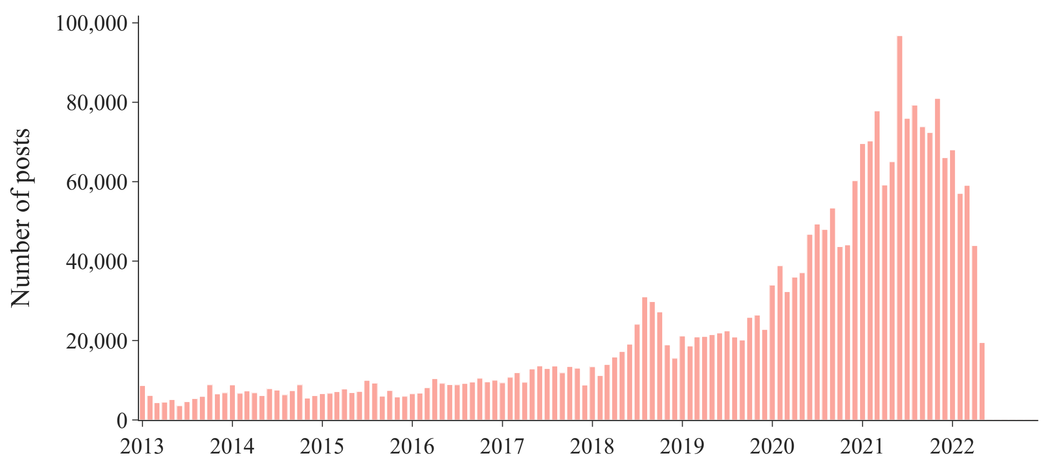
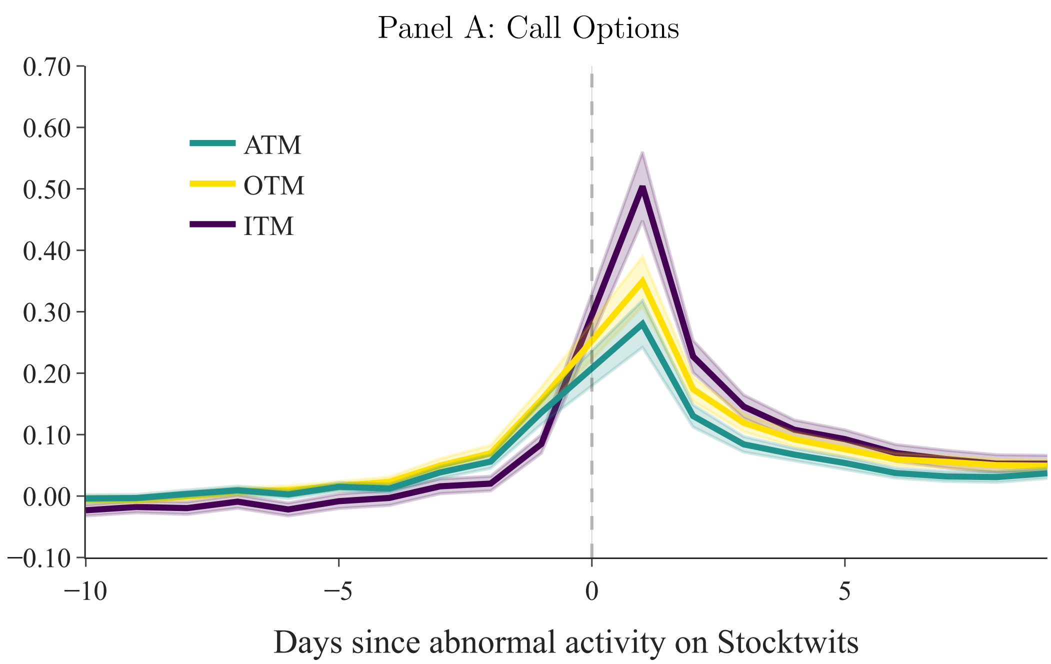


Figure 6. Dollar option volume around abnormal Stocktwits activity of Small Customers

This figure illustrates the dollar volume of options traded by small customers on days with abnormal post activity on StockTwits. The abnormal dollar volume is calculated as the difference in the log dollar volume (in millions) from the average during the benchmark period $t = [-20, -10]$, where $t = 0$ represents the day of abnormal StockTwits activity. Abnormal activity is defined as a daily change in the number of posts for a specific stock that exceeds three standard deviations. The solid line represents the average, while the shaded area indicates the 95% confidence intervals. Panel A and Panel B depicts the results for call options and put options, respectively. The events considered occured from January 1, 2013, to December 31, 2022.



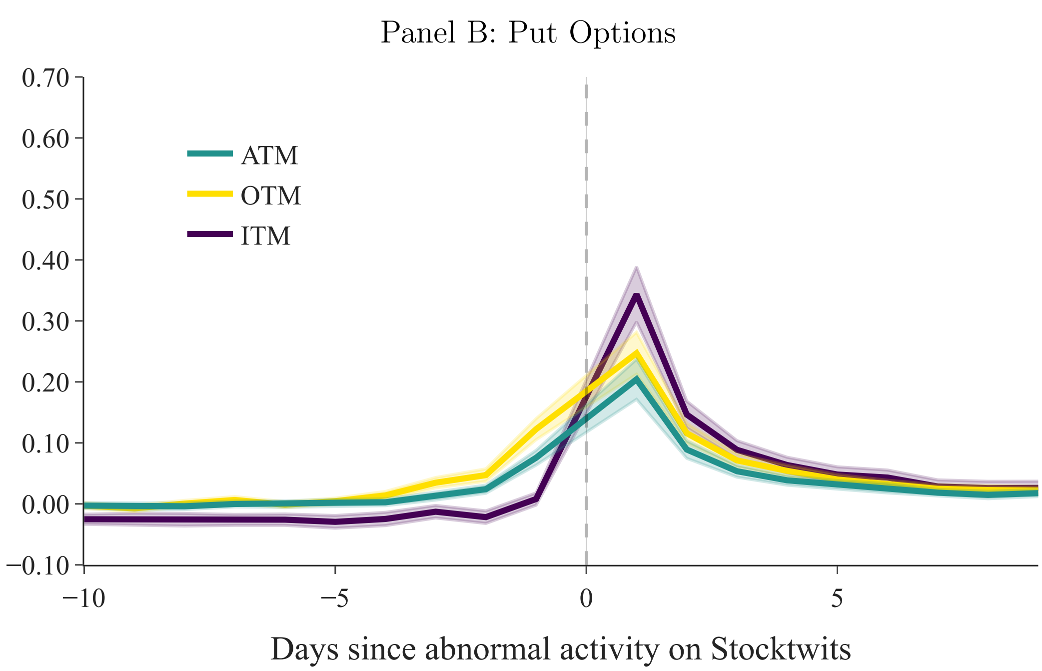


Figure 7. Call volume of options around abnormal Stocktwits activity of Small Customers

This figure illustrates the ratio of call option dollar volume to the total option dollar volume around days of abnormal StockTwits activity. For each stock j at time t during each event,. Abnormal activity is defined as a daily change in the number of posts for a specific stock that exceeds three standard deviations.

$$Call(j,t)_{Ratio} = \frac{DollarVolume(j,t)^{CALL}}{DollarVolume(j,t)^{CALL} + DollarVolume(j,t)^{PUT}}$$

The solid line represents the average, while the shaded area indicates the 95% confidence intervals. Panel A and Panel B show the results for call options and put options, respectively.The events considered occured from January 1, 2013, to December 31, 2022.

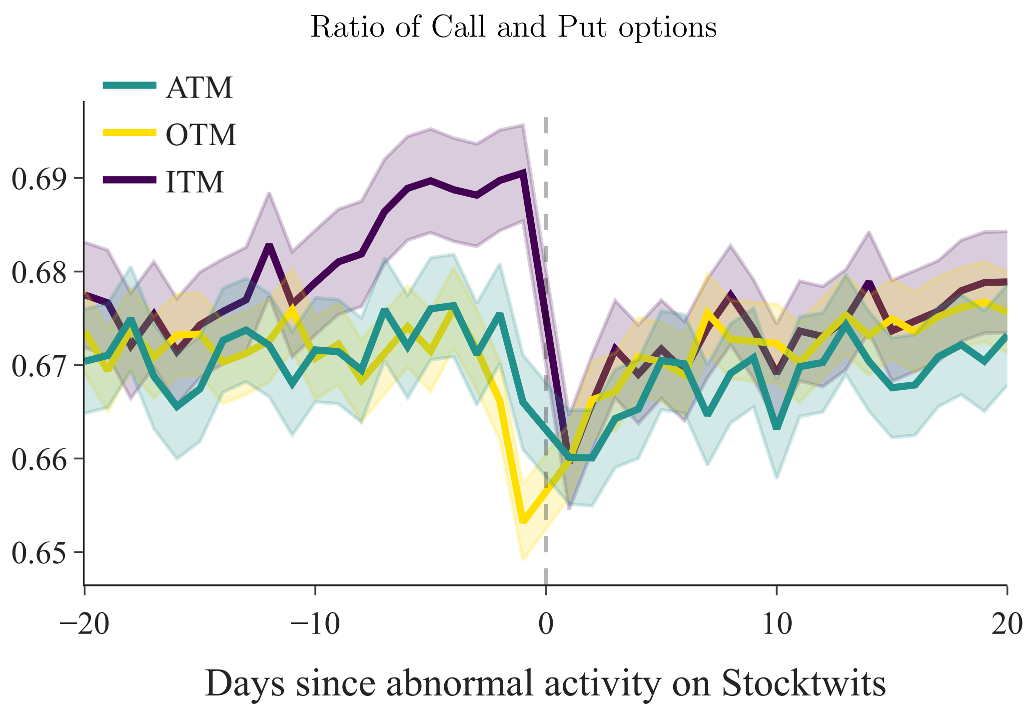
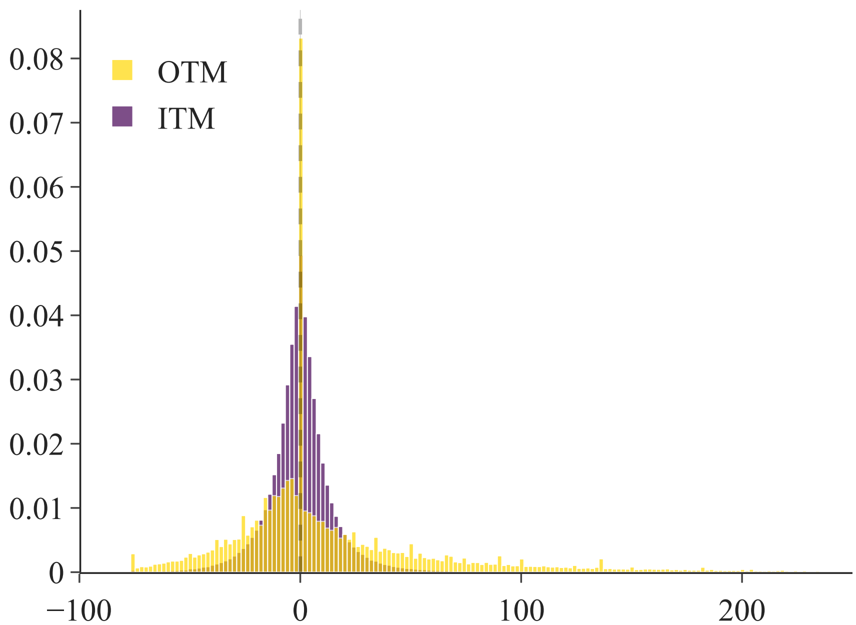


Figure 8. Call options stock-daily return distribution

This figure presents the distribution of daily returns, expressed in percentage (%), for all call option contracts, averaged for each underlying stock. The sample period covers January 1, 2014, to December 31, 2022.

Panel A: Short Maturity Call Options



Panel B: Long Maturity Call Options

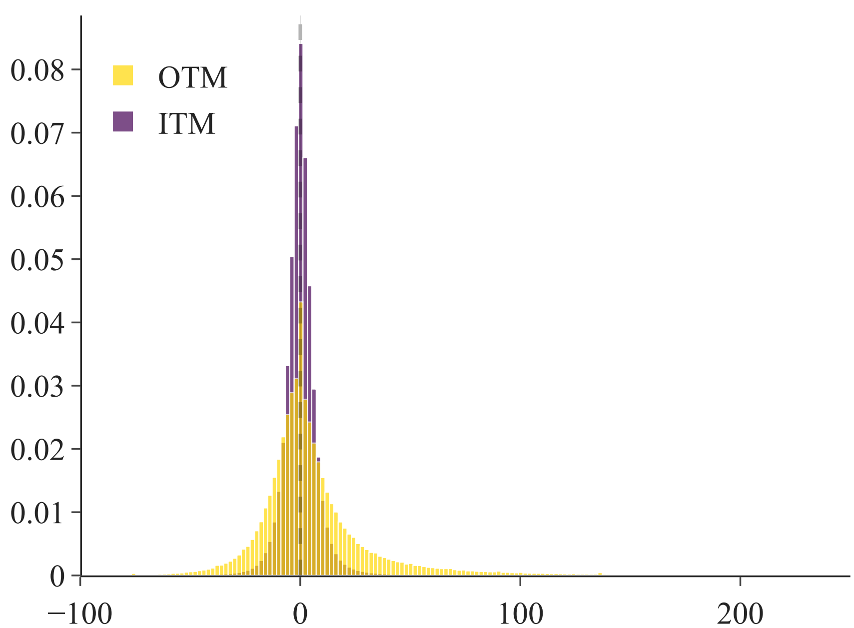


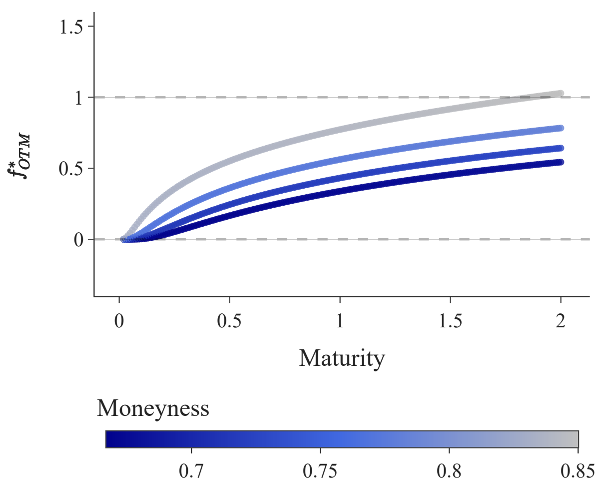
Figure 9. The optimal fraction investment f^* according to Kelly Criterion

This figure shows the optimal fraction of investment f^* according to Kelly Criterion to different levels of Maturity (a and b) and Volatility (c and d) and for a Call OTM and a Call ITM option respectively.

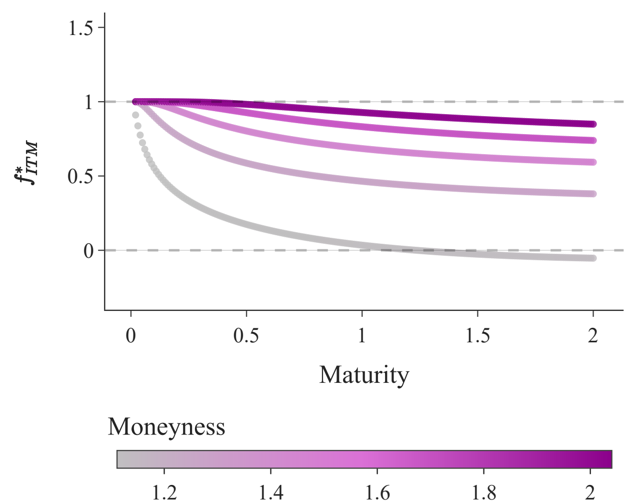
$$f^* = N(d_1) - (1 - N(d1))\frac{C(S,M)}{S_M - K}$$

Panel A: Optimal investment f^* considering different levels of Maturity (M)

(a) OTM Call Options

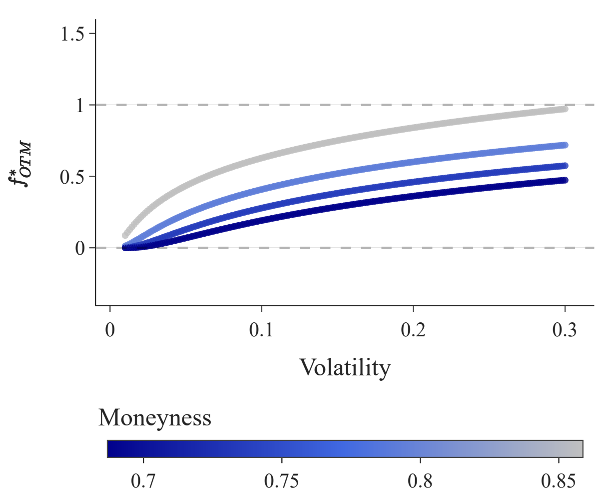


(b) ITM Call Options



Panel B: Optimal investment f^* considering different levels of Volatility (σ)

(c) OTM Call Options



(d) ITM Call Options

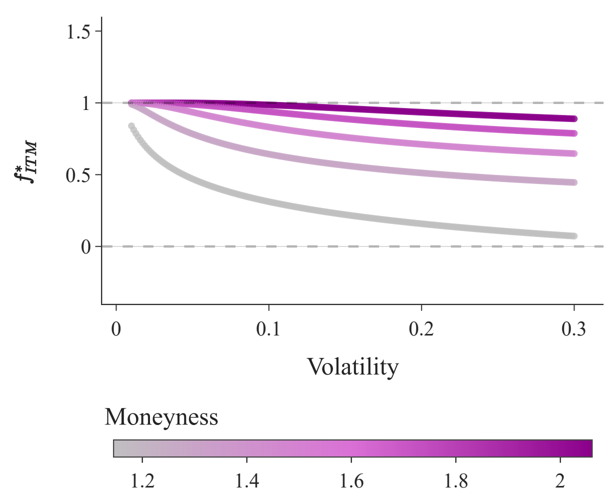


Table 1
Database characteristics

This table reports the average, per year, of the number of unique option contracts, unique stocks, and option observations considered in the database after merging all 8 exchanges considered, at the option contract-daily level, of options traded by Small-size Customers, Professionals and, Firms. The sample period is from January 1, 2014, to December 31, 2022.

Year	# of unique option contracts	# of option observations	# of unique stocks
2014	2,327,362	110,472,482	2,861
2015	2,738,454	126,585,514	3,070
2016	2,740,471	126,354,540	3,003
2017	2,732,423	125,651,794	2,920
2018	3,034,317	134,938,416	2,884
2019	3,032,442	139,029,998	2,840
2020	3,660,093	169,408,389	2,931
2021	4,018,838	200,778,913	3,501
2022	3,907,593	193,689,127	3,481

Table 2
Summary Statistics of Equity Options Dollar Volume by Investor

This table reports the summary statistics the daily-stock average of the dollar volume traded in equity options traded by Small-size Customers, Professionals and Firms. The sample period is from January 1, 2014, to December 31, 2022.

A. Call Options

	Small Customers			Professionals			Firms		
	ITM	OTM	ATM	ITM	OTM	ATM	ITM	OTM	ATM
Mean	201,629	102,435	172,036	28,755	23,490	26,556	51,416	42,830	47,811
5th	305	52	180	320	52	174	254	60	120
25th	1,890	550	1,335	1,438	526	1,233	1,275	560	900
Median	8,970	3,255	6,910	5,355	2,685	5,018	5,541	3,540	4,945
75th	49,285	20,590	39,912	20,000	13,660	19,825	29,242	22,250	27,318
95th	645,062	292,972	516,900	143,414	121,125	125,842	312,400	260,402	290,176
Total (%)	(42%)	(29%)	(29%)	(21%)	(42%)	(38%)	(23%)	(44%)	(33%)

B. Put Options

	Small Customers			Professionals			Firms		
	ITM	OTM	ATM	ITM	OTM	ATM	ITM	OTM	ATM
Mean	147,026	87,552	125,147	33,813	24,987	28,541	67,924	50,753	51,799
5th	242	50	145	368	73	212	277	62	127
25th	1,410	472	983	1,865	742	1,470	1,725	652	1,095
Median	6,450	2,700	4,890	7,121	3,572	5,762	9,350	4,465	6,225
75th	35,185	17,000	28,872	26,790	16,125	22,530	53,808	29,235	34,258
95th	459,870	237,745	347,150	154,402	128,696	136,442	314,512	312,400	312,400
Total (%)	(38%)	(32%)	(29%)	(24%)	(39%)	(37%)	(24%)	(45%)	(31%)

Table 3
Dollar Volume by Maturity and type of Investor

This table reports the daily-stock average dollar volume traded in equity options traded by Small-size Customers, Professionals, and Firms, for different maturities. Panel A reports data for call options, while Panel B focuses on put options. The sample period spans from January 1, 2014, to December 31, 2022.

A. Call Options (dollars)

	Small Customers			Professionals			Firms		
Maturity	ITM	OTM	ATM	ITM	OTM	ATM	ITM	OTM	ATM
0 to 7 days	123,715	36,451	106,212	18,981	4,824	10,881	34,395	11,984	25,050
7 to 30 days	81,959	38,556	74,996	17,772	8,663	15,443	32,955	18,790	28,051
30 to 90 days	73,651	39,787	58,317	17,393	11,690	13,745	34,559	26,288	31,294
$>$ 90 days	102,614	56,515	60,156	27,249	20,024	15,916	52,712	44,288	45,178

B. Put Options (dollars)

	Small Customers			Professionals			Firms		
Maturity	ITM	OTM	ATM	ITM	OTM	ATM	ITM	OTM	ATM
0 to 7 days	102,652	31,645	84,277	19,386	4,569	10,256	35,896	11,737	24,351
7 to 30 days	64,041	33,508	56,127	18,130	8,800	15,727	39,547	19,260	29,637
30 to 90 days	53,007	35,121	41,855	18,461	11,996	14,889	48,043	28,062	35,010
$>$ 90 days	77,500	51,093	45,333	32,517	21,847	18,189	79,725	61,681	59,445

Table 4
Dollar Volume by Market Capitalization and type of Investor

This table reports the daily-stock average dollar volume traded in equity options traded by Smal-size Customers, Professionals, and Firms, for stocks with different market capitalizations. Panel A reports data for call options, while Panel B focuses on put options. The sample period spans from January 1, 2014, to December 31, 2022.

A. Call Options (dollars)

Market Cap	Small Customers			Professionals			Firms		
Quintile	ITM	OTM	ATM	ITM	OTM	ATM	ITM	OTM	ATM
1	41,879	23,812	26,259	13,186	6,993	7,788	21,042	14,227	14,101
2	57,110	35,429	28,831	16,236	9,809	8,634	26,382	18,460	15,526
3	75,224	44,877	34,757	16,096	11,567	9,095	30,591	22,756	19,513
4	104,334	57,294	52,293	17,947	14,820	11,717	36,344	28,627	24,267
5	579,608	332,962	427,803	40,852	36,698	38,009	85,345	74,455	71,928

B. Put Options (dollars)

Market Cap	Small Customers			Professionals			Firms		
Quintile	ITM	OTM	ATM	ITM	OTM	ATM	ITM	OTM	ATM
1	36,687	17,177	17,513	15,363	8,054	8,108	43,099	18,630	18,770
2	55,159	21,485	18,907	17,609	8,673	8,897	50,363	19,654	18,525
3	69,298	28,426	23,944	19,216	10,443	9,928	50,840	23,632	23,149
4	90,229	38,710	34,537	24,331	13,554	12,963	52,487	30,612	26,488
5	371,996	252,278	283,723	47,864	37,066	40,233	95,653	79,540	72,528

Table 5
Dollar Volume by Market Capitalization and type of Investor

This table reports the daily-stock average of the difference between dollar volume of ITM minus OTM options ($DollarVolume^{ITM-OTM}$) traded by Small-size Customers, categorized by market capitalization quintiles. Panel A reports data for call options, while Panel B focuses on put options. The sample period spans from January 1, 2014, to December 31, 2022.

A. Call options

Top 25

Underlying ticker	Market Cap Quintile	$DollarVolume^{ITM-OTM}$
AAPL	5	4,796,994
FB	5	3,973,510
AMZN	5	3,576,562
GOOG	5	2,499,376
GOOGL	5	2,356,070
NFLX	5	2,119,205
MSFT	5	2,047,937
NVDA	5	1,880,446
PCLN	5	1,499,945
TSLA	5	1,498,462
BRK	5	1,331,174
BAC	5	1,233,561
CMG	5	1,071,563
MU	5	888,526
TTD	5	874,276

Bottom 25

Underlying ticker	Market Cap Quintile	$DollarVolume^{ITM-OTM}$
BFT	3	-219,696
CCIV	3	-239,534
DPHC	3	-251,829
CLOV	1	-261,981
RBLX	5	-264,911
AMC	2	-285,961
FUBO	2	-315,851
SHLL	2	-316,542
ABNB	5	-337,648
GME	3	-344,597
RIVN	5	-489,506
SPAQ	1	-533,808
COIN	5	-797,551
META	5	-831,550
PLTR	5	-857,568

B. Put options

Top 25

Underlying ticker	Market Cap Quintile	$DollarVolume^{ITM-OTM}$
META	5	1,783,892
UPST	3	1,447,092
COIN	5	1,271,515
RIVN	5	972,828
HOOD	4	864,491
PLTR	5	852,339
CCIV	3	817,786
DKNG	4	805,457
ROKU	4	794,407
QS	3	727,157
SOFI	4	692,701
BYND	1	675,030
LCID	4	668,683
AFRM	4	668,510
RBLX	5	631,168

Bottom 25

Underlying ticker	Market Cap Quintile	$DollarVolume^{ITM-OTM}$
AVGO	5	-59,620
UNH	5	-61,746
ACT	3	-74,092
GREE	1	-103,824
ZS	5	-132,575
CRWD	5	-136,216
FB	5	-167,069
SHLL	2	-173,905
QCOR	4	-266,256
AAPL	5	-266,531
GOOGL	5	-295,186
NFLX	5	-356,631
TSLA	5	-518,632
NVDA	5	-823,097
AMZN	5	-896,716

Table 6
Abnormal Dollar Volume of options traded by Small-size Customers

This table reports the coefficients of the following regression

$$\begin{aligned}AbnVolume(j)_t^M =& AbnPost(j,\tau)_{t-1} + AbnNews(j,\tau)_{t-1} + |Ret(j)_{[t-5,t-1]}| \\ &+ |Ret(j)_{[t-60,t-1]|} + Vol(j)_{[t-60,t-1]} + \alpha_j + \alpha_t + \varepsilon_{j,t}\end{aligned}$$

Where $AbnVolume(j)_t^M$ represents the abnormal log of option dollar volume for stock j at time t, relative to the average log option dollar volume over the period $[t-60, t-6]$, for different levels of moneyness $M = ITM, OTM, ATM$, traded by small-size customers. $AbnPost(j,\tau)_{t-1}$ is the abnormal log number of posts average on $[t-5, t-1]$, minus the log number of posts average on $[t-60, t-6]$, of underlying stock j. $AbnNews(j,\tau)_{t-1}$ is the abnormal log number of Ravenpack news average on $[t-5, t-1]$, minus the log number of Ravenpack news average on $[t-60, t-6]$, related to underlying stock j. $|Ret(j)_{[t-5,t-1]}|$, and $|Ret(j)_{[t-60,t-5]}|$ is the total return of stock j, in absolute value, on the periods $[t-5, t-1]$ and $[t-60, t-5]$ respectively. Finally, $Vol(j)_{[t-60,t-1]}$ is the standard deviation of the daily returns of stock j on $[t-60, t-1]$. α_j and α_t correspond to stock and day fixed effects, respectively. Newey-West corrected standard errors are clustered by stock and day, and are presented in parentheses. *, ** , and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1, 2014, to December 31, 2022.

	Call options			Put options		
	ITM	OTM	ATM	ITM	OTM	ATM
$AbnPosts(\tau)$	0.0124***	0.0096***	0.0060***	0.0072***	0.0054***	0.0035***
	(0.0004)	(0.0004)	(0.0002)	(0.0003)	(0.0002)	(0.0001)
N	5,792,332	5,792,332	5,792,332	5,792,160	5,792,160	5,792,160
$R^2(\%)$	0.80	0.94	0.54	0.46	0.62	0.42

Table 7
Abnormal Dollar Volume of options: ITV vs OTM

This table reports the coefficients of the following regression

$$
\begin{aligned}
AbnVolume(j)_t^{ITM-OTM} =& AbnPost(j,\tau)_{t-1} + AbnNews(j,\tau)_{t-1} + |Ret(j)_{[t-5,t-1]}| \\
&+ |Ret(j)_{[t-60,t-5]}| + Vol(j)_{[t-60,t-1]} + \alpha_j + \alpha_t + \varepsilon_{j,t}
\end{aligned}
$$

Where $AbnVolume(j)_t^{ITM-OTM}$ represents the abnormal log of the option dollar volume difference of ITM minus OTM options for stock j at time t, relative to the average of the same variable over the period $[t-60, t-6]$. $AbnPost(j,\tau)_{t-1}$ is the abnormal log number of posts average on $[t-5, t-1]$, minus the log number of posts average on $[t-60, t-6]$, of underlying stock j. $AbnNews(j,\tau)_{t-1}$ is the abnormal log number of Ravenpack news average on $[t-5, t-1]$, minus the log number of Ravenpack news average on $[t-60, t-6]$, related to underlying stock j. $|Ret(j)_{[t-5,t-1]}|$, and $|Ret(j)_{[t-60,t-5]}|$ is the total return of stock j, in absolute value, on the periods $[t-5, t-1]$ and $[t-60, t-5]$ respectively. Finally, $Vol(j)_{[t-60,t-1]}$ is the standard deviation of the daily returns of stock j on $[t-60, t-1]$. α_j and α_t correspond to stock and day fixed effects, respectively. Newey-West corrected standard errors are clustered by stock and day, and are presented in parentheses. *, ** , and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1, 2014, to December 31, 2022.

	Call options			Put options		
	Small Customers	Professionals	Firms	Small Customers	Professionals	Firms
$AbnPosts(\tau)$	0.0038***	-0.0002***	-0.0007***	0.0022***	0.0002***	0.0007***
	(0.0003)	(0.0001)	(0.0001)	(0.0003)	(0.0001)	(0.0001)
N	5,766,678	5,766,678	5,766,678	5,766,668	5,766,668	5,766,668
R^2	0.09	0.00	0.00	0.04	0.00	0.00
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Table 8
Abnormal Volume of options traded by Small-size Customers by Maturity

This table reports the coefficients of the following regression

$$AbnVolume(j)_t^{ITM-OTM} = AbnPost(j,\tau)_{t-1} + AbnNews(j,\tau)_{t-1} + |Ret(j)_{[t-5,t-1]}| \\ + |Ret(j)_{[t-60,t-5]}| + Vol(j)_{[t-60,t-1]} + \alpha_j + \alpha_t + \varepsilon_{j,t}$$

Where $AbnVolume(j)_t^{ITM-OTM}$ represents the abnormal log of the option dollar volume difference of ITM minus OTM options for stock j at time t, relative to the average of the same variable over the period $[t-60, t-6]$. $AbnNews(j,\tau)$ is the abnormal average of number of Ravenpack news related to stock j on $[t-5, t-1]$, minus the average on $[t-60, t-6]$. $Ret(j)_{[t-5,t-1]}$, and $Ret(j)_{[t-10,t-5]}$ is the average of return of stock j on the $[t-5, t-1]$ and $[t-10, t-5]$, respectively. Finally, $Vol(j)_{[t-10,t-1]}$ is the average of the historic volatility of stock j on $[t-10, t-1]$. α_s and α_t correspond to stock and day fixed effects, respectively. Newey-West corrected standard errors are clustered by stock and day, and are presented in parentheses. *, ** , and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1, 2014, to December 31, 2022.

	Call options				Put options			
	1 to 7 days	7 to 30 days	30 to 90 days	90 days	1 to 7 days	7 to 30 days	30 to 90 days	90 days
$AbnPosts(\tau)$	0.0077***	0.0023***	-0.0001	0.0004**	0.0060***	0.0013***	-0.0001	0.0000
	(0.0005)	(0.0002)	(0.0002)	(0.0002)	(0.0004)	(0.0002)	(0.0001)	(0.0001)
N	1,730,113	4,634,609	5,541,641	5,762,086	1,730,014	4,634,780	5,540,910	5,759,148
$R^2(\%)$	0.25	0.07	0.01	0.01	0.17	0.03	0.00	0.01
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 9
Abnormal Volume of options by Market Capitalization

This table reports the coefficients of the following regression

$$AbnVolume_{j,t}^{ITM-OTM} = AbnPost(\tau)_{j,t-1} + \mathbb{1}^{\text{Small Size}} + \mathbb{1}^{\text{Big Size}} + AbnPost(\tau)_{j,t-1} \times \mathbb{1}^{\text{Small Size}} + AbnPost(\tau)_{j,t-1} \times \mathbb{1}^{\text{Big Size}} + C + \alpha_j + \alpha_t + \varepsilon_{j,t}$$

Where $AbnVolume(j)_t^{ITM-OTM}$ represents the abnormal log of the option dollar volume difference of ITM minus OTM options for stock j at time t, relative to the average of the same variable over the period $[t-60, t-6]$. $AbnNews(j,\tau)$ is the abnormal average of number of Ravenpack news related to stock j on $[t-5, t-1]$, minus the average on $[t-60, t-6]$. $Ret(j)_{[t-5,t-1]}$, and $Ret(j)_{[t-10,t-5]}$ is the average of return of stock j on the $[t-5, t-1]$ and $[t-10, t-5]$, respectively. Finally, $Vol(j)_{[t-10,t-1]}$ is the average of the historic volatility of stock j on $[t-10, t-1]$. α_s and α_t correspond to stock and day fixed effects, respectively. Newey-West corrected standard errors are clustered by stock and day, and are presented in parentheses. *, ** , and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1, 2014, to December 31, 2022.

	Call options			Put options		
	Small Customers	Professionals	Firms	Small Customers	Professionals	Firms
$AbnPosts(\tau)$	0.0043***	-0.0001	-0.0004***	0.0018***	0.0002*	0.0009***
	(0.0004)	(0.0001)	(0.0001)	(0.0003)	(0.0001)	(0.0001)
$\mathbb{1}^{\text{Small Size}}$	0.0040***	0.0005***	0.0004***	0.0017***	0.0001	0.0012***
	(0.0007)	(0.0001)	(0.0001)	(0.0007)	(0.0001)	(0.0002)
$\mathbb{1}^{\text{Big Size}}$	-0.0092***	0.0017***	-0.0014**	0.0024	0.0007*	0.0028***
	(0.0025)	(0.0005)	(0.0006)	(0.0024)	(0.0004)	(0.0007)
$AbnPosts(\tau) \times \mathbb{1}^{\text{Small Size}}$	-0.0054***	-0.0000	0.0002*	-0.0013***	-0.0001	-0.0004***
	(0.0003)	(0.0001)	(0.0001)	(0.0003)	(0.0001)	(0.0001)
$AbnPosts(\tau) \times \mathbb{1}^{\text{Big Size}}$	0.0269***	-0.0012***	-0.0053***	0.0136***	0.0015***	0.0003
	(0.0016)	(0.0004)	(0.0006)	(0.0014)	(0.0005)	(0.0008)
N	5,766,678	5,766,678	5,766,678	5,766,668	5,766,668	5,766,668
R^2	0.24	0.01	0.01	0.08	0.00	0.01
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Table 10
Abnormal Volume of options traded by Small-size Customers

This table reports the coefficients of the following regression

$$AbnVolume_{j,t}^{ITM-OTM} = AbnPost(j,\tau)_{t-1} + \mathbb{1}_{j,t-1}^{\text{Option}} + AbnPosts(\tau)_{t-1} \times \mathbb{1}_{j,t-1}^{\text{Option}} + AbnNews(j,\tau)_{t-1} + |Ret(j)_{[t-5,t-1]}| + |Ret(j)_{[t-60,t-1]|} + Vol(j)_{[t-60,t-1]} + \alpha_j + \alpha_t + \varepsilon_{j,t}$$

Where $AbnVolume(j)_t^{ITM-OTM}$ represents the abnormal log of the option dollar volume difference of ITM minus OTM options for stock j at time t, relative to the average of the same variable over the period $[t-60, t-6]$. $AbnPost(j,\tau)_{t-1}$ is the abnormal log number of posts average on $[t-5, t-1]$, minus the log number of posts average on $[t-60, t-6]$, of underlying stock j. $\mathbb{1}_{j,t-1}^{\text{Option}}$ is a dummy variable equal to one if a stock j has at least 60 posts related to option trading in the period $[t-60, t-1]$, or zero otherwise. $AbnNews(j,\tau)_{t-1}$ is the abnormal log number of Ravenpack news average on $[t-5, t-1]$, minus the log number of Ravenpack news average on $[t-60, t-6]$, related to underlying stock j. $|Ret(j)_{[t-5,t-1]}|$, and $|Ret(j)_{[t-60,t-5]}|$ is the total return of stock j, in absolute value, on the periods $[t-5, t-1]$ and $[t-60, t-5]$ respectively. Finally, $Vol(j)_{[t-60,t-1]}$ is the standard deviation of the daily returns of stock j on $[t-60, t-1]$. α_j and α_t correspond to stock and day fixed effects, respectively. Newey-West corrected standard errors are clustered by stock and day, and are presented in parentheses. *, ** , and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1, 2014, to December 31, 2022.

	Call options			Put options		
	Small Customers	Professionals	Firms	Small Customers	Professionals	Firms
$AbnPosts(\tau)$	0.0001	-0.0002***	-0.0002***	0.0003	0.0002**	0.0005***
	(0.0003)	(0.0001)	(0.0001)	(0.0003)	(0.0001)	(0.0001)
$\mathbb{1}_{\text{Option}}$	-0.0032***	0.0001	-0.0005***	-0.0004	0.0003	-0.0016***
	(0.0007)	(0.0001)	(0.0001)	(0.0008)	(0.0002)	(0.0002)
$AbnPosts(\tau) \times \mathbb{1}_{\text{Option}}$	0.0112***	0.0000	-0.0010***	0.0054***	0.0001	0.0011***
	(0.0006)	(0.0001)	(0.0002)	(0.0006)	(0.0001)	(0.0002)
N	5,766,678	5,766,678	5,766,678	5,766,668	5,766,668	5,766,668
R^2	0.14	0.00	0.00	0.05	0.00	0.01
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Table 11
Dollar Return of options traded by Small-size Customers

This table reports the coefficients of the following regression

$$\$CumPerf_{j,t,h} = \mathbb{1}_d^{\text{AbnPost}} + \alpha_j + \alpha_t + \varepsilon_{j,t} \quad (6)$$

Where $\$CumPerf(j,M)_{t,h}$ is the sum of the performance of each option contract in millions of dollars from $t-h$ to t. $\mathbb{1}_d^{\text{AbnPost}}$ is dummy variable equal to one if the abnormal attention of that stock in Stocktwits belong to the d decile of the distribution of abnormal attention for all stocks in day t. The abnormal attention is calculated as the number of posts related to stock j over the horizon of h days $[t-h,t]$, minus the average on $[t-60,t-h]$. α_s and α_t correspond to stock and day fixed effects, respectively. Newey-West corrected standard errors are clustered by stock and day, and are presented in parentheses. *, ** , and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1, 2014, to December 31, 2022.

	Call options			Put options		
	ITM	OTM	ATM	ITM	OTM	ATM
$\mathbb{1}^{.10}$	0.0149***	0.0068***	0.0038***	0.0063***	0.0045***	0.0024***
	(0.0024)	(0.0012)	(0.0005)	(0.0023)	(0.0011)	(0.0004)
$\mathbb{1}^{.20}$	0.0136***	0.0065***	0.0041***	0.0078***	0.0052***	0.0027***
	(0.0025)	(0.0013)	(0.0005)	(0.0023)	(0.0011)	(0.0004)
$\mathbb{1}^{.30}$	0.0093***	0.0047***	0.0034***	0.0081***	0.0041***	0.0024***
	(0.0025)	(0.0013)	(0.0006)	(0.0024)	(0.0011)	(0.0004)
$\mathbb{1}^{.40}$	0.0048*	0.0025*	0.0021***	0.0058***	0.0027***	0.0018***
	(0.0025)	(0.0013)	(0.0006)	(0.0022)	(0.0010)	(0.0004)
$\mathbb{1}^{.50}$	-0.0034	-0.0019	-0.0005	0.0031	0.0005	0.0006
	(0.0026)	(0.0014)	(0.0006)	(0.0023)	(0.0011)	(0.0004)
$\mathbb{1}^{.60}$	-0.0053**	-0.0022	-0.0013**	0.0019	0.0004	0.0004
	(0.0026)	(0.0014)	(0.0006)	(0.0023)	(0.0011)	(0.0004)
$\mathbb{1}^{.70}$	-0.0071***	-0.0036**	-0.0021***	-0.0002	-0.0005	0.0003
	(0.0025)	(0.0014)	(0.0006)	(0.0025)	(0.0012)	(0.0004)
$\mathbb{1}^{.80}$	-0.0114***	-0.0051***	-0.0036***	-0.0001	-0.0008	-0.0002
	(0.0029)	(0.0014)	(0.0006)	(0.0025)	(0.0011)	(0.0004)
$\mathbb{1}^{.90}$	-0.0237***	-0.0123***	-0.0078***	-0.0074***	-0.0036***	-0.0023***
	(0.0032)	(0.0016)	(0.0007)	(0.0027)	(0.0013)	(0.0005)
Intercept	-0.0476***	-0.0194***	-0.0106***	-0.0237***	-0.0104***	-0.0054***
	(0.0022)	(0.0012)	(0.0005)	(0.0022)	(0.0010)	(0.0004)
N	5,966,202	5,966,202	5,966,202	5,966,030	5,966,030	5,966,030
R^2	0.04	0.05	0.08	0.01	0.01	0.03

Table 12
Percentage Return options traded by Small-size Customers

This table reports the coefficients of the following regression

$$\%CumPerf(j,M)_{[t,t-h]} = AbnPost(j,\tau)_{t,h} + \alpha_j + \alpha_t + \varepsilon_{j,t}$$

Where $\%CumPerf(j,t,M)$ is the cummulative sun of percentage returns over the horizon of h days $t = [t-h,t]$ of stock j, for different type of moneyeness $M = \{ITM, OTM, ATM\}$. $AbnPost(j,\tau)_{t,h})$ is the abnormal average of number of posts related to stock j over the horizon of h days $[t-h,t]$, minus the average on $[t-60,t-h]$. α_s and α_t correspond to stock and day fixed effects, respectively. Newey-West corrected standard errors are clustered by stock and day, and are presented in parentheses. *, ** , and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1, 2014, to December 31, 2022.

	Call options			Put options		
	ITM	OTM	ATM	ITM	OTM	ATM
$\mathbb{1}^{.10}$	0.2073***	-0.5587***	-0.2499**	0.2833***	0.3236***	0.1132
	(0.0742)	(0.0896)	(0.1247)	(0.0465)	(0.0810)	(0.1353)
$\mathbb{1}^{.20}$	0.1600**	-0.4768***	-0.0649	0.2727***	0.3267***	0.0572
	(0.0743)	(0.0876)	(0.1244)	(0.0462)	(0.0781)	(0.1253)
$\mathbb{1}^{.30}$	0.1380*	-0.4176***	0.0272	0.2739***	0.3253***	0.1138
	(0.0750)	(0.0861)	(0.1208)	(0.0462)	(0.0766)	(0.1235)
$\mathbb{1}^{.40}$	0.1271*	-0.4048***	0.0901	0.2638***	0.2957***	0.1344
	(0.0751)	(0.0868)	(0.1201)	(0.0466)	(0.0744)	(0.1198)
$\mathbb{1}^{.50}$	0.1024	-0.3626***	0.3850***	0.2561***	0.2942***	0.1329
	(0.0760)	(0.0836)	(0.1193)	(0.0466)	(0.0753)	(0.1194)
$\mathbb{1}^{.60}$	0.0767	-0.3968***	0.3871***	0.2627***	0.2939***	0.1897
	(0.0762)	(0.0832)	(0.1207)	(0.0462)	(0.0767)	(0.1195)
$\mathbb{1}^{.70}$	0.0664	-0.3614***	0.4949***	0.2406***	0.2342***	0.1304
	(0.0759)	(0.0854)	(0.1262)	(0.0468)	(0.0778)	(0.1193)
$\mathbb{1}^{.80}$	0.0326	-0.4281***	0.5308***	0.2172***	0.2036**	0.2690**
	(0.0770)	(0.0856)	(0.1256)	(0.0472)	(0.0808)	(0.1225)
$\mathbb{1}^{.90}$	-0.2011***	-0.8354***	0.6966***	0.1364***	-0.0374	0.3302***
	(0.0770)	(0.0933)	(0.1323)	(0.0486)	(0.0881)	(0.1263)
Intercept	-0.2397***	-0.6446***	-0.4164***	-0.1148**	-0.1498**	-0.4987***
	(0.0724)	(0.0812)	(0.1142)	(0.0447)	(0.0738)	(0.1144)
N	5,966,202	5,966,202	5,966,202	5,966,030	5,966,030	5,966,030
R^2	0.03	0.02	0.02	0.02	0.01	0.00

A. Appendix

Table 13
Dollar Volume by Maturity and type of Investor

This table reports the daily-stock average dollar volume traded in equity options traded by Small-size Customes, Professionals, and Firms, for different maturities. Panel A reports data for call options, while Panel B focuses on put options. Panels C and D display the percentage distribution of the average dollar volume reported in Panels A and B, respectively. The sample period spans from January 1, 2014, to December 31, 2022.

C. Call Options (percentage)

	Small Customers			Professionals			Firms		
	ITM	OTM	ATM	ITM	OTM	ATM	ITM	OTM	ATM
0 to 7 days	21	10	28	15	5	17	21	5	21
7 to 30 days	23	22	30	23	18	36	24	18	30
30 to 90 days	22	27	23	24	30	29	24	31	28
$>$ 90 days	33	41	19	37	47	18	31	47	21

D. Put Options (percentage)

	Small Customers			Professionals			Firms		
	ITM	OTM	ATM	ITM	OTM	ATM	ITM	OTM	ATM
0 to 7 days	26	11	33	10	4	14	14	4	18
7 to 30 days	25	24	31	18	17	33	19	15	28
30 to 90 days	21	28	21	25	28	30	24	26	27
$>$ 90 days	28	37	15	47	51	23	43	54	27

Table 14
Dollar Volume by Market Capitalization and type of Investor

This table reports the daily-stock average dollar volume traded in equity options traded by Smal-size Customesr, Professionals, and Firms, for stocks with different market capitalizations. Panel A reports data for call options, while Panel B focuses on put options. Panels C and D display the percentage distribution of the average dollar volume reported in Panels A and B, respectively. The sample period spans from January 1, 2014, to December 31, 2022.

C. Call Options (percentage)

	Small Customers			Professionals			Firms		
	ITM	OTM	ATM	ITM	OTM	ATM	ITM	OTM	ATM
1	5	5	5	13	9	10	11	9	10
2	7	7	5	16	12	11	13	12	11
3	9	9	6	15	14	12	15	14	13
4	12	12	9	17	19	16	18	18	17
5	68	67	75	39	46	51	43	47	49

D. Put Options (percentage)

	Small Customers			Professionals			Firms		
	ITM	OTM	ATM	ITM	OTM	ATM	ITM	OTM	ATM
1	6	5	5	12	10	10	15	11	12
2	9	6	5	14	11	11	17	11	12
3	11	8	6	15	13	12	17	14	15
4	14	11	9	20	17	16	18	18	17
5	60	70	75	38	48	50	33	46	45

Figure AA1. Average Trade and Dollar Volume of options traded by Professionals and Firms

This figure displays in Panel A the average stock-daily trade volume and the average stock-daily dollar volume for call and put options traded by professionals and segmented by different levels of moneyness. Panel B shows the average stock-daily trade volume and the average stock-daily dollar volume for call and put options traded by firms and segmented by different levels of moneyness. The level of moneyeness F/K is calculated as the ratio between the Forward Price of the Stock (F) and the Strike Price of the Option Contract (K). The sample period January 2014 to December 2022 for options of all stocks considered in the analysis.

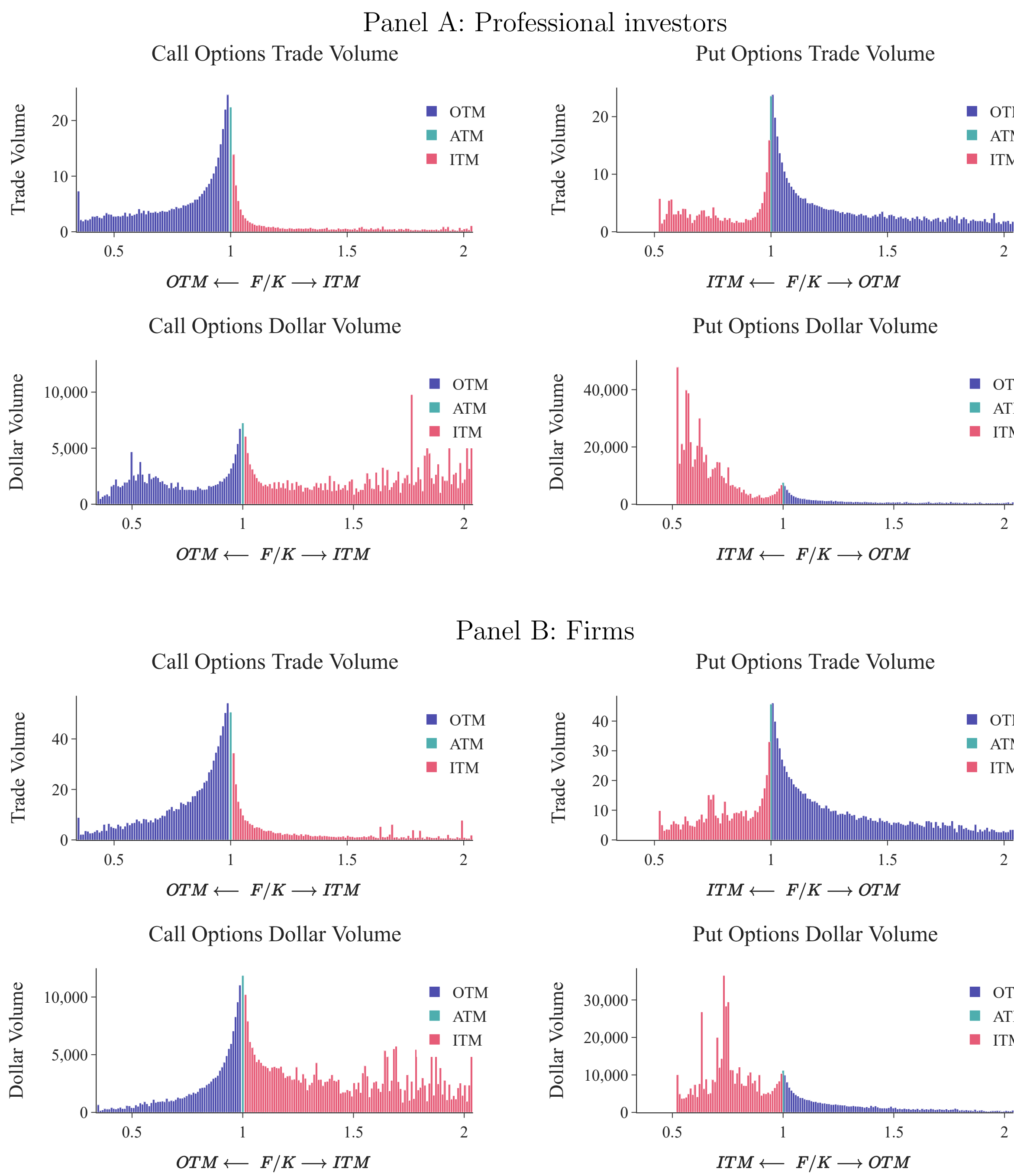


Figure AA2. Why ITM options?: evidence from Stocktwits

This figure provides examples of posts from StockTwits that highlight retail investors' discussions about their motives for trading ITM options.

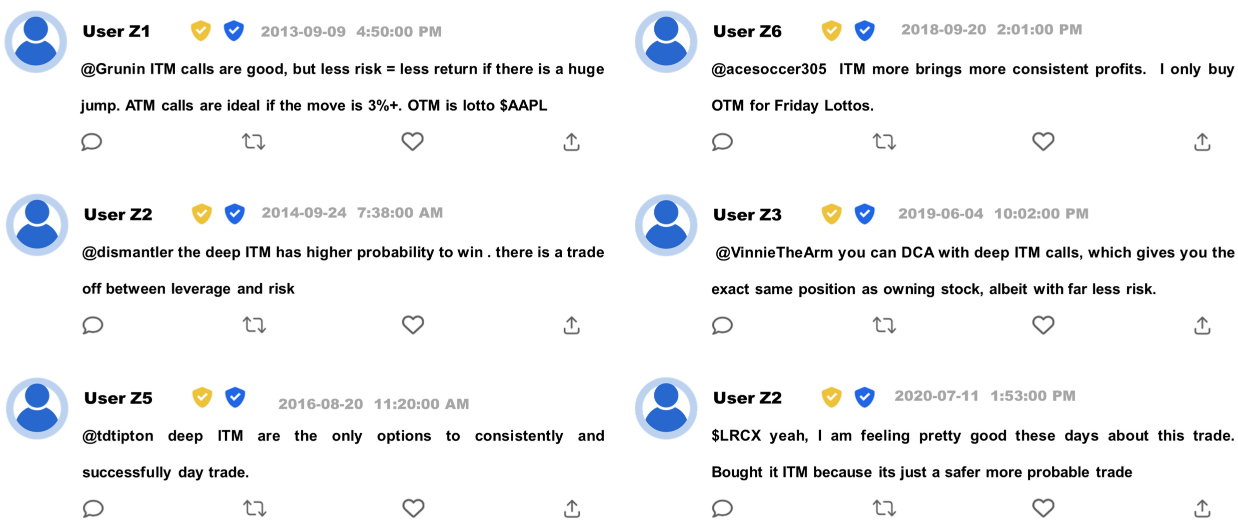


Figure AA3. Kelly Criterion: evidence from Stocktwits

This figure shows some examples of posts from Stoctwits, which illustrate the disucssion of the Kelly Crietion usage among these unsophisticated investors.

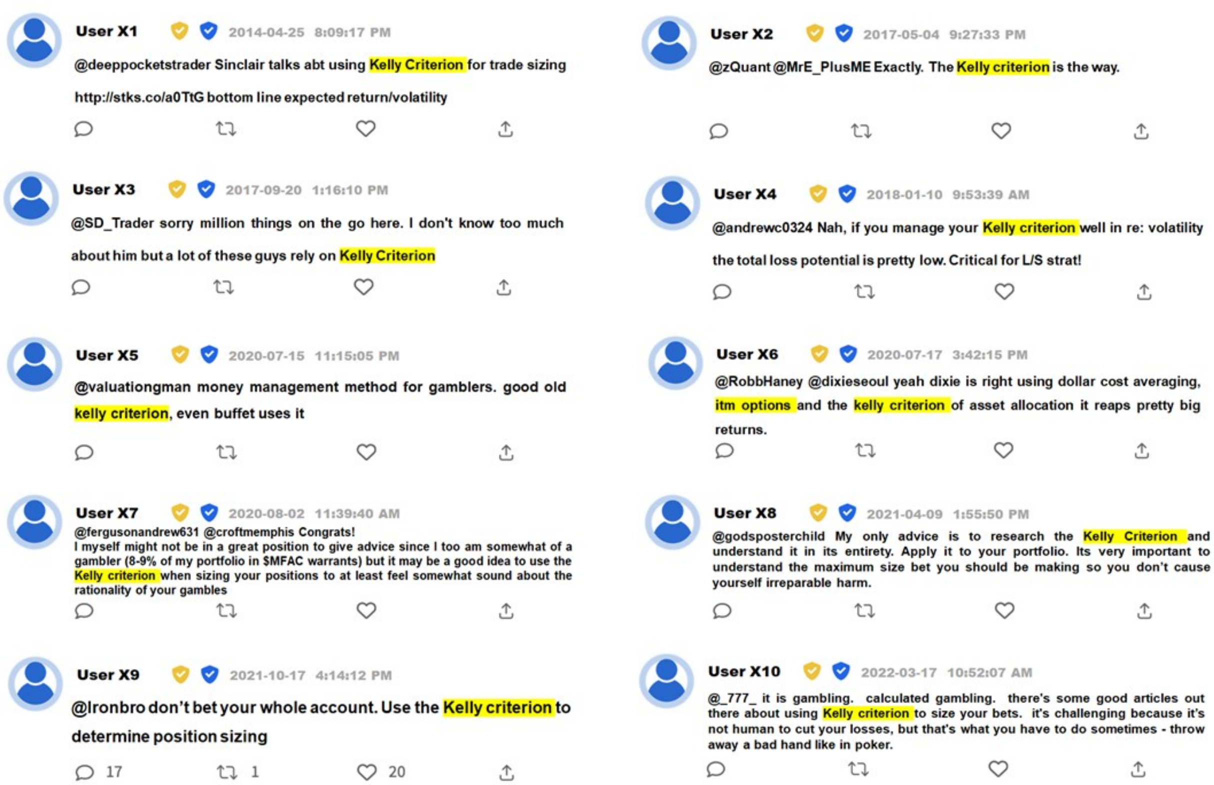


Table 15
Abnormal Volume of options traded by Professionals and Firms by Maturity

This table reports the coefficients of the following regression

$$AbnVolume(j)_t^{ITM-OTM} = AbnPost(j,\tau)_{t-1} + AbnNews(j,\tau)_{t-1} + |Ret(j)_{[t-5,t-1]}| + |Ret(j)_{[t-60,t-5]}| + Vol(j)_{[t-60,t-1]} + \alpha_j + \alpha_t + \varepsilon_{j,t}$$

Where $AbnVolume(j)_t^{ITM-OTM}$ represents the abnormal log of the option dollar volume difference of ITM minus OTM options for stock j at time t, relative to the average of the same variable over the period $[t-60, t-6]$. $AbnNews(j,\tau)$ is the abnormal average of number of Ravenpack news related to stock j on $[t-5, t-1]$, minus the average on $[t-60, t-6]$. $Ret(j)_{[t-5,t-1]}$, and $Ret(j)_{[t-10,t-5]}$ is the average of return of stock j on the $[t-5, t-1]$ and $[t-10, t-5]$, respectively. Finally, $Vol(j)_{[t-10,t-1]}$ is the average of the historic volatility of stock j on $[t-10, t-1]$. α_s and α_t correspond to stock and day fixed effects, respectively. Newey-West corrected standard errors are clustered by stock and day, and are presented in parentheses. *, ** , and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1, 2014, to December 31, 2022.

A. Professionals

	Call options				Put options			
	1 to 7 days	7 to 30 days	30 to 90 days	90 days	1 to 7 days	7 to 30 days	30 to 90 days	90 days
$AbnPosts(\tau)$	0.0004***	0.0000	-0.0001***	-0.0002***	0.0003***	0.0002***	0.0000	-0.0000
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0000)
N	1,730,113	4,634,609	5,541,641	5,762,086	1,730,014	4,634,780	5,540,910	5,759,148
R^2(%)	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

B. Firms

	Call options				Put options			
	1 to 7 days	7 to 30 days	30 to 90 days	90 days	1 to 7 days	7 to 30 days	30 to 90 days	90 days
$AbnPosts(\tau)$	0.0003***	-0.0000	-0.0004***	-0.0006***	0.0009***	0.0005***	0.0001	-0.0001
	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
N	1,730,113	4,634,609	5,541,641	5,762,086	1,730,014	4,634,780	5,540,910	5,759,148
R^2(%)	0.01	0.00	0.00	0.00	0.01	0.01	0.00	0.00
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

A.1. Proofs of Propositions

A.1.1. Maturity

Proposition 4 ***For ITM options, when $F_T - K > 0$, then $\frac{\partial f^*}{\partial T} < 0$ for all strike prices $K < S_0 \exp^{-(r+\sigma^2/2)T}$. That is, there is a negative relationship between the optimal fraction of investment and the maturity of ITM options.***

Proof: I start by examining the partial derivative of f^* with respect to time to maturity T:

$$\frac{\partial f^*}{\partial T} = \frac{-(\mathcal{N}(d_1) - 1)\frac{\partial C(S_0,T)}{\partial T} + (K - F_T - C(S_0, T))\Phi(d_1)\frac{\partial d_1}{\partial T}}{K - F_T}$$

Where $\frac{\partial C(S_0,T)}{\partial T}$ represents the sensitivity of the call option value to the passage of time. Since $\frac{\partial C(S_0,T)}{\partial T} = -\Theta = rK \exp^{rT} \mathcal{N}(d_2) + \frac{\sigma}{2\sqrt{T}} > 0$, I have $-(\mathcal{N}(d_1) - 1)\frac{\partial C(S_0,T)}{\partial T} > 0$, given that $\mathcal{N}(d_1) \leq 1$.

For ITM options, $F_T - K > 0$ and the call price $C(S_0, T) \geq 0$, leading to $K - F_T - C(S_0, T) \leq 0$. Additionally, $(K - F_T - C(S_0, T))\Phi(d_1) \leq 0$ since $\Phi(d_1) > 0$. Now, considering $\frac{\partial d_1}{\partial T}$, there are two possibilities:

- $\frac{\partial d_1}{\partial T} = \frac{T(2r+\sigma^2) - 2log\left(\frac{S_0}{K}\right)}{4T^{3/2}\sigma} > 0 \iff T(2r + \sigma^2) > 2log\left(\frac{S_0}{K}\right) \iff K > S_0 \exp^{-T(r+\frac{\sigma^2}{2})}$
- $\frac{\partial d_1}{\partial T} = \frac{T(2r+\sigma^2) - 2log\left(\frac{S_0}{K}\right)}{4T^{3/2}\sigma} < 0 \iff T(2r + \sigma^2) < 2log\left(\frac{S_0}{K}\right) \iff K < S_0 \exp^{-T(r+\frac{\sigma^2}{2})}$

Given that the condition $K < S_0 \exp^{-T(r+\frac{\sigma^2}{2})}$ encompasses a wider range of strike prices of ITM options, especially for deep in-the-money options, $\frac{\partial d_1}{\partial T} < 0$. Therefore, $(K - F_T - C(S_0, T))\Phi(d_1)\frac{\partial d_1}{\partial T} > 0$, leading to $\frac{\partial f^*}{\partial T} < 0$. Thus, the optimal fraction of investment decreases with increasing maturity of ITM options.

Proposition 5 ***For OTM options, when $F_T - K < 0$, then $\frac{\partial f^*}{\partial T} > 0$ for all strick prices $K > C(S_0, T) + F_T$. That is, there is a positive relationship between the optimal fraction of investment and the maturity of OTM options.***

Proof: I begin by examining the partial derivative of f^* with respect to time to maturity T:

$$\frac{\partial f^*}{\partial T} = \frac{-(\mathcal{N}(d_1) - 1)\frac{\partial C(S_0,T)}{\partial T} + (K - F_T - C(S_0, T))\Phi(d_1)\frac{\partial d_1}{\partial T}}{K - F_T}$$

Where $\frac{\partial C(S_0,T)}{\partial T}$ represents the sensitivity of the call option value to the passage of time. Since $\frac{\partial C(S_0,T)}{\partial T} = -\Theta = rK \exp^{rT} \mathcal{N}(d_2) + \frac{\sigma}{2\sqrt{T}} > 0$, I have $-(\mathcal{N}(d_1) - 1)\frac{\partial C(S_0,T)}{\partial T} > 0$, given that $\mathcal{N}(d_1) \leq 1$.

Considering $\frac{\partial d_1}{\partial T}$, there is two possibilities:

- $\frac{\partial d_1}{\partial T} = \frac{T(2r+\sigma^2)-2log\left(\frac{S_0}{K}\right)}{4T^{3/2}\sigma} > 0 \iff T(2r+\sigma^2) > 2log\left(\frac{S_0}{K}\right) \iff K > S_0 \exp^{-T(r+\frac{\sigma^2}{2})}$
- $\frac{\partial d_1}{\partial T} = \frac{T(2r+\sigma^2)-2log\left(\frac{S_0}{K}\right)}{4T^{3/2}\sigma} < 0 \iff T(2r+\sigma^2) < 2log\left(\frac{S_0}{K}\right) \iff K < S_0 \exp^{-T(r+\frac{\sigma^2}{2})}$

For OTM options, $K - F_T > 0$, which means $K > F_T > S_0 > S_0 \exp^{-T(r+\frac{\sigma^2}{2})}$. Therefore $\frac{\partial d_1}{\partial T} > 0$ and $\Phi(d_1)\frac{\partial d_1}{\partial T} > 0$, since $\Phi(d_1) > 0$.

Regarding $K - F_T - C(S_0, T)$, there are two possibilities:

- $K - F_T - C(S_0, T) > 0 \iff K > F_T + C(S_0, T)$
- $K - F_T - C(S_0, T) < 0 \iff F_T < K < F_T + C(S_0, T)$

Given that the condition $K > F_T + C(S_0, T)$ encompasses a wider range of strike prices of OTM options, especially for deep out-the-money options, then $K - F_T - C(S_0, T) > 0$, leading to $\frac{\partial f^*}{\partial T} > 0$. Thus, the optimal fraction of investment increases with increasing maturity of ITM options.

A.1.2. Call Volatility

Proposition 6 ***For ITM options, when*** $F_T - K > 0$***, then*** $\frac{\partial f^*}{\partial \sigma} > 0$***, for all strike prices*** $K < S \exp^{(r-\sigma^2/2)T}$ ***and*** $\sigma^2/2 > r$***. That is, there is a negative relationship between the optimal fraction of investment and the volatiity of the stock for ITM options.***

Proof: I start by examining the partial derivative of f^* with respect to time to volatility σ:

$$\frac{\partial f^*}{\partial \sigma} = \frac{-(\mathcal{N}(d_1)-1)\frac{\partial C(S_0,T)}{\partial \sigma} + (K - F_T - C(S_0,T))\Phi(d_1)\frac{\partial d_1}{\partial \sigma}}{K - F_T}$$

Where $\frac{\partial C(S_0,T)}{\partial \sigma}$ represents the sensitivity of the call option price with respect to the volatility of the underlying stock. Since $\frac{\partial C(S_0,T)}{\partial \sigma}) = \nu = \sqrt{T} S_0 \Phi(d_1) > 0$, then $-(\mathcal{N}(d_1)-1)\frac{\partial C(S_0,T)}{\partial \sigma} > 0$, given that $\mathcal{N}(d_1) \leq 1$ and $\Phi(d_1) > 0$.

For ITM options, $F_T - K > 0$ and the call price $C(S_0, T) \geq 0$, leading to $K - F_T - C(S_0, T) \leq 0$. Additionally, $(K - F_T - C(S_0, T))\Phi(d_1) \leq 0$. Now, considering $\frac{\partial d_1}{\partial \sigma}$, there are two possibilities:

- $\frac{\partial d_1}{\partial \sigma} = \frac{T(-2r+\sigma^2)-2log\left(\frac{S_0}{K}\right)}{2\sqrt{T}\sigma^2} > 0 \iff T(-2r+\sigma^2) > 2log\left(\frac{S_0}{K}\right) \iff K > S_0 \exp^{T(r-\frac{\sigma^2}{2})}$
- $\frac{\partial d_1}{\partial \sigma} = \frac{T(-2r+\sigma^2)-2log\left(\frac{S_0}{K}\right)}{2\sqrt{T}\sigma^2} < 0 \iff T(-2r+\sigma^2) > 2log\left(\frac{S_0}{K}\right) \iff K < S_0 \exp^{T(r-\frac{\sigma^2}{2})}$

Given that the condition $K < S_0 \exp^{T(r-\frac{\sigma^2}{2})}$ encompasses a wider range of strike prices of ITM options, especially for deep in-the-money options, $\frac{\partial d_1}{\partial \sigma} < 0$. Therefore, $(K - F_T - C(S_0,T))\Phi(d_1)\frac{\partial d_1}{\partial \sigma} > 0$, leading to $\frac{\partial f^*}{\partial \sigma} < 0$. Thus, the optimal fraction of investment decreases with increasing volatility of ITM options.

Proposition 7 ***For OTM options, when $F_T - K > 0$, then $\frac{\partial f^*}{\partial \sigma} > 0$, for all strike prices $K > C(S_0,T) + F_T$ and $\sigma^2/2 > r$. That is, there is a positive relationship between the optimal fraction of investment and the volatility of OTM options.***

Proof: I begin by examining the partial derivative of f^* with respect to time to volatility σ:

$$\frac{\partial f^*}{\partial \sigma} = \frac{-(\mathcal{N}(d_1)-1)\frac{\partial C(S_0,T)}{\partial \sigma} + (K - F_T - C(S_0,T))\Phi(d_1)\frac{\partial d_1}{\partial \sigma}}{K - F_T}$$

Where $\frac{\partial C(S_0,T)}{\partial \sigma}$ represents the sensitivity of the call option price with respect to the volatility of the underlying stock. Since $\frac{\partial C(S_0,T)}{\partial \sigma} = \nu = \sqrt{T} S_0 \Phi(d_1) > 0$, I have $-(\mathcal{N}(d_1)-1)\frac{\partial C(S_0,T)}{\partial \sigma} > 0$, given that $\mathcal{N}(d_1) \leq 1$.

Considering $\frac{\partial d_1}{\partial \sigma}$, there is two possibilities:

- $\frac{\partial d_1}{\partial \sigma} = \frac{T(-2r+\sigma^2)-2log\left(\frac{S_0}{K}\right)}{2\sqrt{T}\sigma^2} > 0 \iff T(-2r+\sigma^2) > 2log\left(\frac{S_0}{K}\right) \iff K > S_0 \exp^{T(r-\frac{\sigma^2}{2})}$
- $\frac{\partial d_1}{\partial \sigma} = \frac{T(-2r+\sigma^2)-2log\left(\frac{S_0}{K}\right)}{2\sqrt{T}\sigma^2} < 0 \iff T(-2r+\sigma^2) > 2log\left(\frac{S_0}{K}\right) \iff K < S_0 \exp^{T(r-\frac{\sigma^2}{2})}$

For OTM options, $K - F_T > 0$, which means $K > F_T > S_0 > S_0 \exp^{T(r-\frac{\sigma^2}{2})}$. Therefore $\frac{\partial d_1}{\partial \sigma} > 0$ and $\Phi(d_1)\frac{\partial d_1}{\partial \sigma} > 0$, since $\Phi(d_1) > 0$.

Regarding $K - F_T - C(S_0,T)$, there are two possibilities:

- $K - F_T - C(S_0,T) > 0 \iff K > F_T + C(S_0,T)$
- $K - F_T - C(S_0,T) < 0 \iff F_T < K < F_T + C(S_0,T)$

Given that the condition $K > F_T + C(S_0,T)$ encompasses a wider range of strike prices of OTM options, especially for deep out-the-money options, then $K - F_T - C(S_0,T) > 0$, leading to $\frac{\partial f^*}{\partial \sigma} > 0$. Thus, the optimal fraction of investment increases with increasing volatility of ITM options.

A.1.3. Put Volatility

The optimal betting fraction, f^*, is:

$$f^* = \frac{p(1+b)-1}{b}$$

Assuming Black and Scholes, we can implement these framework in the context of options. The bet size will be determined by the price paid for the option. In the case of call options, this will be $P(S_0, T)$, where S_0 is the stock price at time $t = 0$ and T is the maturity of the option. The gain per unit bet is the profit earned when the option is exercised, for Call options is $K - F_T$, where $F_T = S_0 \exp^{rT}$ is forward stock price maturing at $t = T$ assuming a risk free r, and K is the strike price of the option. Therefore for Call options b will be:

$$b = \frac{K - F_T}{P(S_0, T)}$$

Furtheremore, the probability of winning the bet p, for options can be interpreted as the probability of exercising the option, which is captured by the Delta of the option Δ and it is defined as $\Delta = N(d_1)$. Thus, plugging all numbers in f^*:

$$f^* = \frac{-\Delta\left(1 + \frac{K-F_T}{P(S_0,T)}\right) - 1}{\frac{K-F_T}{P(S_0,T)}} = \frac{(1-N(d_1))\left(1 + \frac{K-F_T}{P(S_0,T)}\right) - 1}{\frac{K-F_T}{P(S_0,T)}} = N(d_1) - (1-N(d_1))\frac{C(S_0,T)}{F_T - K}$$

Proposition 8 ***For ITM options, when $K - F_T > 0$, then $\frac{\partial f^*}{\partial \sigma} > 0$, for all strike prices $K < S \exp^{(r-\sigma^2/2)T}$ and $\sigma^2/2 > r$. That is, there is a negative relationship between the optimal fraction of investment and the volatiity of the stock for ITM options.***

Proof: I start by examining the partial derivative of f^* with respect to time to volatility σ:

$$\frac{\partial f^*}{\partial \sigma} = \frac{-(\mathcal{N}(d_1) - 1)\frac{\partial C(S_0,T)}{\partial \sigma} + (K - F_T - C(S_0,T))\Phi(d_1)\frac{\partial d_1}{\partial \sigma}}{K - F_T}$$

Where $\frac{\partial C(S_0,T)}{\partial \sigma}$ represents the sensitivity of the call option price with respect to the volatility of the underlying stock. Since $\frac{\partial C(S_0,T)}{\partial \sigma}) = \nu = \sqrt{T} S_0 \Phi(d_1) > 0$, then $-(\mathcal{N}(d_1) - 1)\frac{\partial C(S_0,T)}{\partial \sigma} > 0$, given that $\mathcal{N}(d_1) \leq 1$ and $\Phi(d_1) > 0$.

For ITM options, $F_T - K > 0$ and the call price $C(S_0, T) \geq 0$, leading to $K - F_T - C(S_0, T) \leq 0$. Additionally, $(K - F_T - C(S_0, T))\Phi(d_1) \leq 0$. Now, considering $\frac{\partial d_1}{\partial \sigma}$, there are two possibilities:

- $\frac{\partial d_1}{\partial \sigma} = \frac{T(-2r+\sigma^2)-2log\left(\frac{S_0}{K}\right)}{2\sqrt{T}\sigma^2} > 0 \iff T(-2r+\sigma^2) > 2log\left(\frac{S_0}{K}\right) \iff K > S_0 \exp^{T(r-\frac{\sigma^2}{2})}$

- $\frac{\partial d_1}{\partial \sigma} = \frac{T(-2r+\sigma^2)-2log\left(\frac{S_0}{K}\right)}{2\sqrt{T}\sigma^2} < 0 \iff T(-2r+\sigma^2) > 2log\left(\frac{S_0}{K}\right) \iff K < S_0 \exp^{T(r-\frac{\sigma^2}{2})}$

Given that the condition $K < S_0 \exp^{T(r-\frac{\sigma^2}{2})}$ encompasses a wider range of strike prices of ITM options, especially for deep in-the-money options, $\frac{\partial d_1}{\partial \sigma} < 0$. Therefore, $(K - F_T - C(S_0,T))\Phi(d_1)\frac{\partial d_1}{\partial \sigma} > 0$, leading to $\frac{\partial f^*}{\partial \sigma} < 0$. Thus, the optimal fraction of investment decreases with increasing volatility of ITM options.

Proposition 9 ***For OTM options, when*** $F_T - K > 0$***, then*** $\frac{\partial f^*}{\partial \sigma} > 0$***, for all strike prices*** $K > C(S_0,T) + F_T$ ***and*** $\sigma^2/2 > r$***. That is, there is a positive relationship between the optimal fraction of investment and the volatility of OTM options.***

Proof: I begin by examining the partial derivative of f^* with respect to time to volatility σ:

$$\frac{\partial f^*}{\partial \sigma} = \frac{-(\mathcal{N}(d_1)-1)\frac{\partial C(S_0,T)}{\partial \sigma} + (K - F_T - C(S_0,T))\Phi(d_1)\frac{\partial d_1}{\partial \sigma}}{K - F_T}$$

Where $\frac{\partial C(S_0,T)}{\partial \sigma}$ represents the sensitivity of the call option price with respect to the volatility of the underlying stock. Since $\frac{\partial C(S_0,T)}{\partial \sigma} = \nu = \sqrt{T}S_0\Phi(d_1) > 0$, I have $-(\mathcal{N}(d_1)-1)\frac{\partial C(S_0,T)}{\partial \sigma} > 0$, given that $\mathcal{N}(d_1) \leq 1$.

Considering $\frac{\partial d_1}{\partial \sigma}$, there is two possibilities:

- $\frac{\partial d_1}{\partial \sigma} = \frac{T(-2r+\sigma^2)-2log\left(\frac{S_0}{K}\right)}{2\sqrt{T}\sigma^2} > 0 \iff T(-2r+\sigma^2) > 2log\left(\frac{S_0}{K}\right) \iff K > S_0 \exp^{T(r-\frac{\sigma^2}{2})}$

- $\frac{\partial d_1}{\partial \sigma} = \frac{T(-2r+\sigma^2)-2log\left(\frac{S_0}{K}\right)}{2\sqrt{T}\sigma^2} < 0 \iff T(-2r+\sigma^2) > 2log\left(\frac{S_0}{K}\right) \iff K < S_0 \exp^{T(r-\frac{\sigma^2}{2})}$

For OTM options, $K - F_T > 0$, which means $K > F_T > S_0 > S_0 \exp^{T(r-\frac{\sigma^2}{2})}$. Therefore $\frac{\partial d_1}{\partial \sigma} > 0$ and $\Phi(d_1)\frac{\partial d_1}{\partial \sigma} > 0$, since $\Phi(d_1) > 0$.

Regarding $K - F_T - C(S_0,T)$, there are two possibilities:

- $K - F_T - C(S_0,T) > 0 \iff K > F_T + C(S_0,T)$

- $K - F_T - C(S_0,T) < 0 \iff F_T < K < F_T + C(S_0,T)$

Given that the condition $K > F_T + C(S_0,T)$ encompasses a wider range of strike prices of OTM options, especially for deep out-the-money options, then $K - F_T - C(S_0,T) > 0$, leading to $\frac{\partial f^*}{\partial \sigma} > 0$. Thus, the optimal fraction of investment increases with increasing volatility of ITM options.