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Abstract

We analyze a market-wide panel dataset on retail options trading from India, a market with an 80% share in option contracts traded worldwide. Retail traders both concentrated in and dominate index options trading. They exhibit short-term speculative behavior with significant day trading, short-duration directional bets especially as options converge to 0DTE and make significant losses. Three natural experiments indicate that financial constraints and lottery-like preferences likely shape investor behavior. An exogenous increase in the supply of short-maturity options induces trading. Lot-size increases and delivery margins trying to curb speculation are offset by shifts to small ticket-size, riskier options. While financial market participation increases welfare in canonical household finance models, it can also entrench speculative behavior that is difficult to undo.

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Introduction

There has been a surge in options trading around the world in the recent years, driven in particular by retail traders.[1] We present evidence on retail options trading from the National Stock Exchange of India (NSE), by many measures the world's largest options market. Our dataset includes all investors in the market and provides clear markers for retail traders, obviating the need to infer which trades are retail. We are provided unique (masked) IDs for each investor. The panel structure of the data lets us trace retail trader entry, exit, strategies, and performance.

We provide a quick summary of the main findings. Retail trades are concentrated in – and dominate – index options, specifically two contracts, "NIFTY50" and "BANKNIFTY." Traders have extremely short horizons. Day trading is dominant, reaching 90% of the total volume towards the end of our sample period. The remaining trades are typically simple short-duration directional bets on the underlying. Relatedly, trading shows periodicity: it begins to sharply increase starting at about 5 days before option expiry and surges as options converge to "ODTE" or zero days to maturity. Traders make significant losses that are more pronounced in trades through FinTech brokers, which begin to increase towards the end of our sample period.

We consider three natural experiments, reflecting supply-side interventions in the options market. The first is an exogenous increase in the supply of short-term options. We find that it induces a sharp increase in short-term retail trading at both the extensive and intensive margin. The trades become dominant with a short span of one to three months. Two other experiments increase capital requirements for options traders. These efforts to curb speculative trading are offset by shifts in speculation into affordable alternatives. Speculative habits seem hard to excise once they take root – even if, as in our sample, there are extensive losses from such activity.

[1] See, e.g., https://www.nyse.com/data-insights/trends-in-options-trading.

India is the world's largest derivatives market. Of the 108 billion options contracts traded worldwide in 2023, 78% were on Indian exchanges. The time series evidence shows a significant increase in participation over time. In our sample period from 2007 to 2021, we see a 15-fold growth in the number of retail option traders, 53-fold growth in the contracts traded, 86-fold growth in the premium turnover, and 358-fold growth in the underlying notional amount. The growth in Indian options trading reflects a sharp increase in financial market participation. For example, the 2024 Indian Economic Survey reports that between 2019 and 2024, the number of stock market participants increased from 27 million to 92 million individuals. The growth was especially striking as for decades, Indian households have had limited financial inclusion with little access to even basic bank accounts (Burgess and Pande, 2005; Cole et al., 2013).

We analyze a proprietary dataset of daily option trades of individual retail investors covering option contract expiries from 2007 to 2021. Our options data cover all trades on India's National Stock Exchange (NSE), which is the dominant venue for option trading in India.[2] Our dataset is at the daily level. It includes the number of contracts traded, the prices paid for purchases or sales of each contract for each day, and the name of the underlying stock or index.

We observe striking patterns in the data. One feature is the concentration in index options, which account for 75% of the premium and 93% of the notional volume traded. With 513 options per month on average, index options offer investors many more payoff profiles compared to only 49 for individual stock options. Given their dominance, our analysis focuses on index options. Within this universe, options on the market-wide NIFTY50 index and a bank-specific

[2] The NSE accounts for 99.6% of derivatives trading in India. This pattern has existed across our entire sample period. See, e.g., Bloomberg, October 21, 2016, The NSE 2023 Report, Reuters, May 3, 2024

BANKNIFTY index constitute 99.9% of the trading volume in our sample period.[3] On average, 87% of a contract's volume from inception to expiry occurs in the last five days of its life.

Attractive features of short-term options include their low nominal costs, which lower entry barriers, rapid resolution of uncertainty at fixed dates, and greater skewness relative to longer-lived options or alternatives such as lottery stocks. We provide some computations based on realized returns for the Indian market. 0DTE (zero days to expiry) options are extremally short horizon. These options have attracted scrutiny after complete daily expiries on the U.S. SPX options were introduced in May 2022.[4] Of course, all options eventually become zero-day maturity options. We ask whether investors exhibit preference for 0DTEs. We find that even when only available at the lower monthly or weekly frequencies, retail volume spikes as options approach zero maturity. Retail investors account for 42% of the expiration day volume of the aggregate market. We verify that the late-stage volume surge does not reflect mechanical effects of positions closed just ahead of settlement: 82% of the traders *begin* trading the contract during its last week before maturity. The significant retail share in ODTE index options in our sample mirrors a trend that has emerged in the U.S. market.[5] More broadly, retail preference for short-maturity options is consistent with evidence from other studies (Bryzgalova, Pavlova, and Sikorskaya, 2023; Beckmeyer, Branger, and Gayda, 2023; Bogousslavsky and Muryayev, 2024).

We find other markers of retail trader short-termism. Most starkly, day trading represents 90% of the volume by the end of our sample period. Thus, retail investors not only prefer to trade in short-maturity options but also take short-lived bets on them. A conservative measure of short-

[3] Individual options feature in a natural experiment that we discuss later. For completeness, we also analyze these data and find a pattern of losses like that in index options. The results are available for the interested reader.
[4] The CBOE introduced weekly SPX options in 2005 with Friday expirations, followed by Wednesday and Monday expiries in 2016 and Tuesday and Thursday expiries in 2022, completing the series of daily expiries. See https://www.cboe.com/insights/posts/the-evolution-of-same-day-options-trading.
[5] See, e.g., https://www.cboe.com/insights/posts/0-dt-es-decoded-positioning-trends-and-market-impact/

termism is the end-to-end interval between the date when a trader first opens a position on a contract and either the last date of trading on the same contract or the expiration date if a position is not closed. The end-to-end interval is short with a mean (median) of 2.4 (0) days. These patterns are not consistent with retail investor use of options as hedging instruments.

The trades that do not close within the day are typically simple. 78.7% of open positions on index options (90.7% for single stock options) are directional and unhedged. While simple strategies are not uncommon in the U.S. (Beckmeyer, Branger, and Gayda, 2023), their magnitude has been harder to pin down precisely given the difficulties in identifying retail trades in these data (Han, 2024). In our sample, retail traders are explicitly identified in the data. In our sample, retail traders make substantial losses that have only increased over time, and small traders incur much larger losses relative to their trading volume. A report issued by India's stock market regulator, Securities and Exchange Board of India (SEBI) shows that 9.4 million retail investors participated in options and lost INR 550 billion (about US$6.9 billion) before transaction costs, even though 76% of them are low-income investors.[6] Our results show that these losses have existed for a long period of time.

We consider three natural experiments, supply-side interventions in options markets. The first one is the introduction of short-maturity options. As background, option trading in our sample concentrate in options on two indexes, BANKNIFTY and NIFTY50, the former a traditional index that comprises 50 large cap stocks and the latter an index of 12 large private and state-owned banks. Prior to May 2016, options had monthly expiration cycles. Thus, short-horizon options were available only when options were close to their (monthly) expirations. In May 2016, the NSE

[6] See 2024 SEBI Report. Low-income investors are defined as those with annual income below ₹5 lakh, or US$6,250. We convert local currency INR amounts to US dollar at the rate of US$1 = INR 80.

introduced weekly options on the BANKNIFTY index. We test whether the increase in the supply of weekly options induces investment in these short-term instruments.

While both the BANKNIFTY and NIFTY50 index options had parallel trends before May 2016, there was divergence after the introduction of weekly expirations on the BANKNIFTY. After the shock, both the premium volume and notional amounts of the BANKNIFTY weekly options increase but the NIFTY options volume is virtually unchanged. Thus, the supply of short-term options induces demand. We show that the demand rises at both the extensive and intensive margins. A significant 68% of traders are new, those with no BANKNIFTY trading in the pre-event period. At the intensive margin effect, we show traders who trade BANKNIFTY options in the pre-event period also increase trading, especially male and younger traders, and traders who predominantly traded cheap, short maturity options before the shock. The aggregate retail losses on BANKNIFTY contracts totaled INR 135 billion ($1.7 billion) over the five years from the introduction of weeklies to the end of our sample. Interestingly, there are also spillover effects on the stock market, as the new BANKNIFTY traders reduce stock investments after they start trading BANKNIFTY options.

The next experiment we consider is a policy change, an early attempt by the regulator to reduce speculative trading in options. In August 2015, SEBI attempted to "insulate retail investors from excessive speculation" by increasing the lot size, the smallest possible trading unit, for index options.[7] The change was significant as it tripled the lot size from 25 to 75 contracts on NIFTY50. The policy change had one intended effect: retail volume declines immediately after the shock. For more evidence, we use a difference-in-difference approach. The treated group comprises who always traded small lots below the new lot size cutoffs before the shock. The control group traded

[7] See, for example, https://timesofindia.indiatimes.com/business/india-business/sebi-cuts-fo-lot-size-to-contain-speculation/articleshow/48062894.cms.

just above the new lot size in the pre-period. Consistent with the patterns from the aggregate data, we find reductions in the trading volume of the treated group relative to the controls.

However, we also observe an interesting side-effect. The smaller traders in the treated group shifted to options that were more out of the money, of shorter maturity, and nominally cheaper. Moreover, their holding period in the options decreases. The returns of the investors decrease by 1.5% post the shock. The results are consistent with addictions to speculation in which tastes for speculative trading take root, so curbs on one type of speculation lead to shifts into other contracts, potentially in ways detrimental to overall financial well-being.

A third experiment occurs in October 2019, when the securities regulator mandated physical settlements for in-the-money (ITM) options on single stocks.[8] The settlement rule imposes financial constraints on investors holding open ITM positions close to expiry because buyers (sellers) are required to have enough cash (stocks) in their accounts to take (make) physical delivery. To comply with the new delivery rules, brokers began to impose delivery margin requirements around 6 trading days before expiration with graduated increases as options approached maturity.[9] A difference-in-differences design emerges naturally here as the margin requirements apply to ITM options but not out-of-the-money (OTM) options.

We note that analyzing the delivery margin experiment moves us outside the domain of index options into individual stock options, which at about 25% of the premium volume, are a smaller portion of the options market. The difference-in-differences results are stark. There is a 70% reduction in the volume of ITM options and a 55% increase on OTM options at maturity. The

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[8] The rule does not apply to index options, presumably given the enormous difficulty in settling (possibly fractional and odd lot) shares of the underlying for one options lot. The regulations apply to futures as well, but to maintain focus on options, we restrict our attention to options trades.
[9] See, for example, the delivery margin requirements of Zerodha: https://support.zerodha.com/category/trading-and-markets/margins/margin-leverage-and-product-and-order-types/articles/policy-on-physical-settlement.

switch to OTM options is not inconsequential: traders with a preferred habitat of trading cheap, short-maturity stock options before the shock incur greater losses of INR 23,984 per year compared to the other traders.

In our view, the results of the policy experiments collectively indicate significant challenges in curbing speculative behavior in options once it takes root, particularly among small traders with limited financial resources. Efforts to attempt to make participation costlier encourage speculation-shifting to alternatives that can satisfy the propensity to gamble. In particular, investors are attracted to riskier types of options that may be even less suitable investment choices. We find no evidence that this shift in trading behavior yields better performance. The more plausible interpretation is that the entry into options induces addictive preferences for short-term speculation and instant gratification that are hard to shed. Formal research (e.g., Engelberg and Parsons (2016) on hospital admits and stock returns) and anecdotal evidence in the media suggest that speculative losses have psychological or health effects.[10] Such ill-effects and additional manifestations of addiction to speculation remain interesting questions for future research.

Access to stock trading account data in addition to option trading account data allows us to highlight other indicators of speculative intent. We examine trader histories in the stock market prior to their entry into options. The traders who enter options trading have *worse* prior stock trading performance, inconsistent with models of traders as rational learners who extend their span into more sophisticated instruments when outcomes in simpler instruments are positive. Relatedly, traders who enter options have *less* prior stock trading experience. We also find that traders who enter options have historically preferred stocks with greater volatility and lottery-like features. After entry into options, traders are less likely to exit after positive past returns (but not positive

[10] See, e.g., the 2024 report in India Today, a reputable magazine in India or a related press story in The Mint.

future returns), consistent with overconfidence and ability extrapolation (e.g., Greenwood and Shleifer, 2014).

We examine the role of broker type in shaping retail trading behavior and outcomes. Our dataset identifies the type of broker through which trades occur. "FinTech" brokers attract customers by charging lower commissions, offering cellphone trading apps, and pushing advice on possible strategies with caveats as required by regulators. We observe a significant growth in retail volume via FinTech brokers, with four of them accounting for 55% of the retail volume in the final year of our sample. We analyze traders who use traditional versus FinTech brokers. Traders using FinTech brokers have greater trading volume and incur greater trading losses. A subsample of traders uses both FinTech and non-FinTech brokers. For these traders, we estimate models with trader fixed effects and find that they trade more through FinTech brokers and incur triple the losses of the trades through non-FinTech brokers.

Although the trading volume on single stock options is much smaller than index options, we examine retail participation in this market. We find little evidence to support possible cross-hedging of single stock options with index options. Around 89% of the directional stock option positions either have no simultaneous index option open, or when they do, traders tend to bet in the same direction on both single stock and index options. Trading is greater for options where the underlying stocks have high share prices, as well as options that have lower premiums. These results are consistent with speculative traders facing financial constraints and evidence from the three natural experiments.

I. Related Literature

Our results are relevant to research on financial market participation. The household finance literature (e.g., Badarinza, Campbell, and Ramadorai, 2016; Calvet, Campbell, and Sodini,

2007) has pointed out the benefits of stock market participation that include mitigating the costs of under-diversification and gaining the benefits of equity risk premiums. The Indian market has been a success story in this regard, with expansion in participation from 27 million to 91 million individuals in under a half-decade, driven by digitization and simplified onboarding processes. Our study highlights the cost of the expansion in financial market participation, viz., the facilitation of short-term speculation. India's stock market regulator SEBI has been cognizant of these negative outcomes. In November 2024, it banned the BANKNIFTY contracts on the NSE. A traditional argument against such paternalism is that it imposes constraints on investors choice sets, although these arguments are harder to reconcile with traders making consistent losses of this magnitude. In the U.S., the Securities and Exchange Commission (SEC) and FINRA have raised related concerns about retail participation in complex financial products.[11]

Press reports cite additional concerns about addiction created by trading complex products related to compulsive gambling.[12] Our study focuses on the persistence of speculative habits via options, perhaps induced by frequent lotteries that resolve in simple ways that investors may prefer (Puri, 2025). However, it is by no means the only habit-inducing concern outside or even within finance (see, e.g., Barber, Lee, Liu, Odean, and Zhang (2020) for persistence of day trading habits from stock market data from Taiwan from 1992 to 2007). The evidence in our study is consistent with these concerns and furthermore suggests that interventions to redress them face challenges, complexity, and unintended consequences, even if the strategies cause persistent losses that should normally cause investors to exit.

[11] See https://www.finra.org/rules-guidance/notices/22-08 and https://www.sec.gov/files/approved-iac-060624-rec-re-self-directed-investors.pdf.

[12] See https://www.wsj.com/finance/stocks/stock-market-trading-apps-addiction-afecb07a.

Retail participation in the options market has attracted interest in recent work. An important empirical issue in this literature has been how to identify retail trades (see, e.g., Han (2024)). de Silva, So, and Smith (2022) and Naranjo, Nimalendran, and Wu (2024) use exchange identification of trades by non-professional customers to demonstrate event-related trading and understand the trading costs borne by retail investors. Bryzgalova, Pavlova, and Sikorskaya (2023), Beckmeyer, Branger, and Gayda (2023), and Eaton, Green, Roseman, and Wu (2024) use the single-leg price improvement flag in the Options Price Reporting Authority (OPRA) data to identify retail traders, and assess trading costs, price impact and losses of retail traders. Hendershott, Khan, and Riordan (2022), Ernst and Spatt (2023), and Huang, Jorion, and Schwarz (2024) examine retail order execution and payment for order flows. Our study uses market-wide data on all traders, with a panel structure and identifiers for retail traders. Our focus is on showing speculative behavior mainly (but not only) in index options, characterizing its extremely short-term nature, its drivers, and consequences. We also present evidence from experiments that ease or attempt to rein in speculative behavior.

Bogousslavsky and Muryayev (2024) analyze a group of retail investors who sign up for a trading journal and are, on average, more sophisticated and place relatively larger trades ($3.9 million per trader). They document remarkable heterogeneity across retail traders, and less trading losses within this group of retail traders. Relatedly, Hu, Kirilova, Park, and Ryu (2023) show that sophisticated investors using complex strategies in the Korean market lose less. Our study focuses on the aggregate retail investors in India, including many new to options, their speculative behavior, and the effects of supply shocks that enhance or ease speculative opportunities.

Early research attempts to assess how lottery preferences manifest in *stock* – rather than options – investments. See Barberis and Huang (2008) and Kumar (2008) on stocks with lottery features and Bali, Cakici, and Whitelaw (2011) on a related "high max" portfolio. These lottery stocks tend to be very small, creating the misimpression that lottery preferences are not economically important. For example, the "high max" portfolio in Bali, Cakici, and Whitelaw (2011) has mostly small stocks covering 1.44% of the market. Our study suggests that lottery-like preferences are not unimportant when one incorporates options. With embedded leverage, nonlinear payoff structures, and variations across maturities, moneyness, and trading horizons, options offer a wide suite of bets. Moreover, short-term options appear to be simpler bets, with quick resolution and clear payoffs, especially in the case of 0DTE options. The realized skewness of index option returns far exceeds that of the high skewness stocks as we show in detail in Appendix A.[13] These features of the return distribution appear attractive to retail investors. The notional value of options is 86 times the stock volume for individuals trading in both markets.

II. Data

A. The Aggregate Indian Options Market

The Indian options market is large. For context, we consider some aggregate statistics. India's GDP of $3.6 trillion is about 3.4% of world GDP of $107 trillion and its stock market capitalization of $4.3 trillion in 2023 is about 5% of the world's market cap of $115 trillion (SIFMA 2024 Capital Markets Factbook). Yet, India has an outsized share of the derivatives market. According to 2023 Futures Industry Association statistics, the NSE is top-ranked, accounting for over 80% of the 137 billion derivatives contracts traded in the world. Derivatives

[13] In Appendix A, we construct option portfolios by sorting options into moneyness and maturity buckets and compute the time-series skewness of the option portfolio returns like Boyer and Vorkink (2014). During the last week of maturity, the skewness ranges between 1.1 and 3.9 for at the money options (−0.5%<moneyness<0.5%), and between 7.5 and 18.1 for out-of-the money options (moneyness<−2%), far greater than the skewness of lottery stock portfolios (e.g., 0.219 in Boyer, Mitton, and Vorkink, 2010 and 1.35 in Bali, Cakici, and Whitelaw, 2011).

trading has increased annually by between 40% and over 100% between 2018 to 2024 in terms of notional amounts, culminating in 2024 notional traded of INR 79,927 trillion ($999 trillion).

Data from the regulator (SEBI) reports related options turnover data.[14] It shows that turnover has increased 35-fold from INR 0.6 trillion to INR 1.52 trillion between 2018 and 2024, a 25-fold growth compared to a two-fold increase in stock market value over the same period. Thus, the increase in options volume is not explained by an overall increase in stock index levels. Nor does the premium growth reflect increased propensity to trade in the underlying stock market. Option premium volumes increased from 0.4% to a remarkable 70% of the stock market trading volume over this period.[15] Finally, in the Indian market, options trading is concentrated in the indexes. Index option trading accounts for 91% of the premium volume. The index options volume on NIFTY50 recently surpassed the S&P 500 even in U.S. dollar terms.[16]

B. Our Dataset

We obtain data on all the option trades at National Stock Exchange (NSE) of India. The NSE is an automated electronic trading exchange established in 1992 by India as part of a move towards market reforms and economic liberalization. Regulatory oversight of trading vests in the Securities and Exchange Board of India (SEBI). The NSE introduced derivatives trading beginning in 2000 through 2006 with index futures, single stock futures and options, and index option products. It quickly became the dominant venue for stock trading in India, displacing the Bombay

[14] See the Handbook of Statistics, Table 29, at the SEBI website, accessed on April 11, 2025.
[15] As option premiums are small relative to prices of the underlying, premium to notional multipliers are large, e.g., a 1-month call on a $100 stock at 20% volatility prices to $2.49, giving a 40X notional-to-premium multiplier.
[16] See https://www.ft.com/content/d1daf777-d10c-44d8-b570-462f6c4122eb.

Stock Exchange, a traditional open-outcry market in operation since 1875. The NSE now accounts for over 90% of the overall trading volume and 99.6% of the options volume in India.[17]

We have a panel dataset on option trading of all investors on the NSE at the trader-day-contract level from 2007 to June 2021. Each trader in our dataset is assigned a unique and masked identifier based on a 10-digit "PAN" or permanent account number that corresponds to a unique tax ID. The exchange aggregates daily transaction data for each trader and constructs the average purchase or sale price as the execution price after spread costs at the contract level. For each trader-day-contract observation, the dataset provides the masked trader ID, date, trades in calls and puts, the number of contracts purchased and sold, the average premium paid or received per contract, and option features such as the name of the underlying, the option maturity date and strike price. Importantly, the database flags whether a trader is an individual, which identifies retail traders in our sample. The non-retail traders are a mix of domestic and foreign institutional investors, such as insurance companies and mutual funds. Because options are in zero net supply, these institutions are counterparts for retail traders. Their profits equal the aggregate losses of retail traders.

We define retail traders as those flagged as "Individual" in the database. We refine the dataset in two ways. The first draws on the observation by Bryzgalova, Pavlova, and Sikorskaya (2023) that individual traders include a right tail of "protail" investors, professionals small in number but with significantly greater activity. We analyze them separately because "protail" investors are plausibly different from other retail investors. The evidence in Appendix B supports our empirical strategy.[18] We also trim observations in the left tail as it includes "occasional" traders with tiny trading volumes. To this bucket, we assign traders whose premium volume is less than

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[17] See https://www.bloomberg.com/professional/insights/trading/winner-takes-worlds-biggest-equity-options-market. As another metric, the NSE reports 2024 revenues of INR 164 billion versus INR 1.62 billion for the BSE.

[18] Appendix B shows that the trading volumes of protail investors are significantly higher although their volume-scaled losses are lower than that of retail traders.

INR 5,000 (about $63) over a 15-year period. Our final sample covers the trading record of 4.6 million retail traders in the options market.

We obtain return data and index levels from the National Stock Exchange (NSE). For a small number of tests, we extract firm characteristics from the COMPUSTAT Global database. We match COMPUSTAT firm identifiers with the NSE trading data using a ticker symbol–ISIN (International Securities Identification Numbers) link file provided by the NSE.

C. Key variables

We consider three metrics of option trading volume. One is the number of contracts traded, regardless of the option premium or underlying share price. A related measure, the notional volume is the number of contracts multiplied by the share prices of the underlying asset. A third is the premium volume, the option premium per contract times the number of contracts traded.

For both index and single stock options, one contract corresponds to one unit of index value or one share of underlying stock. In the U.S. options market, the typical multiplier is 100 so one options contract corresponds to 100 stock shares (exceptions are mini and nano contracts). Instead of using a multiplier, the SEBI imposes lot size requirements for trading the contracts. To illustrate, suppose that the lot size on NIFTY50 index options is 75. A trader buys 2 lots at INR 20 per contract, sells one lot next day at INR 19, and lets the other lot settle on expiration day at INR 8. Let the index values on the three days be 30,000, 30,100 and 30,200, respectively. The contract volume over the life cycle is 300 = 150+75+75. The premium volume equals 150×20 + 75×19 + 75×8 = INR 5,025. The notional volume equals (150×30,000) + (75×30,100) + (75×30,200) = INR 9,022,500 and represents the local currency equivalent represented by the options trades.

We track the history of each investor's trades in every options contract from introduction to maturity. We compute profits at the trader-contract level. We add profits or losses for closed positions (sell minus buy prices) to the undiscounted settlement payoffs for contracts held to maturity, which equal position size times $\max(S_T - K, 0)$ or $\max(K - S_T, 0)$ for calls or puts, respectively, where S_T is the closing price on the expiration day T, and K is the strike price.[19] The profit and loss figures are based on execution prices and thus reflect bid-ask spreads but not fees charged by brokerage companies. We deduct a nominal INR 20 for each trader-contract-day observation when the trader buys or sells a contract based on charges set by a prominent discount broker.[20] The actual trader losses that we estimate here underestimate true losses because full-service broker commissions are higher. Moreover, because of splits of intraday round-trip trades, retail traders could incur extra commissions that are not captured in our dataset.

III. Description and Baseline Statistics

A. Summary statistics

Panel A of Table 1 displays the number of traders and trading volume by contract type. We see clear evidence of the dominance of index options, which have 6 to 10 times the mean notional volumes as those of single stock options. The premium values are also greater although, of course, the exact magnitudes by which to scale the premiums are a function of the features of the option and parameters of the stock return forcing process. We also note significant differences between median and mean – which typically vary by orders of magnitude – reflecting the heterogeneity and

[19] In our sample, index options in all periods and single-stock options after 2010 are European-style options. Single-stock American options were traded briefly from 2007 to 2010. Eliminating these has little effect on our results.
[20] This is the fee charged by Zerodha, a leading FinTech broker. See https://zerodha.com/charges/#tab-equities.

skewness in the retail trader population. For example, the mean premium for index calls equals about INR 3.44 million versus median of INR 42,000.[21]

Panel B of Table 1 reports the distribution of losses classified by contract type and the overall profits at the individual trader level. Options trading has been hazardous to investor wealth. The average overall loss per investor is ₹109,900 or about $1,374. The option trades are not small, casual bets: 76% of them are low-income investors with annual earnings below ₹5 lakh (US$6,250) according to a 2024 report by the stock market regulator SEBI discussed earlier in footnote 6. Panel C of Table 1 shows the total number of days that options traders remain active. We exclude the first and last years to mitigate the left and right censoring due truncation. Traders are present for a mean (median) of 548 (147) days in the market. Panel D confirms the short duration of trades that leads to losses. The mean is 2.4 (2.3) days for index calls (puts), and the medians are zero, indicating short-termism options trading. The typical trader in options is in fact a day trader.

B. Detailed Descriptive Statistics

We present descriptive statistics in the form of time-series and cross-section of market participants, their trading strategies in terms of contracts and horizons, and the resulting profits.

Intensive and Extensive Margins in Trading Volume: Figure 1 presents time series evidence on retail option trading for all the three metrics of volume, viz. contracts, notional amount, and premium volume. Over the sample period from 2007 to 2021, the number of retail traders expanded 15 times or about a 22% annual growth rate. Growth is elevated in the later years, likely due to market digitization through the spread of mobile telephony, universal bank account provision, and the establishment of unique digital identity. These steps simplified onboarding processes for digital

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[21] The number of contracts traded on single stock options is greater because the per option price of each contract is lower than the index by a factor of about 10; the relation is reversed when we consider notional amounts.

authentication and KYC (know your customer) and implementation of anti-money laundering norms. The expansion in retail participation in options is also reflected in a 53-fold growth in the contracts traded, 358-fold growth in notional amounts, and an 86-fold expansion in options premium volume. The data suggest that besides the extensive margin growth, which reflects new investor entry, there is also growth in the intensive margin. The average trade is about 3.5 times more in terms of contracts at the end of our sample period. The greater growth in the notional amount relative to premiums indicates that investors gravitate towards "cheaper" contracts over time. We note that while much research has focused on the effects of digitization on payments (Agarwal, Qian, Ren, Tsai, and Yeung 2020; Ghosh, Vallee, and Zeng, 2024; Dubey and Purnanandam, 2024), the effect on options trading has received little attention thus far.

Profits and Losses: Figure 2A plots the monthly profit or loss of all retail options traders. We find that the aggregate retail losses increase as retail trading volume expands, particularly in the recent periods that have witnessed a boom in options trading. The cumulative retail losses equal an uncompounded amount of INR 506 billion (about $6.3 billion).

The sharp increase in losses in March 2020 is noteworthy. Uncertainty due to COVID-19 resulted in a market selloff and a rapid increase in volatility in this period. India's VIX increased from 13.62% on February 13, 2020, to 70.39% on 27 March 2020 and the NIFTY index declined by 25%. Some retail investors (about 5.9% of the population) who adopted short volatility strategies prior to this period suffered losses as VIX started to rise in early March. These investors reduced but did not fully close short put positions as their contracts approach the maturity date on March 26, 2020. These patterns are consistent with the disposition effect in which investors exhibit distaste for realizing losses (Shefrin and Statman, 1985; Benartzi and Thaler, 1995; Dhar and Zhu, 2006; Barberis and Xiong, 2009; Barber and Odean, 2000). This is a remarkable result for another reason. The retail investors in our sample typically have net long positions and short horizons, as we will discuss below. Yet, the aversion to loss realization is so strong that investors lengthen horizons to avoid realizing losses until option expiries force open positions to close. Appendix C provides more detail and some computations related to option returns during these events.

We next plot returns for investor groups sorted by trading volume deciles. The return is computed following Bryzgalova, Pavlova, and Sikorskaya (2023) by assuming that each short position requires the investor to deposit the entire proceeds from shorting as collateral, which earns zero interest. Under this assumption of no netting, the percentage return is net dollar profitability divided by the absolute value of dollar trading volume. Figure 2B shows that traders with the largest volume have the least negative returns, and trading returns decrease monotonically as we move to the group of lowest volume traders, who perform the worst with an average trading return of −21%. Options trading appears to be particularly detrimental for small investors taking small bets. The loss reduces to −1.2% if equally weighed across investors. We note that the statistics probably do not do justice to the true economic magnitude of the losses as they accrue to investors over short horizons of a few days.

Concentration in Index Options: Figure 3A shows the importance of index options, which represent 93% of the total notional volume and 75% of the total premium volume for retail investors.[22] The literature on household finance (e.g., Badarinza, Campbell, and Ramadorai, 2016; Calvet, Campbell, and Sodini, 2007; Gomes, Haliassos, and Ramadorai, 2021) notes that households are under diversified. Thus, investing in indexes could be welfare-enhancing. However,

[22] We omit contract volume here because given price differences, cross-sectional comparisons with single stock options are not meaningful. One might wonder about the affordability of index options to retail investors. The entry point, i.e., the price for one lot of index options, is relatively low, at a median price of INR 3,645 or about $45. Finally, the two names, NIFTY and BANKNIFTY, constitute 99.98% of the index option volume in our sample period, although other indexes have become popular recently such as the S&P Sensex 30.

the case for index options seems less compelling if they are short horizon or held for short maturity, as is the case for the retail traders in our sample.

Index option dominance is a long-lived phenomenon in our sample. These options represent 86% of the notional and 70% of the premium volume even in the first 10 years of our sample. In contrast, individual stock options have been focal in studies of the U.S. market (Lakonishok, Lee, Poteshman, and Pearson, 2007; Bandi, Fusari, and Reno, 2023; Bryzgalova, Pavlova, and Sikorskaya, 2023; de Silva, So, and Smith, 2024), where index options volume is only one-fifth of the total volume in all individual stock options (Chordia et al., 2021), and index options trading is driven by institutional hedging demand (Lemmon and Ni, 2014). 26% of the 5,118 "protail" traders in the trading journal sample of Bogousslavasky and Muryayev (2024) involve index options. Figure 3B shows that in our sample, the proportion of traders who only trade single stock options has become increasingly smaller in recent years.

Tastes For Short Maturities and Short Horizons: Figure 4A tracks options volume by time to maturity. Investors exhibit preference for shorter maturities: 87% of the notional volume occurs in the 6 days prior to maturity. The last day alone accounting for around 38% of the volume. A mechanical explanation for the greater volume on short maturity options is investor stasis, or inattention to earlier positions that lets the positions lapse until expiry. However, Figure 4B shows that most of the trading volume close to the expiration day is from new traders, i.e., those who first ever start to trade the options. A sequence of options with expirations every day, or 0DTE options are not available in the Indian market. The only 0DTE options are those that reach expiration dates. The increased volumes in these options suggest that even in these periods without daily 0DTE options, retail investors exhibit a preference for ultra-short options.

Day trading is quite significant in our sample. For fully closed positions during the day, we attribute 100% of the volume to day trading, while for partially closed positions, we count only the lesser of the number of shares purchased or sold towards day trading volume. To ensure the results are not driven by the underlying index prices, we also measure day trading activities by the contract volume. Figure 5A plots the day trading volume as a proportion of total volume for index options over time. We witness a significant increase in the percentage of day trading volume, reaching as high as 90% towards the end of our sample period.

What types of contracts do day traders prefer? We aggregate the trading contract volume by the time to maturity (from day -6 to day zero) and percentage moneyness at different levels. Figure 5B reports the data. We see that the trading activity is concentrated among short maturity (especially 0DTE), at-the-money, and slightly out-of-the-money options. The results can be explained by preferences for contracts with low nominal prices and those with lottery-like features. Short maturity options offer both features, although we note that option skews and smiles can make the options more expensive in implied volatility terms and trading costs are greater in a proportional sense. In Figure 5C, which shows the fraction of day trading volume relative to the total volume, we see preferences manifest in at-the-money or slightly out-of-the-money options.

We consider another metric of investor horizon, the length of time that traders hold positions. A conservative measure of trade duration is the number of days between the first day that an investor initiated a contract and the last date the investor traded if the position is completely closed, or if not closed, the contract expiration day.[23] We show this statistic for each time-to-maturity bucket in the right axis of Figure 4A. Interestingly, trade duration is short even when investors hold longer-term options. For example, traders who start trading when there are two

[23] For example, if a trader opens and completely closes an option position when there are 6 days to maturity, then opens and completely closes 1 day before maturity, this algorithm will still count horizon as 5 days.

weeks (one week) to maturity, only hold the position for an average of 5 (2) days. Figure 6 breaks down the trades into zero days, 1−3 days and greater than 3-day duration. While the 3+ day bucket dominates prior to 2016, day trading is now dominant for both calls and puts.

Short-Horizon Trading and Disposition Effect: To help standardize comparisons, we rank trader by duration deciles across all contracts in our sample. For each decile, we compute profits or losses as a percentage of premium volume, resulting in a metric akin to average return. The broken line in Figure 7A shows the raw unadjusted returns are similar across all horizons. However, this computation ignores the fact that returns are realized over different horizons. When standardized to 5-days, the solid line shows that returns are significantly lower for short-duration traders. Figure 7B decomposes total trading profits or losses into portions from day trading and non-day trading activities. Day trading profits are flat to weakly positive on average, indicating a preference for closing what is profitable before the end of the day. The strategy likely reflects trader disposition effect. Positions not closed in day trading result in significant losses.

Investor Trading Strategies: We compute the end-of-day net positions of each investor on each contract, starting from the first day the trader trades a contract until the contract expires. We perform a recursive inventory calculation of the net position at the trader-contract-day level by aggregating all the historical trades up to the end of each trading day. We then aggregate the data to the trader-day-underlying level to examine what option or combination of options are held as open positions for the same underlying name.

Directional unhedged positions are single leg positions or split strike strategies. Directional hedged positions are where the trader takes a directional bet along with an opposite position to hedge losses. Such strategies include covered call, protective put, as well as bull and bear spreads. A third category includes volatility strategies such as straddles, strangles, and butterfly spreads.

Panel A of Table 2 shows the statistics of directional unhedged, directional hedged, and volatility strategies. Panel B gives a more detailed breakdown of each of the three categories. Most trades are directional unhedged positions. For example, 90.8% of the day-end open positions on single stock options and 78.7% on index options are directional, unhedged strategies, more than the 56.8% found in South Korean markets (Hu, Kirilova, Park, and Ryu, 2023) and in line with data for individual stock options noted in Eaton, Green, Roseman, and Wu (2024) and others.[24]

Counterparty Institutions: While institutions are not our focus in this study, we comment briefly on this population of investors. Institutional investors are less likely to use FinTech brokers, have complex position exposures, and are more likely to be net sellers of options. Domestic institutions, foreign institutions, and individuals (including retail and protail) constitute approximately 56%, 11% and 33% of the market volume, respectively. We check that the aggregate losses borne by retail investors are the aggregate profits of the institutions.

IV. Natural Experiments

A. Introduction of Weekly Index Options

Starting on May 27, 2016, the National Stock Exchange (NSE) launched a new sequence of weekly option contracts on "BANKNIFTY," an index of 9 private and 3 state-owned banks whose shares are listed on the exchange. Prior to this date, both the NIFTY50 index options and the BANKNIFTY options had one expiration date per month, viz., the last Thursday of each month. The weekly options that the NSE introduced were designed to expire on all Thursdays, thus adding about three weekly expiration days per month. We assess trading in BANKNIFTY options that

[24] Short index calls are uncovered. For individual stocks (which we analyze briefly later), it is possible that call writes correspond to covered calls based on legacy inventories accumulated well before our sample period. Excluding the small number of these positions gives similar results.

have monthly expiries before the shock and weekly expiries after the shock, and NIFTY options that only have monthly expiries before and after the shock to facilitate comparison.

Figures 8A and 8B characterize the notional and premium volumes for both the NIFTY and BANKNIFTY index option contracts for a one-year pre-event window from May 2015 to May 2016 and the post-event period from June 2016 to May 2017. The figures scale the NIFTY50 volume by a factor of 5 to facilitate comparisons. The trading volumes for both the BANKNIFTY and NIFTY50 options show parallel trends before the introduction of the weekly BANKNIFTY options. The BANKNIFTY volume in this pre-event period is about 20% of the NIFTY50 volume. However, the volume on BANKNIFTY options jumps immediately after the weeklies are introduced. The BANKNIFTY shows a 7.3-fold growth in the notional volume and 2.2-fold growth in the premium volume. The post-event notional (premium) volume on NIFTY options is only 1.03 (0.89) of its pre-event volume. In 2021, the final year of our sample, the volume on BANKNIFTY is 160% of the NIFTY50 volume versus 20% during the pre-event period.

The panel nature of our data lets us assess the intensive and extensive drivers of this change. There are about 40,000 traders in the bank monthly options up to the introduction of the weekly options. Figure 8C shows a growing number of investors trading the BANKNIFTY options in each post-event month, while the number of NIFTY option traders is virtually constant. How many of these investors are new? Figure 8D shows a steady growth in the number of new traders, defined as those who did not have any BANKNIFTY trading in the pre-event period. Overall, 68% of weekly BANKNIFTY options traders had no pre-event trading in the contract. 46% of the weekly traders did not have *any* options experience in the pre-event period. Thus, the introduction of shorter-maturity options draws in investors who had not previously participated in the options market. Supply seems to create demand. The new clients prefer cheaper options. The new

BANKNIFTY traders have comparable per capital notional volume as the old traders (Figure 8E), yet significantly lower premium volume (Figure 8F).

Does options participation impact stock market participation? We consider evidence from the introduction of weekly BANKNIFTY options. We focus on new investors who began BANKNIFTY trading during the 3-year period after weekly BANKNIFTY introduction in May 2016 but had never traded options before the shock. For each trader, we calculate the net stock investment, defined as net shares purchased scaled by the average of shares purchases and sales, around the entry into BANKNIFTY. With a different entry time for each trader, we have a dynamic difference-in-differences model in which the not-yet-treated investors serve as the controls. Figure 8G shows the estimated dynamic treatment effects. We omit the entry month as it serves as the benchmark. Before entering options, traders show positive net investments in each month, averaging 6.9% for the 12 months, i.e., a net buy of 6.9 shares per 100 shares traded. The net investment in stocks turns negative after starting options trading, averaging −4.7% for the one-year period after options participation. Thus, entry in the options market coincides with withdrawal from the stocks and reduced stock market participation.

We consider the intensive margin next. Figures 8E and 8F show that within the subset of the old investors who traded BANKNIFTY prior to the introduction of weekly BANKNIFTY options, there is a subsequent increase in the per capita volume. We next ask whether the increase in weekly options is more pronounced among investors who predominantly focus on short-term options. For a one-year period before the introduction of weekly options, we compute the average time to maturity of traded positions for each trader. We define short-term investors as those who primarily traded index options with average time to maturity less than one week. These traders constitute 16% of the sample of traders in the pre-event period. When there are no weekly expirations, traders focus on the last 5 trading days prior to expiration.

At the intensive margin, do weeklies induce extra trading by these former short horizon traders? Does profits change? Panel A of Table 3 presents the evidence. Short-horizon investors have economically and statistically larger growth in trading volumes. For these traders, the premium volume increased by INR 0.55 million and the notional volume by INR 55.21 million compared to the other traders. The increases represent 56% and 24% of the sample means during the event period, respectively. The short-horizon traders also lost INR 6,534 more during the post event period relative to the other investors. Therefore, the weeklies indeed induce more trading and more losses for the short-horizon traders.

Because short maturity trading constitutes most of the index options volume, the introduction of weeklies increased investors' trading opportunity set from the last week in a month to all four weeks in a month. We next examine how participation frequency and trading intensity change, respectively. For each expiration date before and after the shock, we focus on the trading activities within 6 days until expiration. Next, we compute the number of active weeks (*numactiveweek*) during the pre-event and post-event periods. Panel B shows that during the one-year pre-event period, investors on average traded in 2.4 (out of a total of 12) expiry weeks, and increased the number of actives to 6.6 (out of the total 52 weeks) after the shock, i.e., the participation frequency increased by 2.75-fold. Conditional on participation, the investors show a decrease in average premium volume per week (*avg_premvol*) from INR 78.9 thousand to 64.2 thousand per week, yet an increase in average notional volume *avg_undervol* (21.9 to 36.1 million) and contract volume *avg_contravol* (1,332 to 1,831) per week. There is a significant shift by investors to options that are nominally cheaper. In the regressions with trader fixed effects in Panel

C, columns (1)−(4) show that for the same trader, the number of active weeks increases eight-fold, while the per week premium volume decreased slightly, and the notional and contract volume increased substantially. All these findings are consistent with the summary statistics in Panel B.

We have demographics information for a subgroup of investors including gender, age, and investor location. We construct indicator variables for male investors (male), investor age groups (*age18_40* for age between 18 and 40, *age41_60* for age between 41 and 60, and age above 60 is the benchmark), and for investors located in tier one cities (*tier1*) including Mumbai, Delhi, Bengaluru, Chennai, Kolkata, Hyderabad, Pune, and Ahmedabad. Panel D reports the changes in investor trading behavior for different demographics groups around the introduction of weekly NIFTY options, and Panel E further controls for trader fixed effects. Panel D shows that male investors show more total trading volume (columns 1-3) and incurred more losses (column 4). They also have more active trading weeks (column 5), and average trading per week (column 7-8). The results are stronger in models with trader fixed effects (Panel E). The results for younger traders show similar patterns. Investors located in tier 1 cities show more total trading volume, whereas the evidence for the active weeks, volume per week, and P&L is mixed.

We summarize the findings from this natural experiment. The weekly contracts generate significant volume on BANKNIFTY shortly after introduction. The spike in volume can be attributed to both extensive and intensive margins. New option traders trade in large volume and reduce their stock market participation after entering options trading. Existing traders also participate more, especially those with a preference for short maturity options before the shock. Traders increased the frequency in short maturity options, as well as trading intensity upon participation. Male and younger traders trade more frequently and actively after the shock. Greater trading volume generally induces greater trading losses.

B. Change in lot size

Policy makers and India's stock market regulator, Securities and Exchange Board of India (SEBI) have been concerned about retail investor losses from options trading. One approach to curb speculation was to increase lot size. If investors are constrained, the lot size increase will reduce their ability to trade options.

The lot size represents the smallest unit in which investors can trade options contracts. On August 07, 2015, the stock market regulator SEBI tripled the lot size for NIFTY from 25 to 75 contracts per lot and doubled that for BANKNIFTY options from 15 to 30 contracts. These changes were made effective starting from the November 2015 expiry contracts. At the contract closing prices on November 26, 2015, this amounts to an increase in the notional amount of ₹394 thousand on NIFTY and ₹256 thousand on the BANKNIFTY contracts. This increase in lot size is designed to impose participation burden on retail investors, especially those that are financially constrained.

Figure 9A plots the average premium volume per trader on index options around the shock. Our event window ends in April 2016 to avoid overlap with the introduction of weekly BANKNIFTY contracts. Trader volumes exhibit an upward trend before the shock and declines subsequently, particularly in the last quarter of 2015. Figure 9B reveals a structural shift in retail trading activity across different time to maturity and moneyness bins. We compute the relative trading volume for maturity-moneyness bin as a fraction of the total volume, both before and after the shock. The bars in the figure denote the change in the relative trading volume after the shock compared to before. We observe a significant shift to shorter maturity options, especially 0DTE, and more activity in out of the money options after the shock.

We next exploit investor heterogeneity to conduct a difference-in-differences analysis around the shock. We classify treated investors as those whose preferred habitat is below the new cutoff, i.e., those who always traded below 75 contracts on NIFTY and below 30 on BANKNIFTY during the per-event period. These investors are directly impacted by the lot size change rule. We identify as the control group those who always traded above the *new* minimum lot size pre-event in the neighborhood of the running treatment variable. These investors should be like the ones below the new cutoff but are less impacted by the rule change. We define the near-neighbor traders who were in the [75, 250] range for NIFTY50 options and [30, 90] for BANKNIFTY options. The treatment and control groups consist of 36,885 and 7,650 traders, respectively. *post* is an indicator variable that is equal to one for NIFTY (BANKNIFTY) contracts post the rule change with a new lot size of 75 (30), and zero if the lot size is 25 (15). During the transition from August to November 2015, legacy and new contracts may have coexisted, although it does not affect our results since the *post* variable precisely identifies contracts subject to the revised lot size.

Panel A of Table 4 shows that the trading volume for the smaller-lot group is significantly reduced after the shock relative to the control group. This reduction is as the policy intended.[25] An interesting result is in Panel B, which traces the side-effects of the lot size rule on the small traders. Column (1) shows that investors move into options that are 0.26% less in the money. They shift to options with maturities shorter by 1.9 days (column 2) and trade more in contracts with lower nominal prices (column 3).

Column (4) examines trade duration. Treated small-lot investors reduce trade duration, reflecting their lower capacity to hold positions or a short-term mindset. As column (5) shows, their trading returns, i.e., trading losses scaled by premium volume, are 1.51% lower. This result

[25] It is also possible that lot size induces option writing as the premiums received would increase per lot traded, but this effect is mitigated by margin requirements on option selling imposed by the NSE.

is consistent with the fact that out of the money options and options with shorter maturities have greater skewness and lower returns (Boyer and Vorkink, 2014). Relatedly, losses in our sample are incurred over shorter durations and thus are even greater if converted to a constant-maturity basis. Column (6) shows that the combined impact of reduced volume and lower returns yields an insignificant effect on dollar profit. Finally, we note that attrition rate difference between the treated and control group, 47% for the treated versus 53% for the control group, is not significant.

Overall, we find that the growth in retail participation in options is muted after lot size increases, both in the aggregate data and a difference-in-differences test with controls. In both cases we also observe a significant shift to cheaper options, characterized by shorter maturity and less moneyness, resulting in greater skewness and lower trading returns.

C. Physical Settlement

We next investigate a SEBI rule change that mandated physical settlements for single stock options. Starting from October 2019, if traders keep single stock option positions open upon expiry, they must take or make physical deliveries of the underlying stocks. As options approach expiry, traders must maintain more funds (or clear stock holdings for short positions) in anticipation of delivery. The cash amount, namely the delivery margin requirement, typically increases as contracts approach maturity date.[26] The delivery margin requirements apply to all trades regardless of the actual intent to take delivery. Moreover, the brokers would block the margin at the beginning of the trading day, thus affecting intraday orders even if they are subsequently closed at the end of the day.[27] If a client fails to post the delivery margin, positions are automatically squared off.

[26] For example, Upstox requires 10% of the contract value at day -4 and raises the requirement to 70% at day -1.
[27] See examples from ICICI: https://www.icicidirect.com/faqs/fno/will-these-margins-be-levied-during-the-day-or-at-eod-where-can-i-see-the-required-delivery-margin and Upstox: https://community.upstox.com/t/important-update-on-physical-settlements-of-contracts-with-a-march-2025-expiry/8574.

We exploit the fact that the delivery margin requirements primarily apply to the in-the-money positions as they are subject to actual physical delivery. Certain at-the-money positions may be affected as well given their greater likelihood of closing in the money.[28] We also note that these requirements apply to options on individual stocks and not options on the indexes – presumably given the enormous complications associated with basket delivery and the absence of delivery options in treasury futures. Thus, our analysis in this section is based on options on individual stocks, which are a smaller 25% slice of the options market in India.

As before, we investigate investor trading behavior one year before and one year after the implementation of the physical settlement rules. We classify a trade as an out of the money (OTM) trade if the premium weighted moneyness is below −5%. These trades are substantially out of the money and have little risk of being subject to delivery margin requirements. Figure 10 shows the pre- and post-event trading volumes on in-the-money (ITM) and out-of-the-money (OTM) options as options approach maturity.[29] The top part, Figure 10A, shows that trading volume increases as options near maturity, as we saw before for index options. However, this pattern is reversed after the rule change: volume decreases as we approach option maturity. The maturity date volume for ITM options after the event shows a reduction of 70% from the level before the rule change. Turning to OTM options in Figure 10B, the trading volume decreases as options are near maturity, but this pattern holds both before and after the shock. The settlement rule change does not impact OTM options; if anything, the post event volume shows a 55% increase in maturity day volume

[28] For example, the broker Zerodha considers strikes close to the last traded price and up to three out-of-the-money strikes from the last traded price. See https://support.zerodha.com/category/trading-and-markets/margins/margin-leverage-and-product-and-order-types/articles/policy-on-physical-settlement.

[29] We display the notional volume because the premium volume on OTM options has a mechanically decreasing component as options move to maturity. Regressions that include contract fixed effects control for option features.

from the pre-event level. The results are consistent with the view that financial constraints matter and drive the nature and extent of retail options trading.

Our next tests focus on trader style. We first rank all investors who traded single stock options in the pre-event period by the average time to maturity of their traded positions. We identify investors who rank in the bottom 25% of the population as treated investors. These traders traded shorter maturity options, perhaps reflecting the unavailability of funds or the unwillingness to deploy them due to self-imposed constraints on longer-maturity positions.

Columns (1) to (3) in Table 5, Panel A show that the treated group does not decrease trading volumes. Instead, they increase volume in economically significant ways. For example, the premium volume for the treated group increases by INR 0.42 million, equivalent to 22% of the sample average, in the post-event year. In untabulated results, we find that the treated investors show a moderate increase in the contract and notional volumes in index options, although the premium volumes are flat, suggesting yet again that there is speculation *shifting* to index options that have lower contract prices. The shift is not profitable with INR 23,984 loss per trader as indicated in Column (4).

Why do the treated investors increase their trading volume relative to the controls, rather than decrease? We next examine activities at the contract level, using contract fixed effects specifications that control for features such as contract-specific strikes, interest, and notional value. Panel B of Table 9 reports the results. The treated group shows greater demand for OTM options after the new margin rules come into effect. The estimates on $treat \times post \times otm$ suggest an increase of 470 contracts on a given option series or 15.4% of the sample mean. The underlying notional volume in Column (2) also indicates a similar change in demand for OTM options.[30] In contrast,

[30] The premium volume is absent from Panel B because it is highly correlated with moneyness (and thus OTM).

the estimated coefficient on *treat×post* is negative for both the contract and notional volumes, indicating that the treated investors indeed decrease their trading volume relative to the controls on ITM options, yet their greater shift into OTM options lead to an overall increase. Finally, Column (3) shows that the trading in OTM options concentrates in the ones with low contract prices (coefficient for the variable *Contraprice*). The rule change also leads to a systematic shift to trading OTM options, as indicated by the positive and significant coefficient on *post×otm*.

Faced with financial constraints that aim to reduce speculation, we see that investors continue and shift speculative activities. The new options they move to are deeper out of the money options that have less risk of physical delivery and thus mitigate the need for cash financing or stock positions. Constraints matter: they alter the nature of speculative activity of traders.

V. Other Analyses

A. Trader Entry into and Exit from Options

We examine the propensity of retail investors to enter options trading. In particular, we are interested in whether investors gather experience in the stock market before entering options, and if so, what type of formative experience is likely to drive entry into options. The results are based on a random 10% sample based on all IDs in our database. We cross-verify the results in a second 10% random sample.

For each trader in each month, we calculate measures based on the prior three months of stock trading activity. The variable *Performance* measures the retail investor's stock trading performance. For each stock trade, we calculate its raw return from the day of trading until the end of the month and subtract the market return (proxied by the return on the NIFTY50 index) over the same horizon and value weight the risk-adjusted returns by trading volume over the past 3 months. We construct two other variables, viz, *Highperf* and *Lowperf*, which are indicators for the top and bottom deciles of *Performance* among all traders during a given month. Following Bali, Cakici, and Whitelaw (2011), we compute the variable *Maxret*, which is the trade-volume-weighted maximum return of a stock that serves as a proxy for stocks with lottery-like features. To measure the risk of traded stocks (*Retvol*), we first compute the stock volatility at the stock level using daily stock returns over the last 3 months, then aggregate the stock volatilities to the investor level by value weighing the volatilities by the investor's trading volume on the stocks. *Stockvol* is the logarithm of the past three months of stock trading volume. Finally, *Experience* is the number of months since the trader started trading stocks. If the trader has no stock trading activity during the last three months, all the measures are set to zero. Our results are robust after excluding no-trade observations. *Entry* is a dummy variable that is zero for all months before a trader enters the options market and one for the month of entry.

Panel A of Table 6 reports the estimation results of a linear probability model of trader entry. We observe a negative coefficient on *Performance* in column (1), suggesting that traders who entered options trading had *worse* stock trading performance. This is further evidence of a betting motive for retail traders' participation in options: traders use options to double down and bet when they experience losses. Rational learning models in stock trading (e.g., Seru, Shumway, and Stoffman, 2010) suggest that losses modulate trader stock investments, especially in risky assets. Access to options appears to inhibit learning, instead inducing risk-taking as a response to losses. Likewise, column (2) shows that *Highperf* reduces probability of participation while *Lowperf* increases participation probability. The economic magnitudes are significant. The mean value of *entry* is 0.004, which implies that *Lowperf* increases the probability of entry by 50% and

Highperf reduces the probability by 25%. Thus, good performers in the stock market are less likely to enter the options market while losers from the stock market gravitate towards options trading.

Stock characteristics are also informative. Trading more volatile stocks (*Retvol* in columns (1) and (2)) and lottery stocks (*Maxret* in column (3)) are both associated with greater probability of initiating option trading. Since return volatility and max returns are highly correlated, in column (4) we use indicator variables to separate their effects. Specifically, *Highretvol* is an indicator variable for whether *Retvol* is above the 75th percentile but *Retmax* is below its 75th percentile. Analogously, *Highretmax* is a proxy for *Retmax* (*Retvol*) above (below) the 75th percentile. *Highretvol&max* is an indicator for both *Retvol* and *Retmax* being above their 75th percentiles. The results in column (4) demonstrate that trading in more volatile stocks, lottery stocks, and stocks with both features increase participation probability.

The remaining variables indicate that options trading initiators have greater stock trading volume, but a shorter history in stock trading. These results seem consistent with trader overconfidence seen in stock market trading (Odean, 1999; Barber and Odean, 2000). Overall, the entry results indicate speculative and gambling for resurrection motives for trading options.

We now consider trader exit. In each month, traders are sorted into 16 groups based on quartile sorts (independent, instead of sequential) of premium volume and trading returns as shown in the upper panel of Panel B, Table 6. We estimate the probability of continued participation in options markets in the next month. The middle panel shows the attrition rate of traders for each group. We observe that the attrition rates are negatively related to past performance: those with the better past performance are more likely to continue, and worse performers in the previous month are more likely to abandon. However, continuation does not guarantee future performance, as evidenced by the bottom part of Panel B. Traders extrapolate their ability from their past successes without any evidence for skill persistence.

B. Single Stock Options

Single stock options are relatively small in the Indian options market, accounting for less than 25% of the premium volume. The statistics in Table 2 include the positions taken by traders for single stock options. The most popular position taken on single stock options is long call, followed by long put, short call, and short put, all on only one option series. Other than those strategies, the most prevalent strategies are volatility strategies in both single stock options and index options, which account for 5.8% and 12.5%, respectively. Complex strategies such as simple call spreads (1.16%) and simple put spreads (0.49%) are a small fraction of retail options activity.

The statistics in Table 2 do not include day trading. However, within the day trades, most of the investors also use simple strategies. For example, 63% of the trades correspond to purchase and sales of only one call option series and 26% correspond to purchase and sales of only one put option series. 3.6% (1.2%) of the trades are due to purchases and sales of two call (put) option series. Thus, about 93.8% of day trading activities are simple unhedged directional strategies.

Next, we consider the strategies of traders who trade both in the index and individual stock options to examine if what we call speculation reflects cross-hedging across asset classes. For example, investors may take positions in individual stock options and eliminate market risk by cross-trades in index options. While we considered this implausible given the evidence on speculation and the sheer size differences between the markets, we briefly consider this possibility. 74% of the single stock positions do not have any end-of-day open interest on index options. Of the remaining 26%, 56%, or more than half bet in stocks and indexes in the same direction. Thus, we estimate that the lower bound for *not* using index options for cross-hedging purposes is 88.56% (74%+26%×56%). We find that 21% of stock option positions involve index bets in the opposite direction, so cross-hedging accounts for a small 5.46% (26%×21%) portion of the options volume.

What stock options attract retail trader interest? Following Roll, Schwartz, and Subrahmanyam (2010) and Johnson and So (2010), we compute the option-to-stock ratio (O/S) by scaling the options volume by the stock volume for better comparison across different stocks. We focus on a sample of single stock options trading prior to 2019 due to the settlement rule change discussed in Section IV.C. Table 7 reports the results. The *high* stock price indicator is statistically significant, indicating greater trading on options whose underlying stocks have a high price per share. The top 90th percentile is roughly INR 2,000 per share. Thus, retail investors seem to seek the leverage embedded in options to lever up capital and gain exposure to high priced stocks; they do not "double up" lottery features of stocks with lower prices. Second, retail investors prefer options with shorter maturity and cheaper nominal prices, consistent with financial constraints at play in determining speculative motives. The coefficient on lag return is negative, indicating down movements driving put demand, although the result on call demand is insignificant, i.e., trend chasing is not a dominant driver of the names in which retail traders exhibit options interest.

C. FinTech brokers

As in the U.S., India has also witnessed rapid growth of discount brokers based on "FinTech" that facilitate trades through low commissions, the ability to execute complex strategies with a single click, and mobile-centered platforms. For example, Zerodha, a FinTech broker, provides a "Kite Connect" API to build, back test, and execute algorithmic trades based on userdefined rules. The brokerage platform is often used to suggest ideas to investors. Do these business practices correlate with investor trading styles? We consider some evidence on this issue.

Our dataset identifies the brokers through which trades are executed. We note that the practices of payment for order flow and execution through dark pools have not developed in India, so the broker identifiers for trades are accurate. We have 4 FinTech brokers in our sample. The growth of FinTech brokers is evident within our sample period. Figure 11 shows that both the premium and notional volumes grow particularly rapidly for FinTech brokers starting around January 2020. Within about six months, the volume through the 4 FinTech brokers (5paisa Capital, Zerodha, Angel One, and Choice Equity) exceeds that for *all* other brokers put together. The combined market share of FinTech brokers is over 60%.

Our dataset allows us to identify investor-broker pairings. Approximately 2 million traders ever used FinTech brokers, 155,000 traders switched from traditional to FinTech (and never used traditional brokers afterwards in our sample period), 52,000 from FinTech to traditional (and never used FinTech afterwards in our sample), and 418,000 used both types of brokers.

Panel A of Table 8 depicts daily premium volume for a particularly interesting set of investors, the ones who use both traditional and FinTech brokers. When the traders in this sample switch from traditional to FinTech brokers, their trading volumes increase by 55%. Conversely, traders who switch from FinTech back to traditional brokers show a 17% reduction in volume. These findings indicate that the FinTech broker volume is not merely a reflection of increasing volume over time. Finally, for the 418,000 investors who use both traditional and FinTech brokers, the volume is 31% more on FinTech brokers.

We estimate both trading volumes and profits for trades conducted via FinTech and traditional brokers. Panels B and C of Table 8 report these results in terms of regression coefficients. In Panel B, we do not have trader fixed effect while Panel C leverages the panel feature of the data and includes investor fixed effects. The individuals not dropped from this regression trade both at FinTech and non-FinTech brokers. We find that traders place more bets and lose more for orders via FinTech brokers. The economic magnitude is stronger when we include trader fixed effects in Panel C. For example, the premium volume via FinTech brokers is INR 2.78 million greater than that through traditional brokers. This amount is economically significant; it represents about 81% of the average premium volume of INR 3.42 million for this group of traders. The contract and notional volume both show similar results. The differential performance of trades through FinTech brokers is positive, with an estimated return differential of 1.65%. However, the net effect of greater participation and smaller loss conditional on trading is negative, e.g., the switchers lose INR 24,159 more for orders placed via FinTech platforms.[31]

VI. Concluding remarks

Our study examines retail participation in the options market from India. While India has had high levels of financial exclusion, home to the world's highest population of unbanked individuals for several decades, digitization has transformed this landscape. A major facet of this expansion is a boom in retail investor participation in options markets. The Indian derivatives market has been the largest for several years and the recent surge in retail investing has increased India's share to 80% of the global options contract volume.

We study retail options trading using a panel dataset of all retail trades in options from this market at the investor-contract-day level. We find that retail option trading concentrates in

[31] Interestingly, the FinTech broker effect is different from the non-effect of stock app adoption (Liu, Mithas, Pan, and Hsieh, 2024). The App (non)-result may not be surprising, given the ubiquity of Apps and mobile platforms. In our view, the results indicate that the entities behind the tech – rather than the tech itself – matter.

index options, a feature now being observed in other markets now. In the Indian markets, retail volume also constitutes a large fraction of the aggregate market volumes, reaching 42% for options with zero days to expiry (ODTE) towards the end of our sample. We show that retail options trading reflects significant short-termism. Day trading is rampant. Moreover, retail trading begins to increase about 5 days prior to expiration and spikes as options approach 0DTE. The remaining trades typically reflect simple directional bets on the underlying index. These trades are not profitable: retail investors lose significant amounts of capital in each year of our sample.

We consider natural experiments in the shape of supply-side shocks to options markets. One experiment that introduces a cycle of weekly index options on a different and narrower index. We see increased participation in the short-term options both at the extensive and intensive margins. New traders enter the short-term options markets and traders already in the market increase trading, to the point that volumes in new weeklies quickly exceed those with monthly cycles. Thus, the supply of short-term speculative opportunities seems to create its own demand.

Two other experiments attempt to reduce speculation by erecting financial barriers through an increase in the minimum lot size and through stock or cash margin deposits for any open in-the-money options. Here, we find evidence of speculation shifting to other "cheaper" options. These positions generate additional losses, especially for small traders who exhibit preferences for short term cheaper contracts. Speculative habits seem hard to erase once they take root, even if the habits cause financial harm, as in our sample.

Our study suggests avenues for future research. One side effect is the issue of wealth redistribution. The high speculative volume by retail traders creates excess liquidity in the options market and opens the door for profitable arbitrage trades between options and the underlying and wealth transfers from retail investors to sophisticated institutions. This issue has attracted considerable attention in the press and is under investigation by India's securities regulator, SEBI.[32] While the household finance literature has examined the portfolio benefits of financial inclusion, our study suggests that the effect of stimulating stock market participation on initiating trading habits, the persistence of these habits, and financial well-being are interesting research questions. Another open question is whether the negative wealth effects of speculative trading extend to health and other dimensions of well-being. We leave these issues to future research.

[32] Following up on a cautionary note on June 2, 2025, from the stock exchange, the regulator SEBI passed Order WTM/AN/MRD/MRD-SEC-3/31516/2025-26 that restrained JS Group from trading and impounded $500 million out of estimated profits of over $4 billion from such arbitrage activities.

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Figure 1: Retail options market participation

This figure shows retail participation in the options market over time. Retail traders are traders with “Individual” flags in the database, excluding those who rank in the top 1% by the rolling past 6 months’ total trading volume, and those with small trading volume of less than 5,000 rupees of premium turnover during our entire sample period. The four subplots show the monthly numbers of active retail options traders, total numbers of contracts traded, total premium paid and received, and total notional amount traded, respectively. The notional value is equal to the number of contracts traded in a day multiplied by the closing price of the underlying security or index. The trading volume numbers are aggregated across all trading days and all retail traders in a month.

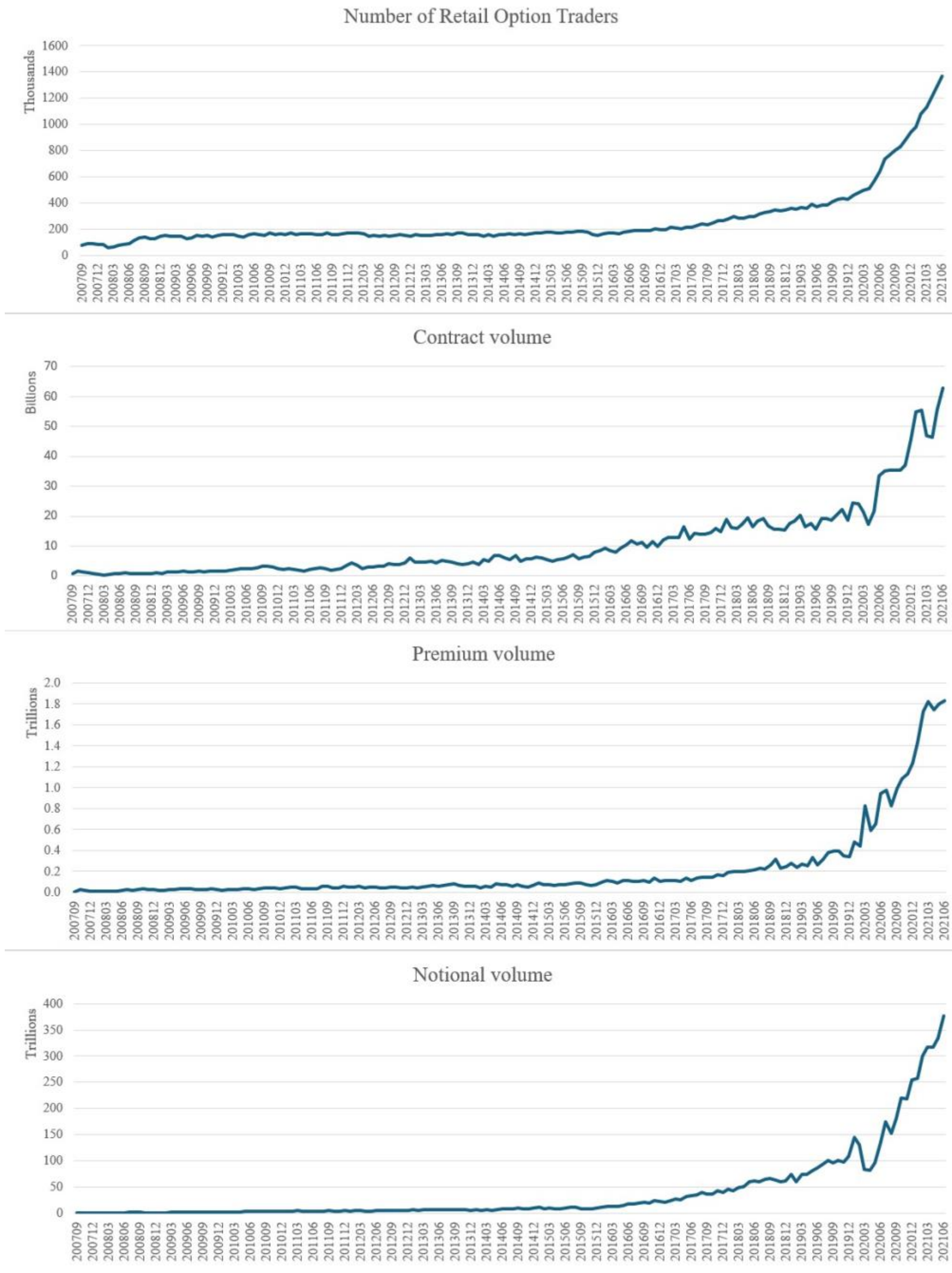
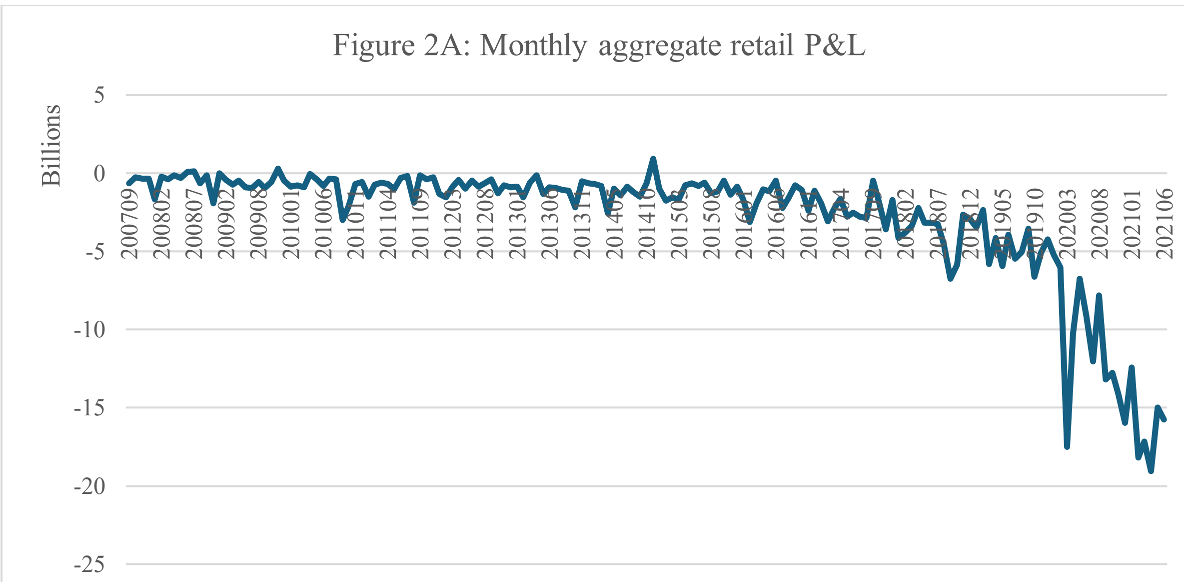


Figure 2: Trading Profits and Losses and returns

Figure 2A shows the monthly aggregate profit and loss (P&L) for retail option trades. For each trader and contract, profit or loss is the total sale price minus the total purchase price if the positions are completely closed out before maturity, or if not completely closed out, plus the settlement P&L. The profits and losses of all retail investors on all contracts expiring in each month are then aggregated to compute the aggregate monthly profit or loss figures for a given expiry month. In Figure 2B, Traders are ranked into deciles based on their total premium volume in the cross-section. Within each decile, the plot shows the average return of investors, and the one-standard deviation confidence intervals. The return for each trader is their total P&L scaled by the total amount traded, defined as the total premium paid and received plus the absolute value of the settlement amount.



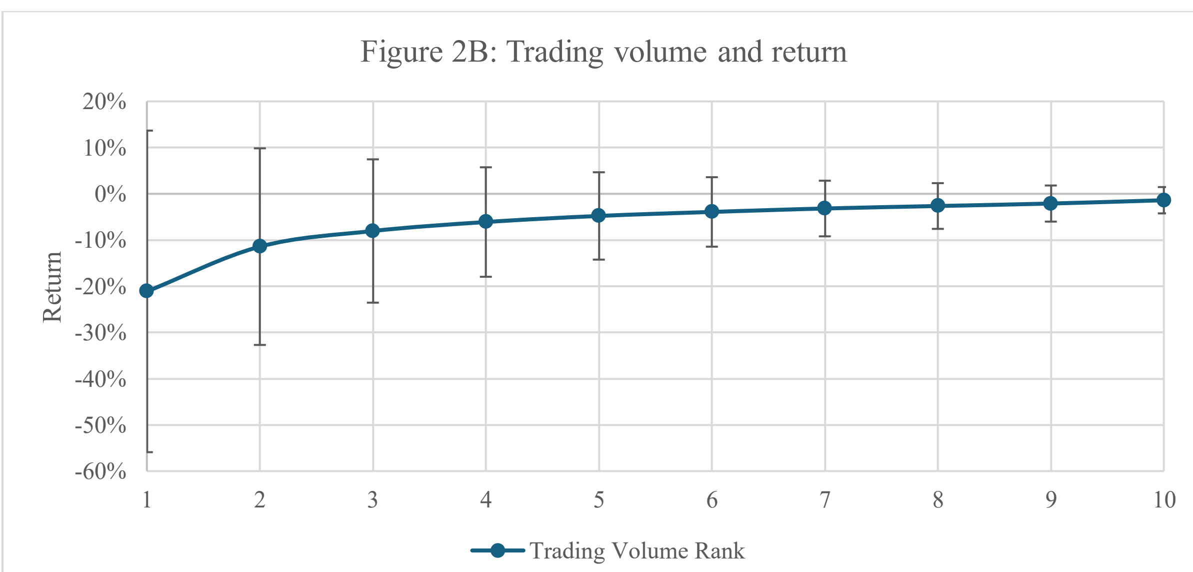
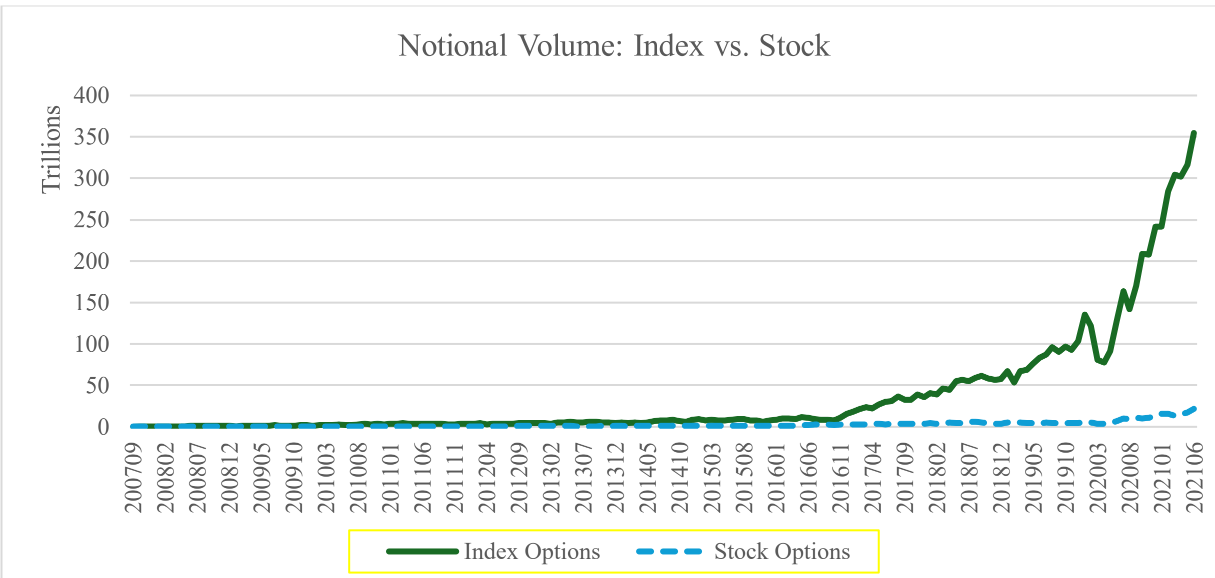
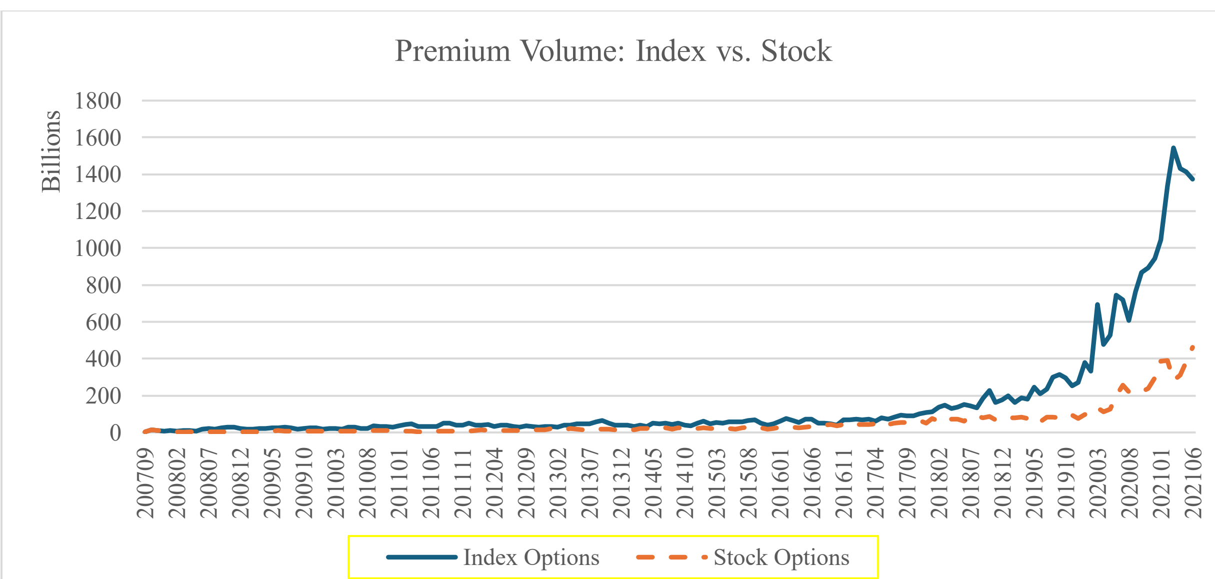


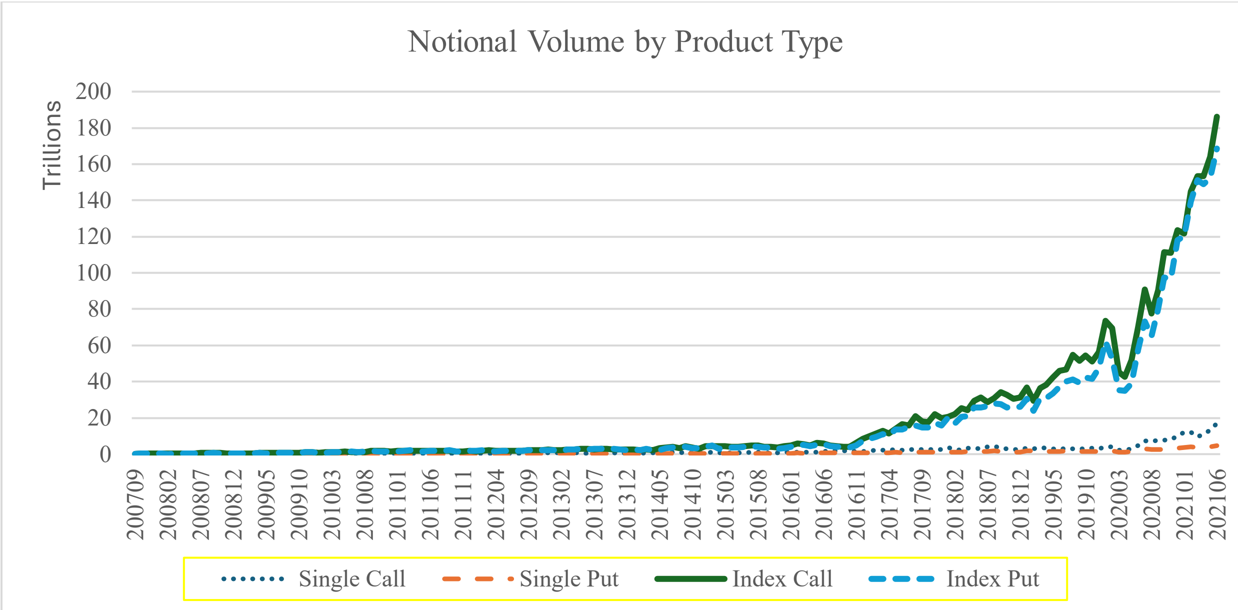
Figure 3: Trading volume on index and single stock options

In figure 3A, the first two subplots display the retail option trading volume on index options (solid lines) and single stock options (dashed lines), measured by the notional amount of the underlying securities traded and the premium paid in each month. The next two figures display the trading volume by each product category. The dotted, dotted-dash, solid, and dashed lines are trading volumes for single stock call options, single stock put options, index call options, and index put options, respectively. In figure 3B, the first subplot shows the proportion of traders who trade only index options, only single stock options, or both in each month. The second subplot shows the proportion of traders who trade only call options, only put options, or both in each month.

Figure 3A: Trading volume on different products






Notional Volume by Product Type
Trillions
200
180
160
140
120
100
80
60
40
20
0
200709
200802
200807
200812
200905
200910
201003
201008
201101
201106
201111
201204
201209
201302
201307
201312
201405
201410
201503
201508
201601
201606
201611
201704
201709
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201812
201905
201910
202003
202008
202101
202106
Single Call
Single Put
Index Call
Index Put

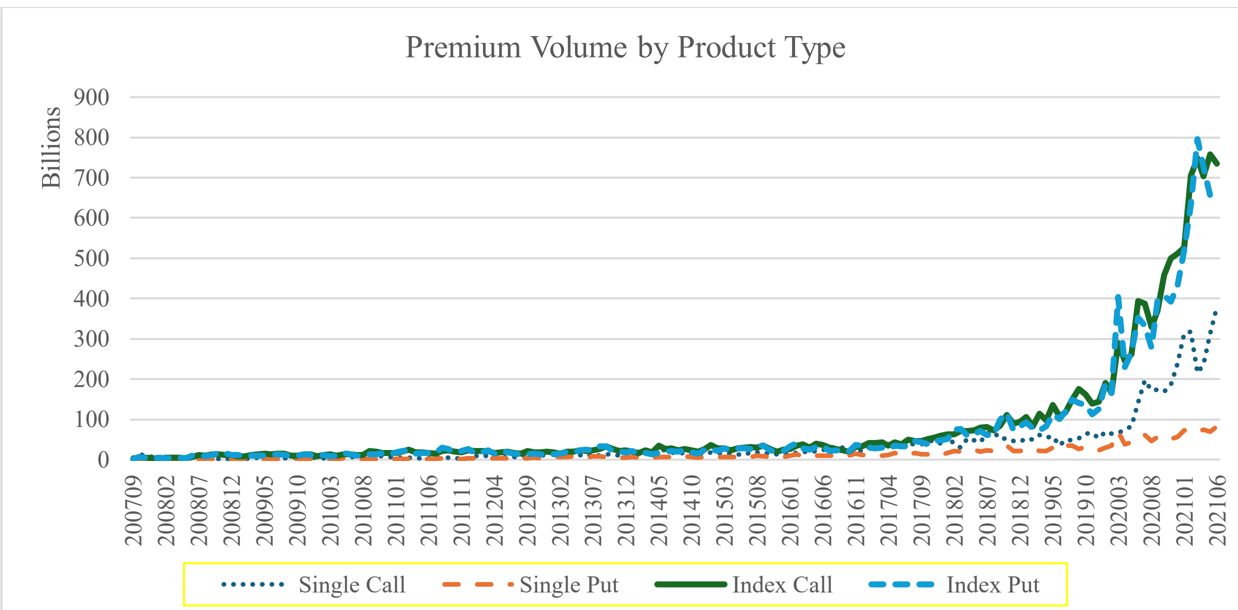
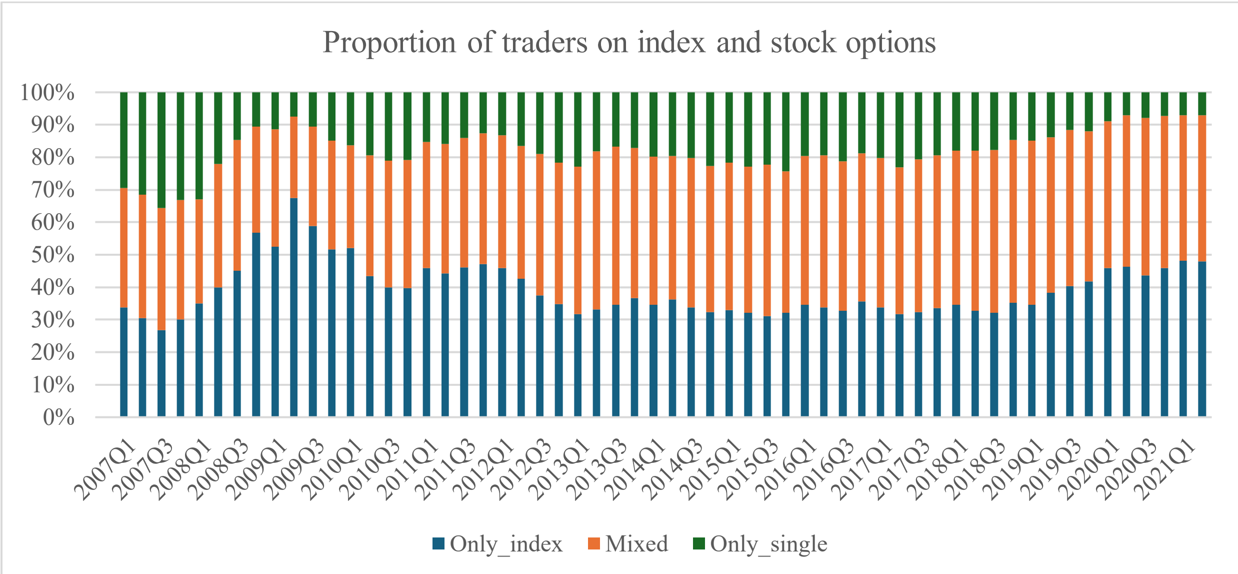

Premium Volume by Product Type
Billions
900
800
700
600
500
400
300
200
100
0
200709
200802
200807
200812
200905
200910
201003
201008
201101
201106
201111
201204
201209
201302
201307
201312
201405
201410
201503
201508
201601
201606
201611
201704
201709
201802
201807
201812
201905
201910
202003
202008
202101
202106
Single Call
Single Put
Index Call
Index Put

Figure 3B: Fraction of traders on different products



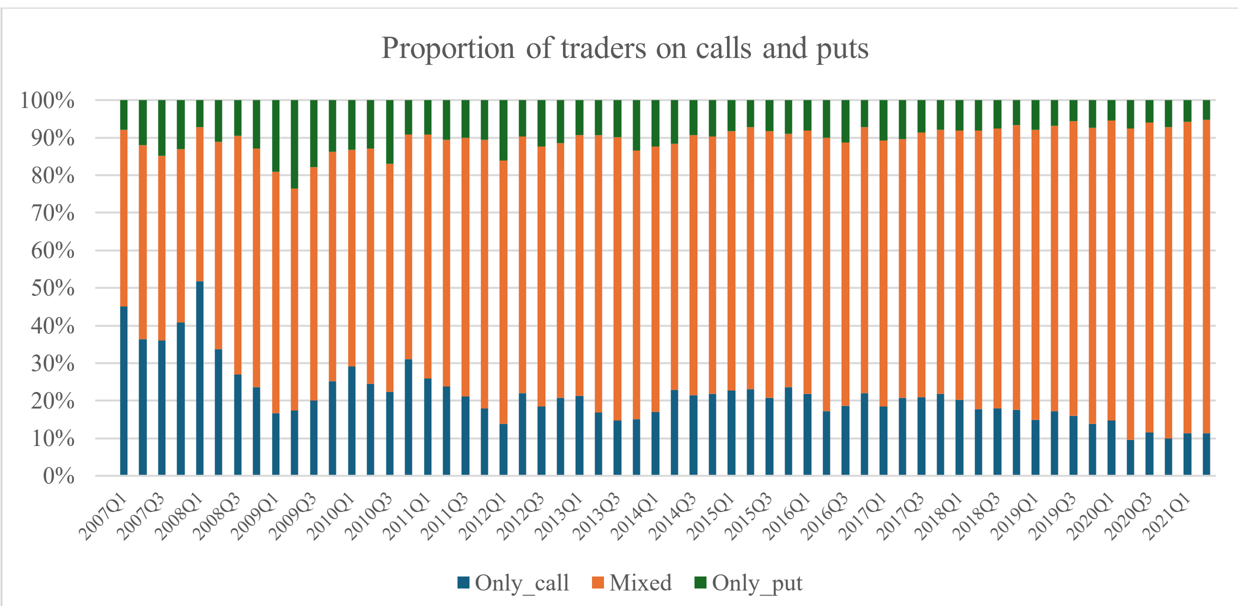


Figure 4: Time to maturity and trading behavior

Figure 4A shows the proportion of index options trading volume (left y-axis), and the duration for holding the position (right y-axis), for different tenor (remaining time to maturity) on the x-axis. The trading volume for each maturity date is the value of the securities underlying the traded options, scaled by the total volume across all maturity days. Trade duration for each investor on each contract is the number of days from the first day when an investor starts trading a contract, to the complete closure of the trading position; or if the position is not completely closed before option maturity, to the expiration date of the contract. Options mature on Thursdays and days 4, 5, 11, and 12 are omitted because they correspond to weekends. Figure 4B shows the notional volume generated by new and old traders. The new traders are those who first ever trade a given contract at a given time to maturity.

Figure 4A: Volume and duration for different times to maturity

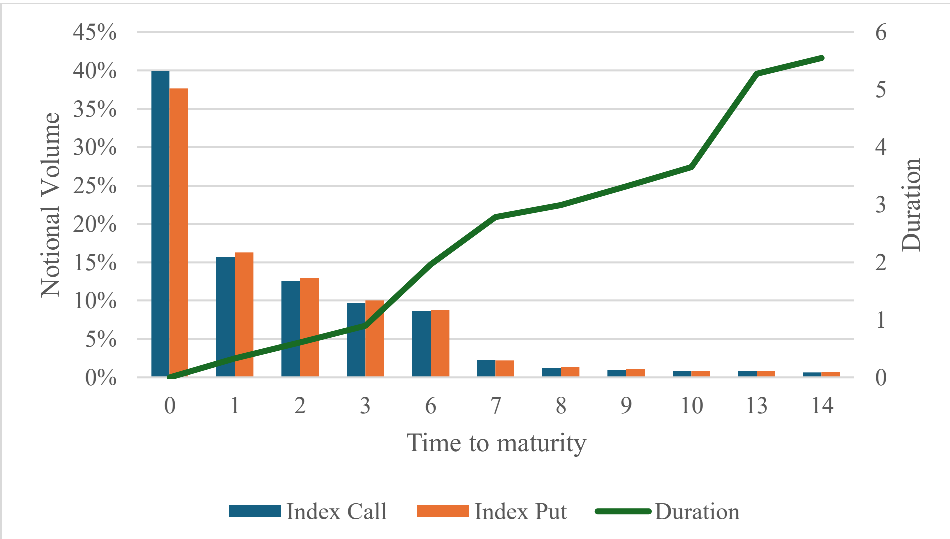


Figure 4B: Volume by new and old traders

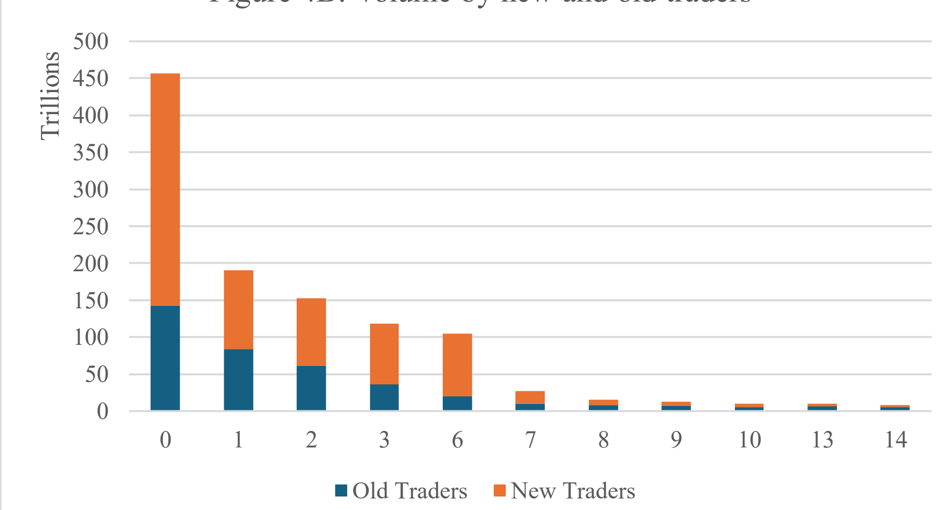
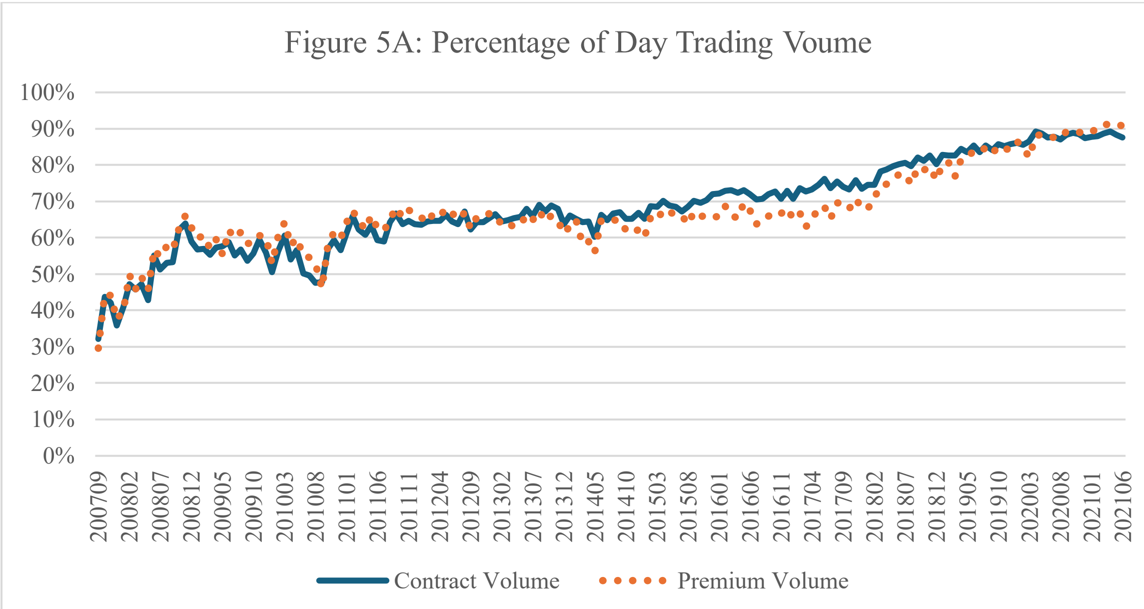
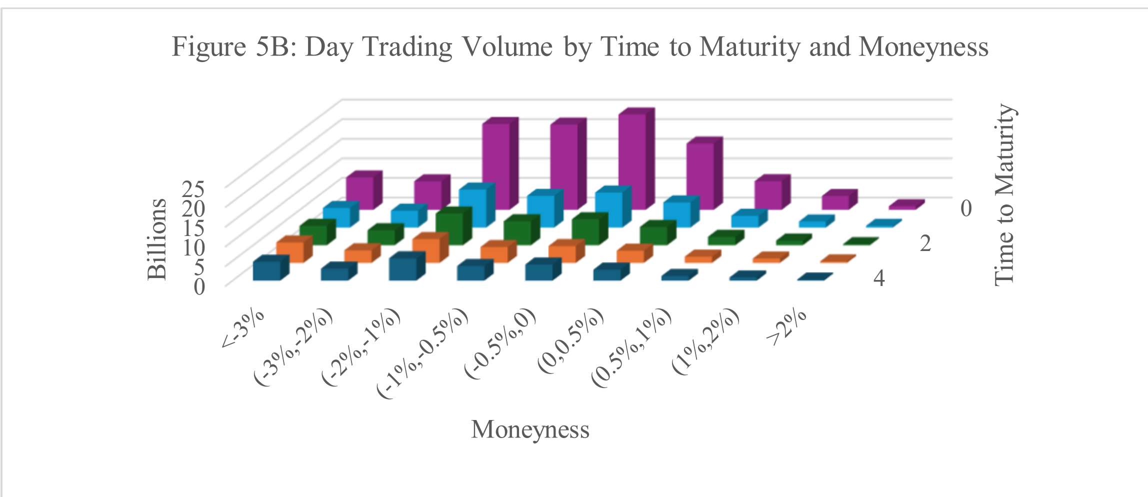


Figure 5: Day trading

Figure 5A displays the day trading volume as a percentage of total trading volume over time. Day trading is defined as the lesser of the amount of purchases and sales on a contract for a trader during a given day. Figure 5B reports the day trading contract volume by different levels of moneyness and time to maturity. Figure 5C reports the fraction of day trading contract volume relative to the total volume by different levels of moneyness and time to maturity.





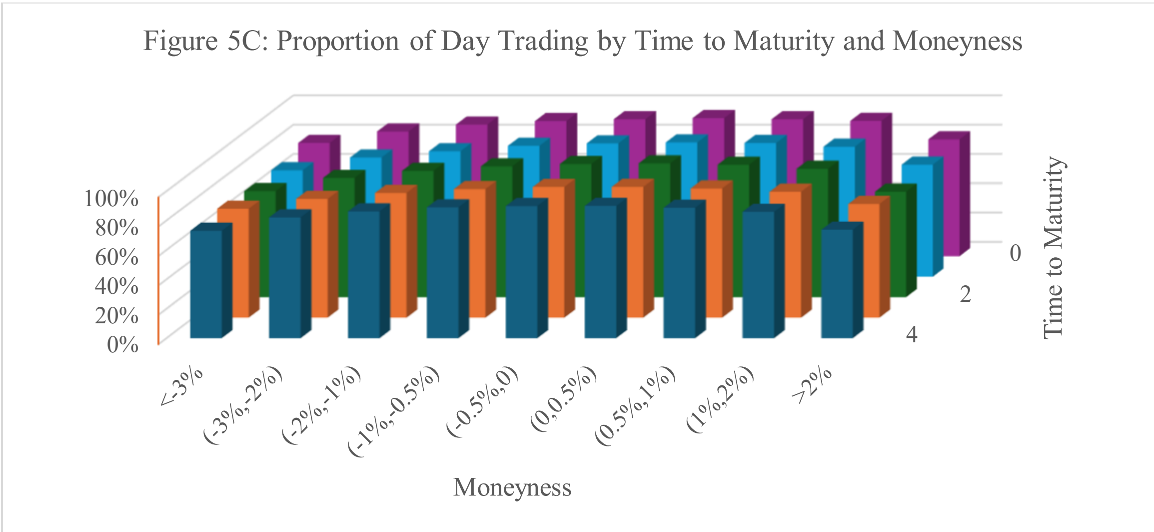
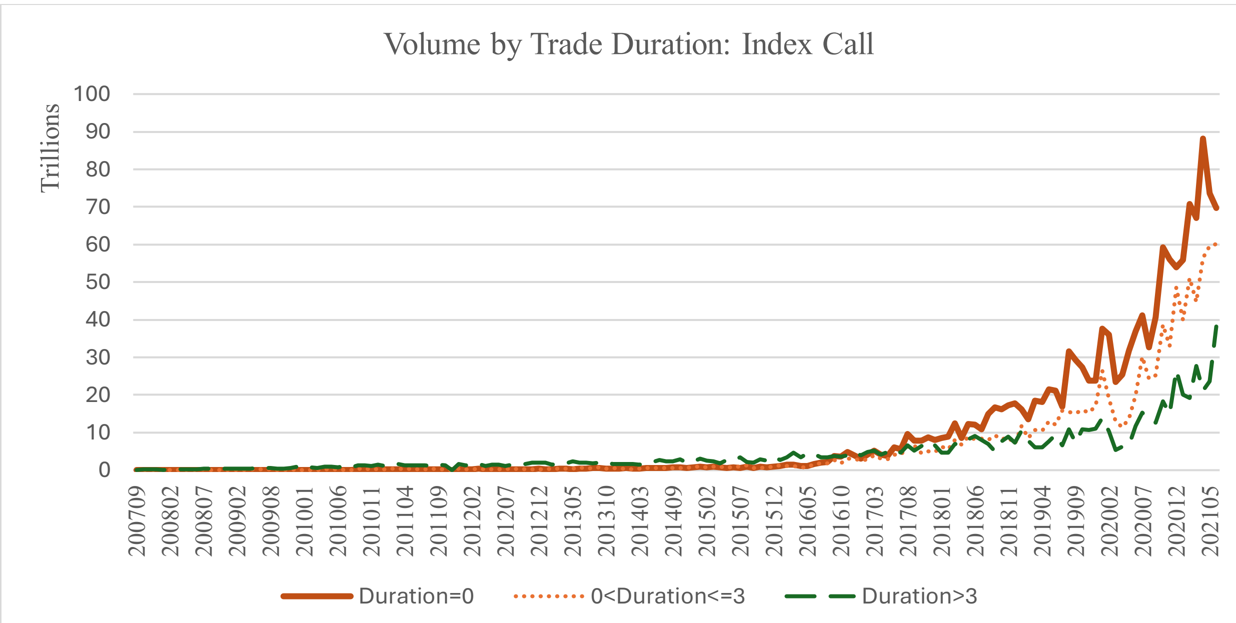


Figure 5C: Proportion of Day Trading by Time to Maturity and Moneyness
100%
80%
60%
40%
20%
0%
<-3%
(-3%,-2%)
(-2%,-1%)
(-1%,-0.5%)
(-0.5%,0)
(0,0.5%)
(0.5%,1%)
(1%,2%)
>2%
Moneyness
0
2
4
Time to Maturity

Figure 6: Trading volume and trade duration

Trade duration for each investor on each contract is the number of days from the first day when an investor starts trading a contract, to the complete closure of the trading position; or if the position is not completely closed before option maturity, to the expiration date of the contract. The trader-contract observations are then classified into 3 groups: trade duration of zero, between 0 and 3 days, and over 3 days. The solid, dotted, and dashed lines show the monthly aggregate trading volume of those three groups, respectively, where the trading volume is measured by the notional value of the underlying securities.



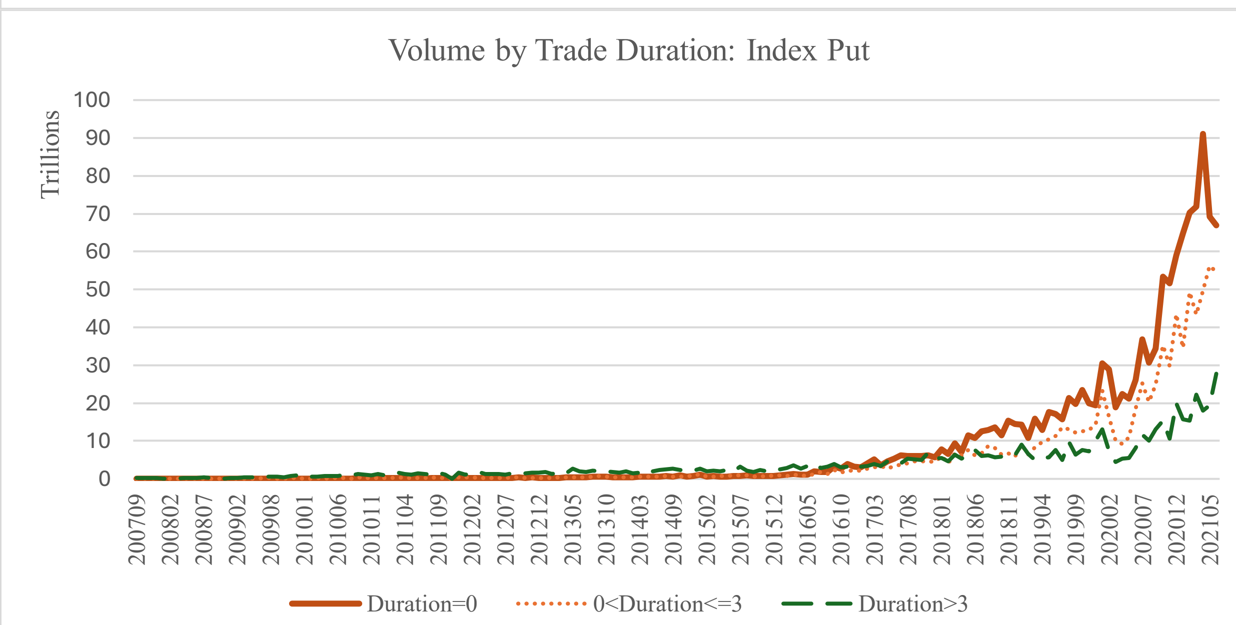
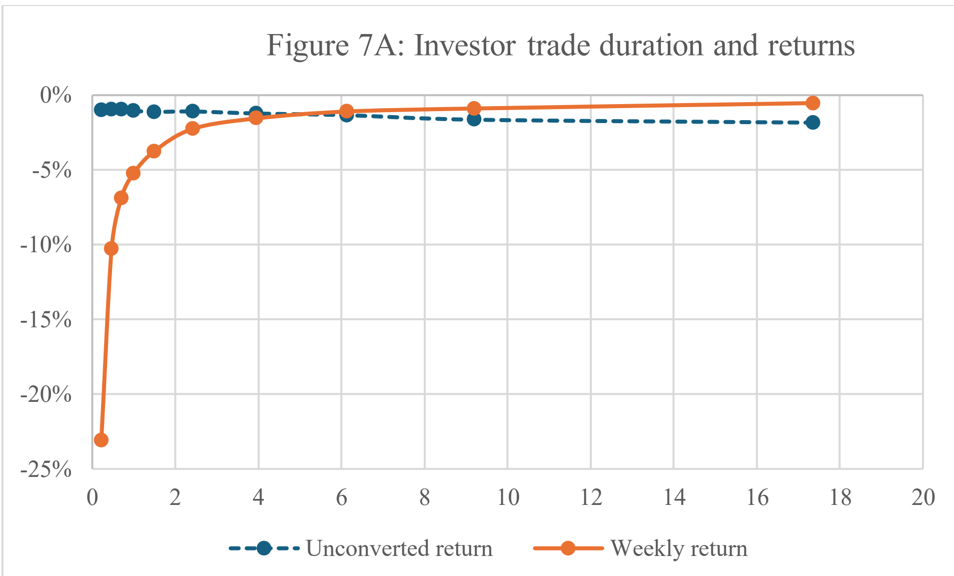


Figure 7: Trader duration and returns

In Figure 7A, traders are ranked into deciles based on their average trade duration. Within each decile, the plot shows the average trading return of investors (unconverted return), and the returns converted to the weekly horizon (weekly return). The weekly returns are equal to the unconverted returns scaled by the average trade duration within each investor group, then multiplied by 5, the number of trading days in a week. The x-axis is the average trade duration within each investor group, and the y-axis is the returns in percentage. Figure 7B reports the breakdown of total trading P&L into those from day trading and those from the non-day trading activities. The P&L due to day trading for a given trader on a contract is min (buy share, sell share) × (sell price−buy price). The P&L from non-day-trading activities is the total P&L minus the day trading P&L.



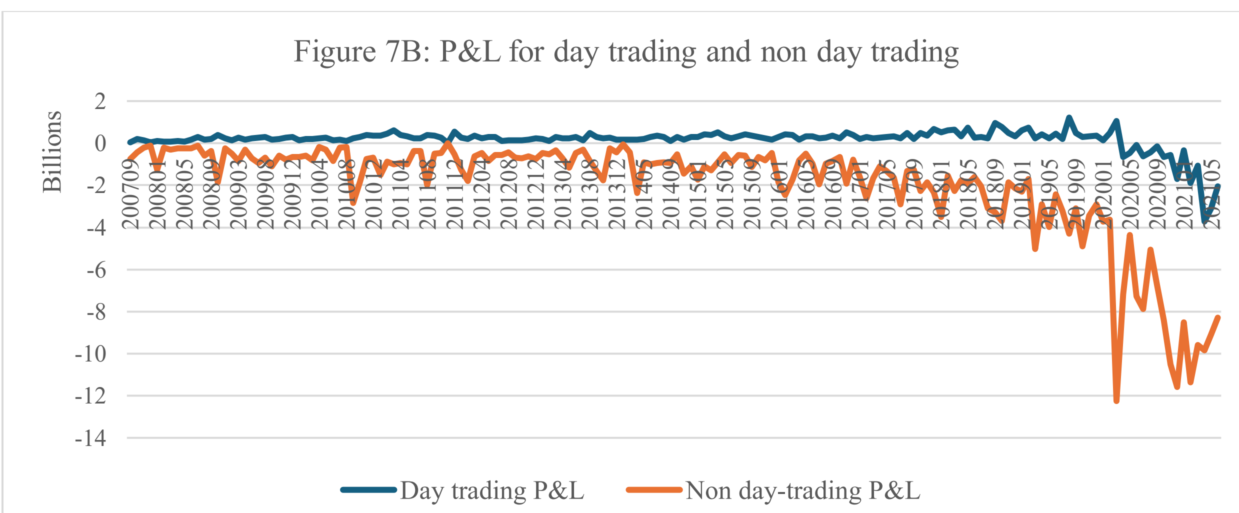
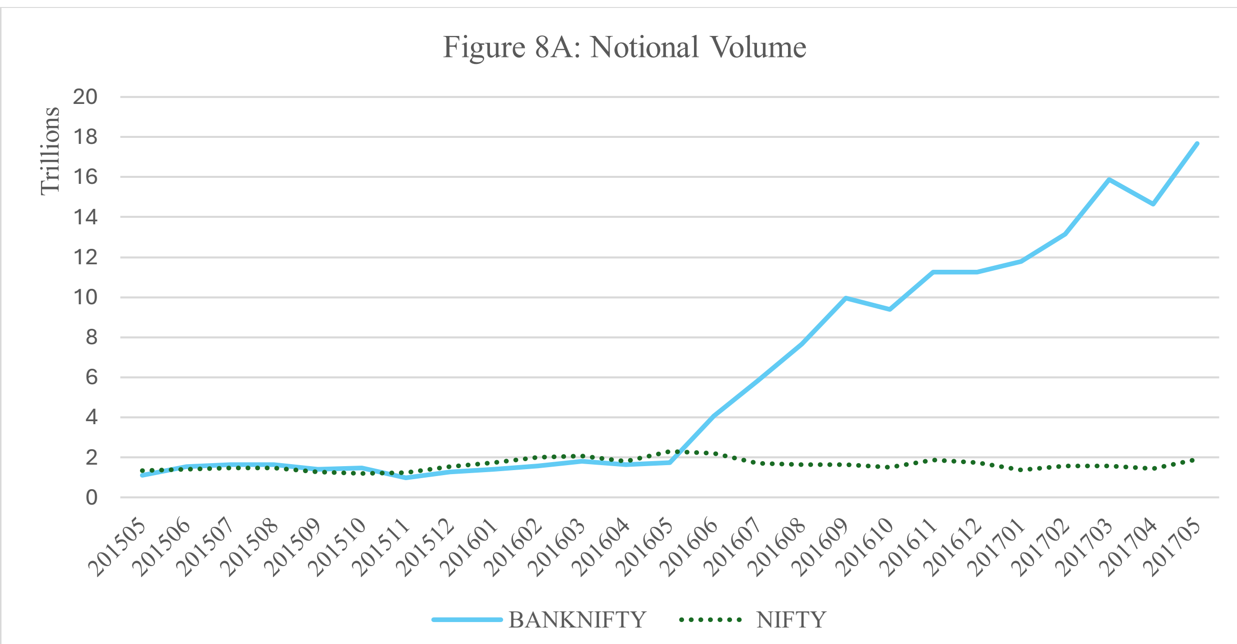


Figure 8: Introduction of weekly BANKNIFTY

Figures 8A and 8B show the monthly aggregate retail notional volume and premium volume, respectively, around the introduction of BANKNIFTY weekly contracts in May 2016. The volume of NIFTY50 contracts is scaled by 5 for expositional purposes. Figure 8C shows the number of traders trading each type of contract. The number of NIFTY50 traders is scaled by 3 for expositional convenience. In Figures 8D through 8F, the old (new) investors are defined as those who traded (not traded) BANKNIFTY options in the pre-event period. Figure 8G shows the net stock investment around entry into BANKNIFTY options. New investors are defined as those who began BANKNIFTY trading during the three years following the introduction of weekly contracts (May 2016–April 2019) but had not traded options beforehand. For each trader, net stock investment is measured as monthly net shares purchased, scaled by the average of purchases and sales, over the two years surrounding their entry. The figure plots the dynamic treatment effects based on a difference-in-differences model, where the not-yet-participated investors are in the control group, and the entry month is omitted and serves as the benchmark. The error bars denote the band for one-standard deviation.



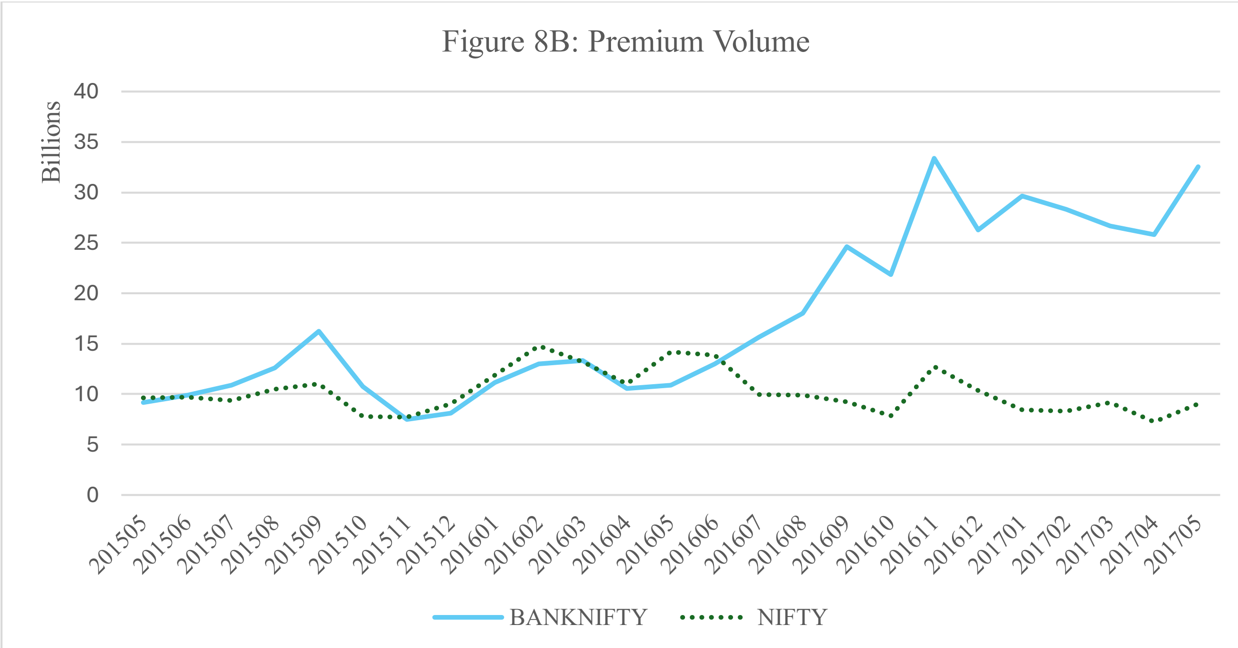


Figure 8B: Premium Volume
Billions
40
35
30
25
20
15
10
5
0
201505
201506
201507
201508
201509
201510
201511
201512
201601
201602
201603
201604
201605
201606
201607
201608
201609
201610
201611
201612
201701
201702
201703
201704
201705
BANKNIFTY
NIFTY

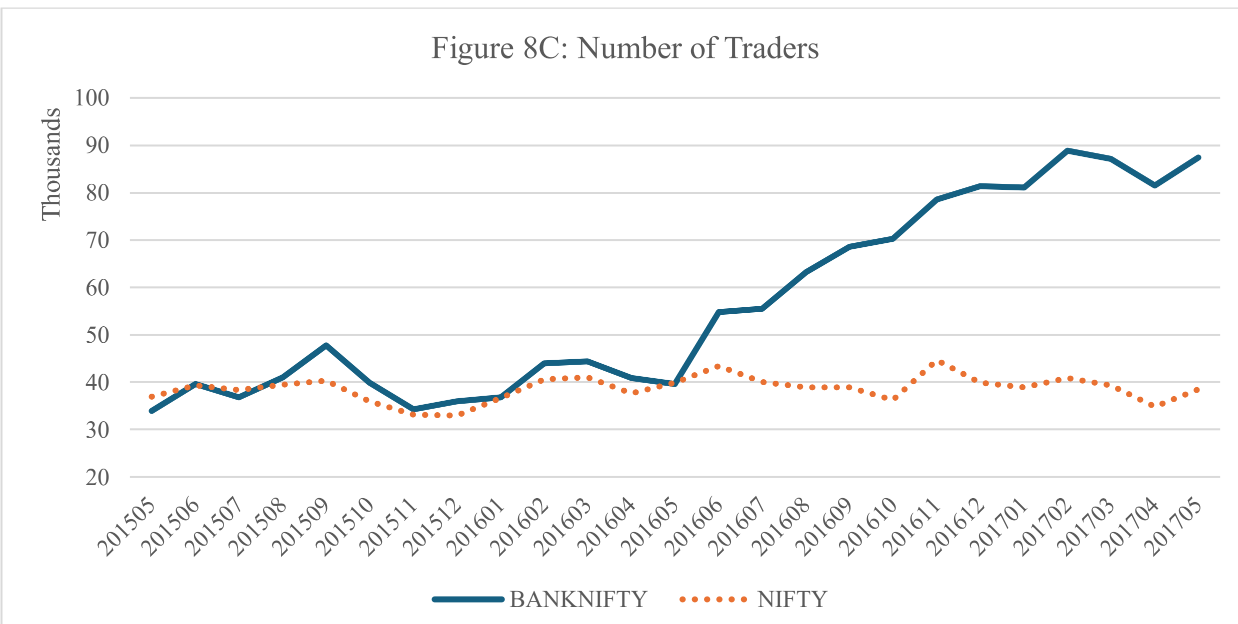


Figure 8C: Number of Traders
Thousands
100
90
80
70
60
50
40
30
20
201505
201506
201507
201508
201509
201510
201511
201512
201601
201602
201603
201604
201605
201606
201607
201608
201609
201610
201611
201612
201701
201702
201703
201704
201705
BANKNIFTY
NIFTY

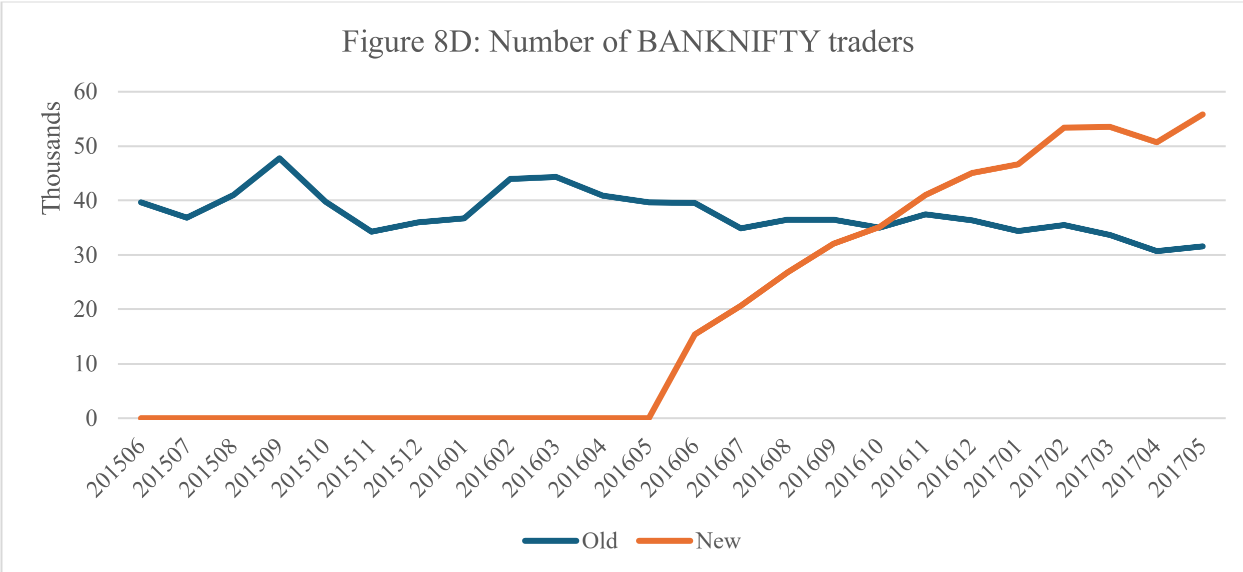


Figure 8D: Number of BANKNIFTY traders
Thousands
60
50
40
30
20
10
0
201506
201507
201508
201509
201510
201511
201512
201601
201602
201603
201604
201605
201606
201607
201608
201609
201610
201611
201612
201701
201702
201703
201704
201705
Old
New

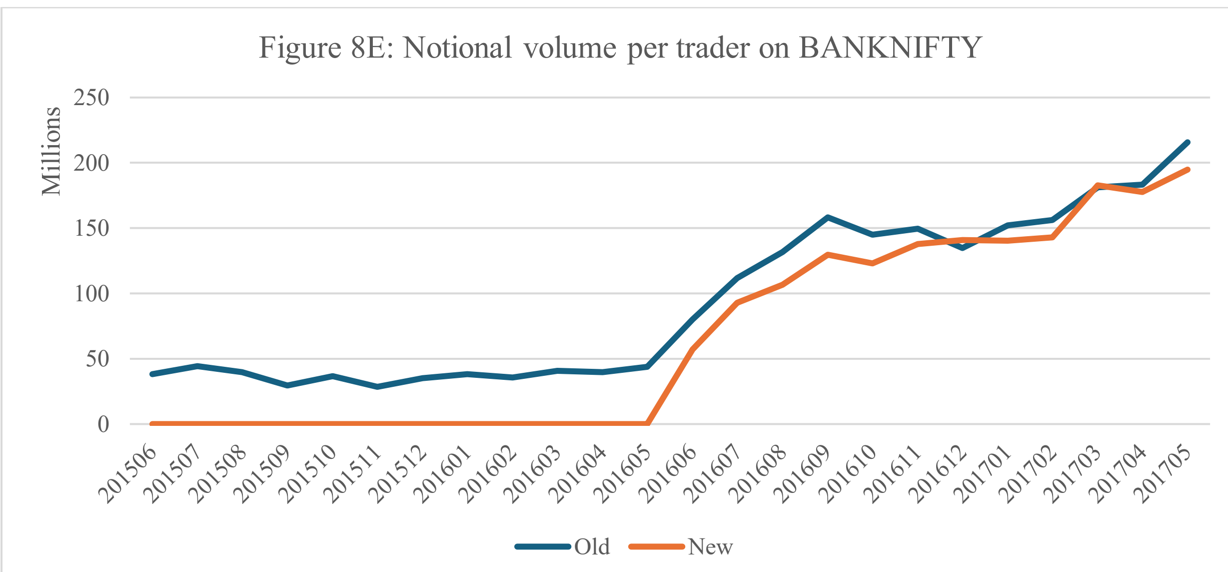


Figure 8E: Notional volume per trader on BANKNIFTY
Millions
250
200
150
100
50
0
201506
201507
201508
201509
201510
201511
201512
201601
201602
201603
201604
201605
201606
201607
201608
201609
201610
201611
201612
201701
201702
201703
201704
201705
Old
New

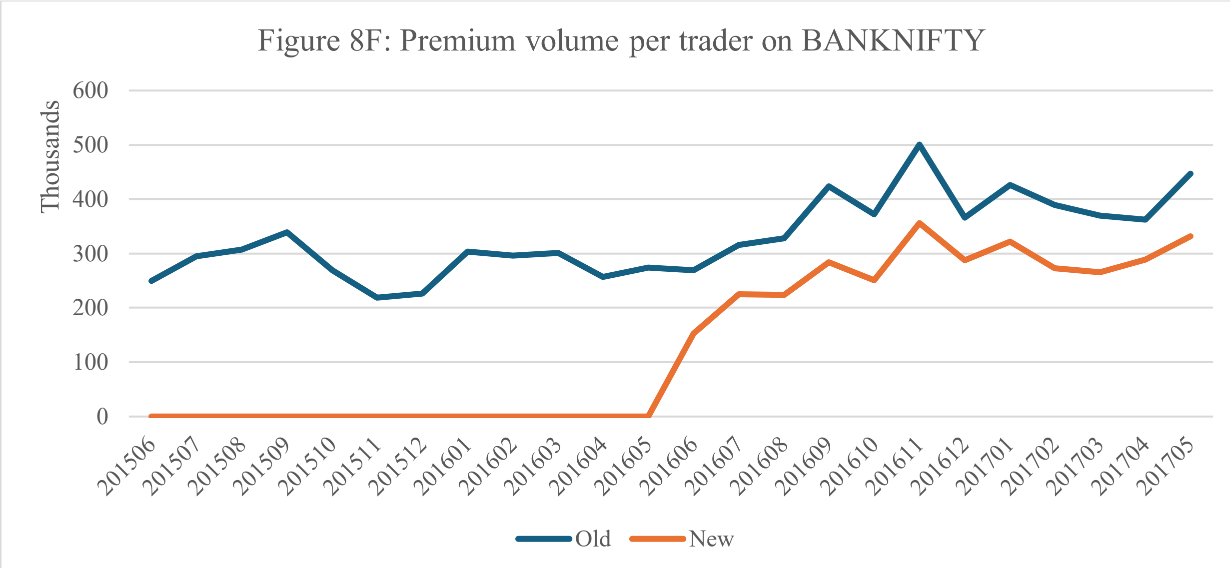


Figure 8F: Premium volume per trader on BANKNIFTY
Thousands
600
500
400
300
200
100
0
201506
201507
201508
201509
201510
201511
201512
201601
201602
201603
201604
201605
201606
201607
201608
201609
201610
201611
201612
201701
201702
201703
201704
201705
Old
New

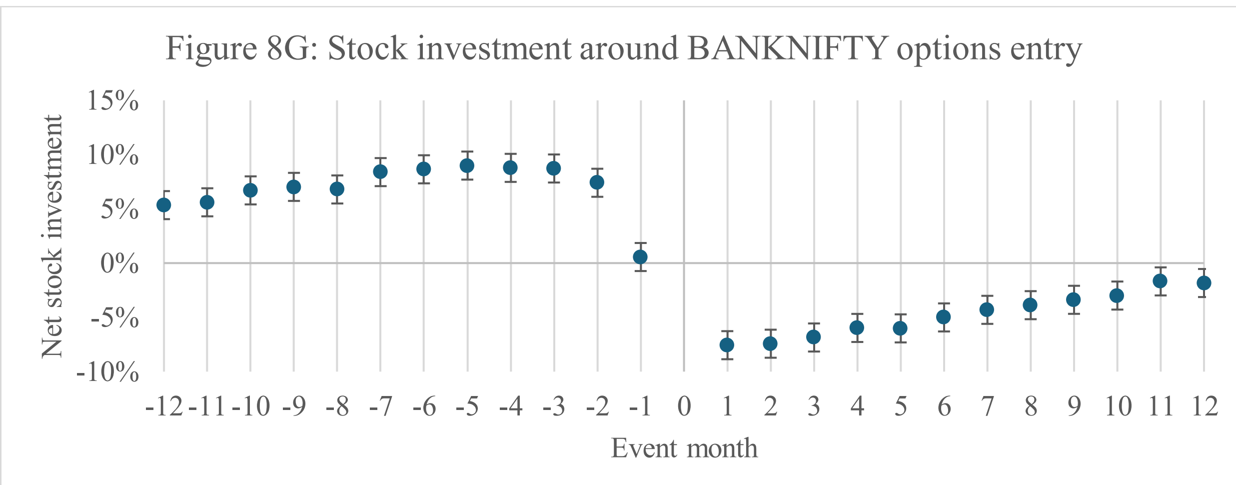
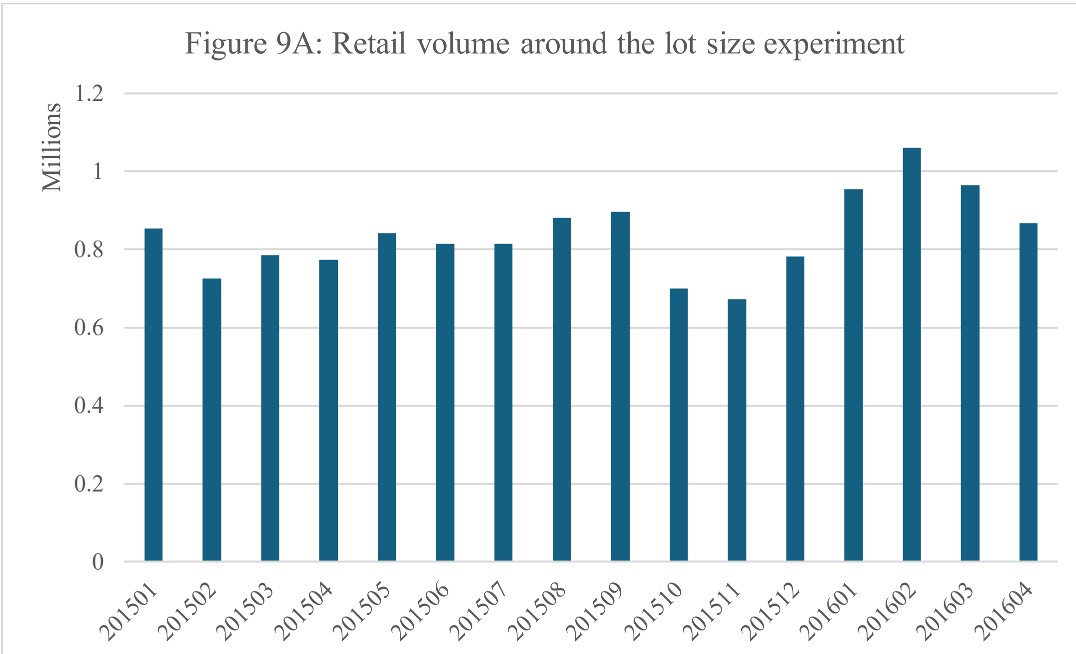


Figure 8G: Stock investment around BANKNIFTY options entry
Net stock investment
15%
10%
5%
0%
-5%
-10%
-12 -11 -10 -9 -8 -7 -6 -5 -4 -3 -2 -1 0 1 2 3 4 5 6 7 8 9 10 11 12
Event month

Figure 9: Lot size change

Figure 9A plots the average premium volume for each month on index options around the lot size experiment. Figure 9B shows the change in relative trading volume for each time to maturity − moneyness bin. The relative trading volume is defined as the aggregate retail volume for each bin, scaled by the total volume. The bars denote the change in relative trading volume after the shock compared with before.



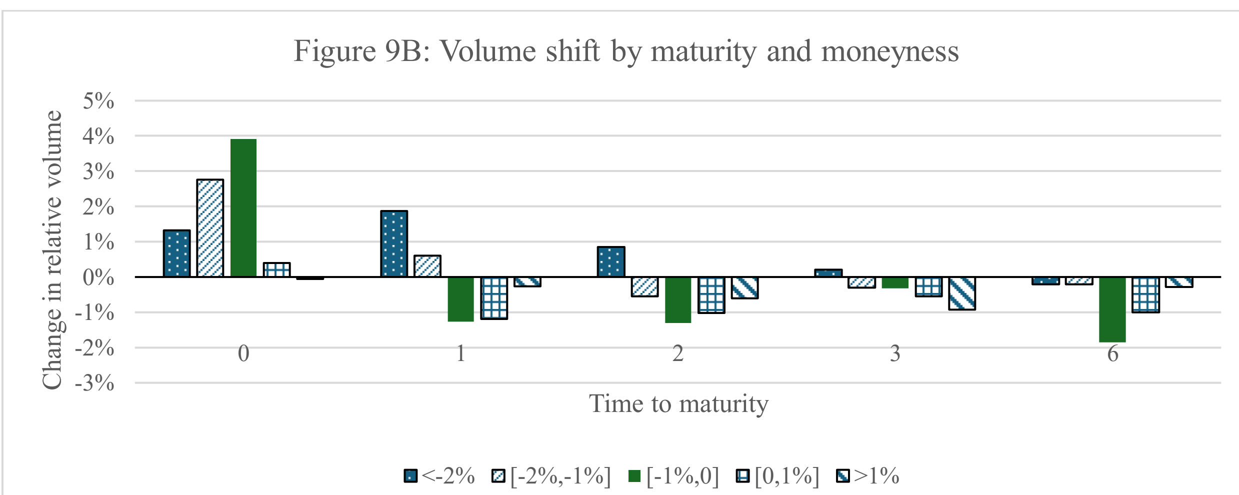


Figure 10: Physical settlement and trading on ITM and OTM single stock options

This figure shows the notional trading volume on single stock options that are in the money (Figure 10A) and out of the money (Figure 10B) for different times to maturity, before and after the October 2019 rule change that mandates physical delivery of ITM single stock options. OTM options are defined as those with moneyless less than −5%.

Figure 11: FinTech brokers

This figure displays the monthly trading volume for retail orders placed through FinTech brokers and traditional brokers. The FinTech brokers include Zerodha, Angel, Choice Equity, and 5PAISA.

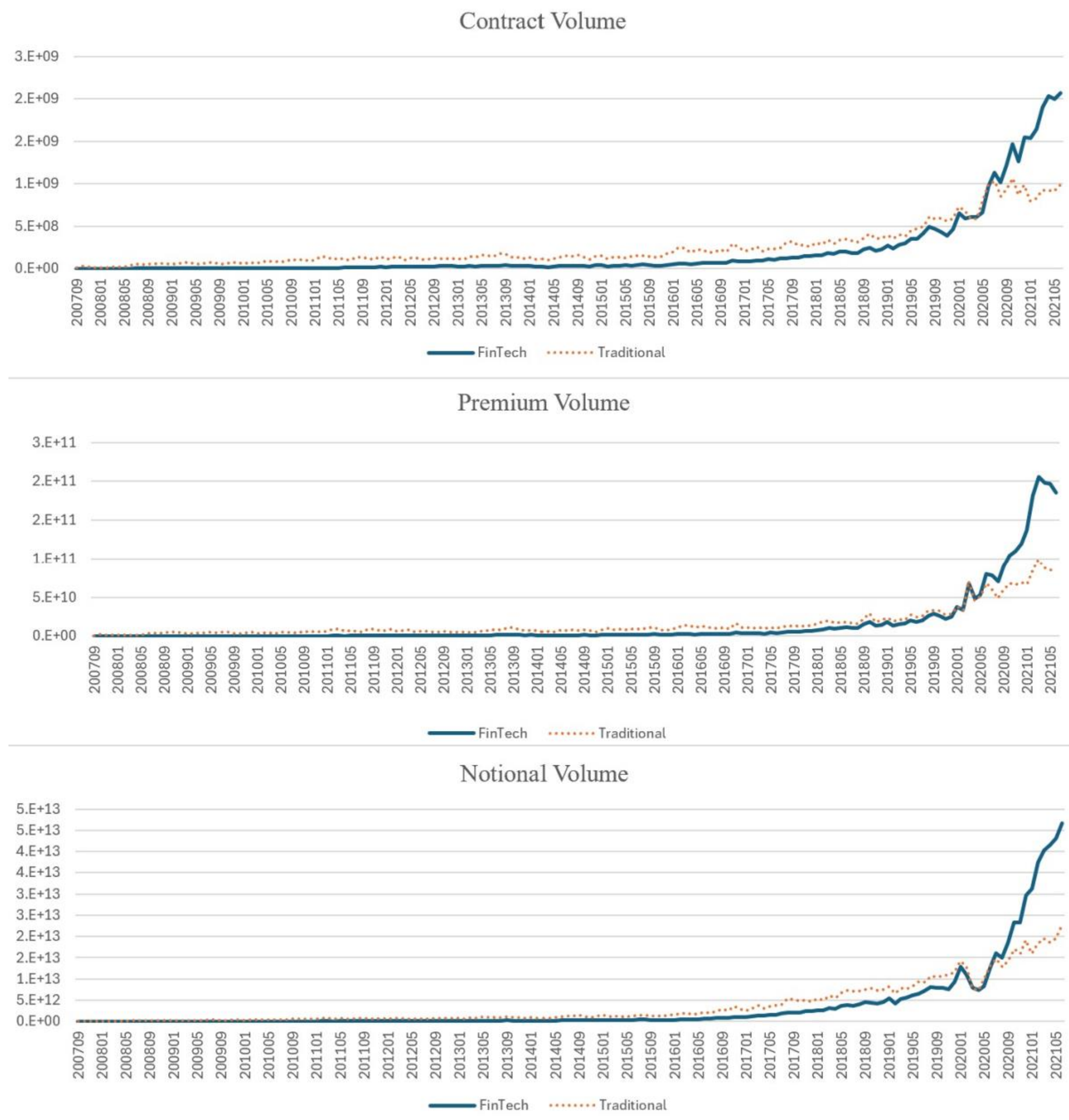


Table 1: Summary statistics

This table reports the descriptive statistics of retail options trading. Panel A shows the number of traders (in millions) in each type of contract, and the trading volume for each investor measured by the total premium, number of contracts, and total notional amount. The notional amounts are scaled by 1,000,000 and the premium and contract volume are scaled by 1,000 for expositional convenience. Panel B shows the statistics of trading profits and losses at the investor level in thousand Rupees. For each trader trading each option contract, the gross profit or loss is equal to the total premium received from selling options, minus total premium paid for buying options, plus the final settlement amount. Profits and losses at the investor-contract level are then aggregated to the investor level, with ₹20 brokerage fees being subtracted for each buy or sell activity on each contract per day. Panel C shows the total number of days in the market at the trader level, starting from the first day until the last day in our sample, and the total number of active trading days. Entry in 2027 and exit in 2021 are excluded to mitigate truncation bias. Panel D shows the trade duration at the trader-contract level, defined as the number of days from the first till the last day of trading a contract if the position is completely closed out before maturity, or if not completely closed out, till the expiration date of the contract.

Panel A: Trading volume

	Type		#Trader	Mean	25th	Median	75th
Premium volume	Single	Call	2.8	2,238	235	42	1,216
		Put	2.1	1,067	120	27	551
	Index	Call	3.9	3,443	261	42	1,449
		Put	3.8	3,271	236	39	1,320
Contract volume	Single	Call	2.8	350	35	6	170
		Put	2.1	181	18	4	82
	Index	Call	3.9	51	4	1	20
		Put	3.8	47	4	1	18
Notional volume	Single	Call	2.8	110	14	3	64
		Put	2.1	60	8	2	33
	Index	Call	3.9	821	56	9	312
		Put	3.8	742	49	8	280

Panel B: Trader performance

Type		Mean	10th	25th	Median	75th	90th
Single	Call	−50.5	−141.0	−41.9	−8.1	0.0	9.3
	Put	−12.6	−60.3	−16.6	−2.6	1.0	12.4
Index	Call	−42.9	−103.3	−28.6	−5.4	−0.1	6.1
	Put	−40.6	−107.3	−29.5	−5.5	−0.1	5.9
Overall		−109.9	−285.1	−82.5	−17.1	−1.9	4.4

Panel C: Trading lifecycle

Total number of days in market		Mean	10th	25th	Median	75th	90th
		548	3	28	147	610	1,777
Active trading days							
Single	Call	35	2	3	10	30	78
	Put	35	1	3	10	29	76
Index	Call	44	1	3	9	32	91
	Put	26	1	2	6	19	53
Overall		94	2	6	22	73	206

Panel D: Trade duration

Type		Mean	10th	25th	Median	75th	90th
Single	Call	5.0	0	0	1	7	17
	Put	4.9	0	0	1	6	17
Index	Call	2.4	0	0	0	2	6
	Put	2.3	0	0	0	2	6

Table 2: Trading strategies

The historical purchases and sales of each investor in each contract are netted out to reach the end-of-the-day net positions using the recursive inventory method. These trader-day-contract level positions are aggregated to the trader-day-stock or trader-day-index level and classified into different trading strategies. Panel A shows the broad classification of directional unhedged, directional hedged, and volatility strategies. Panel B shows the granular classifications.

Panel A: Broad classification

	Stock	Index
Directional unhedged	90.8%	78.7%
Volatility	5.8%	12.5%
Directional hedged	1.6%	2.0%
Others	1.8%	6.8%
Total	100.0%	100.0%

Panel B: Granular classification

		Stock	Index
Directional Unhedged	one call series +	48.79%	28.18%
	one call series −	11.95%	4.63%
	one put series +	14.78%	26.54%
	one put series −	7.38%	3.42%
	multiple call series +	3.66%	5.84%
	multiple call series −	1.75%	1.36%
	multiple put series +	1.10%	5.99%
	multiple put series −	1.06%	1.02%
	long call short put	0.25%	0.70%
	long put short call	0.04%	0.99%
Directional Hedged	simple call spread	1.16%	1.03%
	simple put spread	0.49%	0.95%
Volatility	butterfly spread with calls	0.24%	0.30%
	butterfly spread with puts	0.07%	0.28%
	long straddle/strangle	1.58%	4.67%
	short straddle/strangle	2.42%	2.93%
	Iron condor	0.15%	0.77%
	long strip/strap	0.29%	1.91%
	short strip/strap	1.04%	1.69%

Table 3: Introduction of weekly BANKNIFTY

This table reports the effect of the introduction of weekly BANKNIFTY on retail investors' trading behavior. The sample period is between May 2015 to May 2017. The pre-event period is from May 2015 to May 2016, and the post-event period is from June 2016 to May 2017. Panel A shows the regression results for short-term traders. Investors whose average time-to-maturity of their traded contracts is less (more) than 7 days before the event date are in the treated (control) group. *post* is an indicator variable that is equal to one for the post-event period. Each investor has two observations: the aggregate trading volume or P&L in the pre-event period (*post*=0), and the aggregate volume or P&L in the post period (*post* =1). The sample only includes investors who traded in both the pre- and post-event periods. The regressions include trader and time fixed effects, and the standard errors are double clustered at the trader and time levels. The premium volume and notional volume are scaled by 1,000,000 for expositional purposes. Panels B and C report the statistics of and changes in weekly trading frequency and average trading intensity before and after the shock. For each expiry date and each investor, trading activities are aggregated over the last week (TTM<=6) before expiration. The number of active weeks (*numactiveweek*) is the number of expiries for which investors participated during either the pre- or post-event periods. *avg_premvol*, *avg_undervol*, and *avg_contravol* are the average weekly premium volume, notional volume, and contract volume per trader conditional on participation. Panels D and E related trading behavior to investor demographics. *male* is an indicator variable for male investors, *age18_40* is an indicator for ages between 18 and 40, *age41_60* is an indicator for age between 41 and 60, and *tier1* is an indicator for investors located in tier one cities including Mumbai, Delhi, Bengaluru, Chennai, Kolkata, Hyderabad, Pune, and Ahmedabad.

Panel A: Introduction of weekly BANKNIFTY and short-term traders

	(1) *premvol*	(2) *undervol*	(3) *contravol*	(4) *P&L*
treat_post	0.55***	55.21***	3,506***	−6,534***
	(17.26)	(5.31)	(6.51)	(-6.58)
Trader FEs	Yes	Yes	Yes	Yes
Observations	157,852	157,076	157,852	157,852
Adjusted R^2	0.736	0.676	0.689	0.609

Panel B: Summary of trading frequency and intensity

post	*numactiveweek*	*avg_premvol*	*avg_undervol*	*avg_contravol*
0	2.4	78.9	21931.2	1331.6
1	6.6	64.2	36140.4	1831.0

Panel C: Trading frequency and intensity

	(1) *numactiveweek*	(2) *avg_premvol*	(3) *avg_undervol*	(4) *avg_contravol*
post	8***	−7.37***	10,384***	312***
	(185.19)	(−6.64)	(26.44)	(14.46)
Trader FEs	Y	Y	Y	Y
Observations	118,230	118,230	117,632	118,230
Adjusted R^2	0.667	0.686	0.682	0.685

Panel D: Trader demographics

	(1) *premvol*	(2) *undervol*	(3) *contravol*	(4) *P&L*	(5) *numactiveweek*	(6) *avg_premvol*	(7) *avg_undervol*	(8) *avg_contravol*
male×post	0.08***	59.74***	2,978***	−1,887**	0.70***	2.49	2,036**	94*
	(6.56)	(11.74)	(11.27)	(−2.32)	(16.98)	(0.91)	(2.23)	(1.88)
age18_40×post	0.02	39.75***	1,993***	−3,257***	0.25***	4.27	1,584	67
	(1.59)	(6.05)	(5.82)	(−3.20)	(4.60)	(1.11)	(1.28)	(0.97)
age41_60×post	0.02	20.21***	1,078***	−3,292***	0.28***	5.45	2,858**	160**
	(1.33)	(2.90)	(2.97)	(−3.00)	(4.72)	(1.34)	(2.19)	(2.24)
tier1×post	0.04***	32.03***	1,493***	1,354*	−0.10***	−8.47***	571	−30
	(4.01)	(6.64)	(5.98)	(1.86)	(−2.69)	(−3.16)	(0.63)	(−0.60)
male	−0.00	6.33**	370**	−1,806**	0.06***	−2.72	1,503**	82**
	(−0.21)	(2.57)	(2.56)	(−2.50)	(3.48)	(−1.05)	(2.23)	(2.04)
age18_40	−0.05***	−3.43	−169	2,375***	−0.30***	−10.08***	430	35
	(−4.61)	(−1.06)	(−0.89)	(2.64)	(−13.09)	(−2.73)	(0.44)	(0.60)
age41_60	−0.02*	−6.50*	−376*	935	−0.03	−8.94**	−2,274**	−129**
	(−1.66)	(−1.93)	(−1.91)	(0.96)	(−1.36)	(−2.32)	(−2.31)	(−2.24)
tier1	0.08***	18.28***	1,085***	−5,158***	0.10***	24.99***	6,607***	397***
	(10.37)	(7.92)	(8.01)	(−7.94)	(5.98)	(9.62)	(9.28)	(9.52)
post	0.30***	168.44***	7,933***	1,948*	3.47***	−18.22***	9,579***	285***
	(17.42)	(23.22)	(21.01)	(1.68)	(58.17)	(−4.50)	(7.58)	(4.07)
Trader FE	N	N	N	N	N	N	N	N
Observations	289,944	289,172	289,944	289,944	289,944	289,944	289,172	289,944
Adjusted R^2	0.012	0.021	0.018	0.001	0.073	0.002	0.003	0.002

Panel E: Trader demographics with fixed effects

	(1) *premvol*	(2) *undervol*	(3) *contravol*	(4) *P&L*	(5) *numactiveweek*	(6) *avg_premvol*	(7) *avg_undervol*	(8) *avg_contravol*
male×post	0.20***	133.32***	6,708***	−4,635***	1.36***	8.27***	5,125***	243***
	(7.69)	(11.00)	(10.97)	(−3.10)	(11.90)	(2.76)	(5.08)	(4.38)
age18_40×post	0.21***	144.25***	7,296***	−7,402***	0.61***	9.23**	3,902***	159**
	(6.71)	(10.15)	(10.18)	(−4.39)	(4.53)	(2.52)	(3.11)	(2.32)
age41_60×post	0.09***	61.95***	3,222***	−3,107*	0.49***	5.51	2,070*	126*
	(3.00)	(4.33)	(4.47)	(−1.75)	(3.55)	(1.46)	(1.72)	(1.92)
Tier1×post	0.09***	38.60***	1,883***	−1,265	−0.35***	−2.83	1,088	15
	(3.92)	(3.38)	(3.26)	(−0.99)	(−3.46)	(−0.97)	(1.05)	(0.27)
post	0.49***	221.75***	10,537***	−5,729***	6.57***	−19.38***	3,624***	−1
	(14.26)	(14.08)	(13.24)	(−2.87)	(43.49)	(−4.63)	(2.73)	(−0.01)
Trader FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	98,176	97,642	98,176	98,176	98,176	98,176	97,642	98,176
Adjusted R^2	0.662	0.623	0.637	0.615	0.670	0.682	0.676	0.680

Table 4: Change in lot size of index options

This table reports the estimation results of a difference-in-differences regression on trading activity and performance around an increase in the lot size of index options in 2015. *treat* is an indicator variable for treated investors, defined as those who always traded below the cutoff (75 for NIFTY50 and 30 for BANKNIFTY) for the one-year period before the shock from August 2014 to July 2015. The control group consists of investors who traded equal to or above 75 but below 250 on NIFTY50, or equal to or above 30 but below 90 for BANKNIFTY before the shock. *post* is an indicator variable for the post-event period from December 2015 to December 2016. Panel A shows the change in premium volume (*premvol*), contract volume (*conravol*), and notional volume (*undervol*) at the trader-contract level. Panel B shows the change in percentage moneyness (*%Moneyness*) of contracts traded and the contract price (*ContraPrice*) at the trader-contract level, and the trader duration (*Duration*), trading return (*%Return*), and profit and loss (*P&L*) at the trader level. The trading return and P&L are computed based on all contracts traded by a trader, aggregated once before and once after the shock to reduce estimation errors.

Panel A: Trading volume

	(1) *premvol*	(2) *contravol*	(3) *undervol*
treated×post	−4,700***	−59.17***	−0.40***
	(−3.47)	(−4.91)	(−4.20)
Time Fes	Yes	Yes	Yes
Contract Fes	Yes	Yes	Yes
Trader Fes	Yes	Yes	Yes
Observations	630,761	630,761	630,761
Adjusted R^2	0.421	0.483	0.468

Panel B: Unintended consequences

	(1) *%Moneyness*	(2) *TTM*	(3) *ContraPrice*	(4) *Duration*	(5) *%Return*	(6) *P&L*
Treated×Post	−0.26***	−1.93***	−8.09***	−1.20***	−1.51**	₹284
	(−5.16)	(−2.96)	(−3.16)	(−5.49)	(−2.37)	(1.54)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Trader FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	630,761	630,761	630,761	630,761	56,138	56,138
Adjusted R^2	0.402	0.515	0.555	0.283	0.187	0.333

Table 5: Physical settlement of single stock options

This table reports the estimation results of difference-in-differences regressions on trading activity and performance around the physical settlement rule change in October 2019. The pre- and post-event periods are one year before and one year after October 2019. *post* is an indicator variable for the post-event period. *treat* is an indicator variable for treated investors. For each trader, the average time to maturity of traded positions for all stock option trades placed in the pre-event period is computed and ranked. Treated investors are those who rank in the bottom 25% of the population. The control group are the other investors who traded single stock options in the pre-event period. *otm* is an indicator variable for trading out-of-money options at the trader-contract level. *otm* is equal to one if the premium-weighted moneyness across all trading days on the contract is less than −5%, and zero otherwise. Panel A shows the trading activities at the trader level before and after the event. The trading volume, return, and P&L are aggregated across all contracts traded by each trader before and after the shock, respectively. *contravol* is scaled by 1,000 while *undervol* and *premvol* are scaled by 1,000,000. The regressions control for trader and time fixed effects and the standard errors are double clustered at the trader and time levels. Panel B shows the trading activities at the trader-contract level. The regressions control for the trader, time and contract fixed effects and the standard errors are triple clustered at the trader, time, and contract levels.

Panel A: Trading volume and performance

	(1) *premvol*	(2) *contravol*	(3) *undervol*	(4) *P&L*
treat_post	0.42***	156.99***	68.67***	−23,984***
	(18.13)	(33.86)	(23.08)	(−17.19)
Time FEs	Y	Y	Y	Y
Trader FEs	Y	Y	Y	Y
Observations	160,772	160,772	160,772	158,478
R−squared	0.779	0.785	0.799	0.635

Panel B: Trading activity on single stock OTM options

	(1) *contravol*	(2) *undervol*	(3) *Contraprice*
post×otm	1.65***	0.51***	−3.55***
	(59.82)	(29.26)	(−4.03)
treat×post×otm	0.47***	0.28***	−1.61***
	(3.75)	(3.54)	(−4.88)
treat×post	−0.27*	−0.20*	1.32***
	(−1.94)	(−1.67)	(3.31)
treat×otm	−0.41***	−0.12**	2.57***
	(−5.81)	(−2.09)	(9.15)
otm	−0.07**	0.02	−6.07***
	(−2.57)	(1.11)	(−14.57)
Time FEs	Y	Y	Y
Contract FEs	Y	Y	Y
Trader FEs	Y	Y	Y
Observations	10,862,259	10,862,259	10,862,259
Adjusted R^2	0.534	0.220	0.805

Table 6: Trader entry and exit in the options market

Panel A reports the estimation results of a linear probability model of a trader's entry into options trading. The data panel is based on a random sample consisting of 10% of the retail stock traders at the monthly frequency. For each trader in each month, *Performance* is the trader's stock trading performance during the past three months calculated by volume-weighting market-adjusted stock returns, measured from the day of trading till the beginning of the current month. *Highperf* and *Lowperf* are indicator variables for the top and bottom deciles of *Performance* among all traders during a given month, respectively. *Retvol* is the volume-weighted stock return volatility for all stocks traded during the past three months. *Maxret* is the volume-weighted maximum daily return of the stock traded during the past three months. *Stockvol* is the logarithm of the past three months of stock trading volume. *Experience* is the number of months since a trader started trading stocks in the sample. *Highretvol* is an indicator variable for *Retvol* above the 75th percentile but *Retmax* below 75th; *Highretmax* for *Retmax* above 75th but *Retvol* below 75th; and *Highretvol&max* if both *Retvol* and *Retmax* are above the 75th percentiles. All stock activity measures are set to zero for non-trading activities during the last three months. The dependent variable *entry* is equal to 1 for the month when a trader started options trading; and 0 for all months before entry. The observations after the entry month are removed from the regression. *entry* is also equal to 0 if the stock trader never initiated options trading. In Panel B, traders are sorted into 4×4 groups in each month based on their premium volume and trading returns. The top, middle, and bottom panels report the in-sample trading returns, probability of trading in the next month, and trading returns in the next month for different groups of traders.

Panel A: Entry into options trading

	(1)	(2)	(3)	(4)
	entry	*entry*	*entry*	*entry*
Performance	−0.004***		−0.004***	−0.004***
	(−4.45)		(−4.48)	(−4.42)
Highperf		−0.001***		
		(−3.12)		
Lowperf		0.002***		
		(3.46)		
Retvol	0.002***	0.002***		
	(10.24)	(10.41)		
Highretvol				0.008***
				(7.56)
Highretmax				0.003***
				(9.77)
Highretvol&max				0.006***
				(8.99)
Maxret			0.001***	
			(9.61)	
experience	−0.276***	−0.276***	−0.276***	−0.276***
	(−20.65)	(−20.63)	(−20.61)	(−20.22)

Continued on next page

Stockvol	0.001***	0.001***	0.001***	0.001***
	(18.00)	(18.00)	(20.33)	(21.16)
Time FEs	Y	Y	Y	Y
Observations	45,824,487	45,824,487	45,824,487	45,824,487
Adjusted R^2	0.009	0.009	0.009	0.010

Panel B: Trader performance and attrition

Trading return in month t

	1 (low R_t)	2	3	4 (high R_t)
1 (low Vol_t)	−44.67%	−7.91%	−0.89%	23.90%
2	−29.98%	−7.41%	−0.92%	14.63%
3	−25.45%	−6.67%	−0.96%	9.66%
4 (high Vol_t)	−23.97%	−5.86%	−0.82%	6.30%

Probability of exiting in t+1

	1 (low R_t)	2	3	4 (high R_t)
1 (low Vol_t)	55.00%	48.61%	48.37%	40.52%
2	38.02%	33.77%	33.92%	26.54%
3	25.86%	21.11%	20.46%	14.35%
4 (high Vol_t)	17.99%	11.93%	9.84%	7.46%

Trading return in month t+1

	1 (low R_t)	2	3	4 (high R_t)
1 (low Vol_t)	−3.04%	−2.12%	−1.85%	−1.87%
2	−3.41%	−2.39%	−1.90%	−1.87%
3	−3.26%	−2.33%	−1.60%	−1.56%
4 (high Vol_t)	−2.78%	−1.99%	−0.89%	−0.96%

Table 7: Participation in single stock options

This table reports the determinants of retail trading in single stock options using option-day observations. The dependent variables are option-to-stock ratio (*O/S*) constructed following Roll, Schwartz, and Subrahmanyam (2010) and Johnson and So (2010). For each trading day and each options contract, the *O/S* is equal to the dollar notional amount of options traded from the retail volume, scaled by the dollar volume of the underlying stock during the same day. The *O/S* is multiplied by 1,000 for expositional convenience. *highprice* is an indicator variable that is equal to one if the stock's price per share ranks above the 90th percentile during the previous day, and zero otherwise. *lagret* is the lagged daily stock return. *premium* is the average price per contract paid by the representative retail investor during the trading day. *ttm* is the time-to-maturity in days. *moneyness* is the percentage moneyness, defined as the difference between the stock's closing share price and the strike price for call options (opposite for put options), scaled by the stock price. *stockvol* is the logarithm of stock trading volume during the past month. *mktcap* is the logarithm of the stock's market capitalization. The regressions control for time fixed effects and the standard errors are double clustered at the stock and day levels.

	(1) *Cal O/S*	(2) *Put O/S*
highprice	11.963***	6.824***
	(8.39)	(6.61)
lagret	0.041	−0.050**
	(1.39)	(−2.16)
premium	−0.236***	−0.106***
	(−9.81)	(−10.89)
ttm	−0.854***	−0.556***
	(−27.35)	(−23.07)
moneyness	80.808***	32.524***
	(22.30)	(11.57)
stockvol	5.130***	2.517***
	(10.26)	(8.01)
mktcap	−2.852***	−0.306
	(−5.73)	(−1.19)
Observations	2,130,473	1,492,381
Adjusted R^2	0.163	0.136

Table 8: FinTech brokers

Panel A reports the daily premium volume per investor for orders placed through FinTech brokers and traditional brokers. FinTech brokers include Zerodha, Angel, Choice Equity, and 5PAISA, and the rest are traditional brokers. Statistics are reported for traders who have used both FinTech and traditional brokers, including those who switched from traditional to FinTech brokers and never switched back during our sample period, those who switched from FinTech to traditional brokers and never switched back during our sample period, and those who switched back and forth or use both types of brokers simultaneously. Panels B and C report the regression estimates based on the sample of all traders, and traders who have used both FinTech and traditional brokers, respectively. *finbroker* is an indicator variable that is equal to one if the trading is placed through FinTech brokers, and zero otherwise. For each trader, the dependent variables are aggregated for all trading activities via FinTech and traditional brokers, respectively. The premium volume and notional volume are scaled by 1,000,000 for expositional convenience.

Panel A: Trading volume via FinTech and traditional brokers

	Traditional to FinTech	Transitory	FinTech to Traditional
Volume via Traditional	10,261	10,902	12,612
Volume via FinTech	15,820	14,277	14,822

Panel B: Trading volume and performance: all investors

	(1) *premvol*	(2) *contravol*	(3) *undervol*	(4) *%Return*	(5) *P&L*
finbroker	1.36***	326.61***	7.23***	1.70***	−7,728***
	(73.74)	(104.46)	(9.90)	(65.49)	(−28.48)
Trader FEs	N	N	N	N	N
Observations	1,317,477	1,317,422	1,317,477	1,296,162	1,296,162
Adjusted R^2	0.00	0.01	0.00	0.00	0.00

Panel C: Trading volume and performance: switchers

	(1) *premvol*	(2) *contravol*	(3) *undervol*	(4) *%Return*	(5) *P&L*
finbroker	2.78***	495.33***	66.00***	1.65***	−24,159***
	(73.47)	(77.25)	(44.78)	(36.15)	(−44.80)
Trader FEs	Y	Y	Y	Y	Y
Observations	1,317,477	1,317,422	1,317,477	1,296,162	1,296,162
Adjusted R^2	0.52	0.43	0.49	0.48	0.53

ONLINE APPENDIX

Appendix A: Return skewness of index options and lottery stocks

In this appendix, we estimate the skewness of realized returns of index option, as well as the return skewness of lottery-type stocks.

We begin by collecting data on NIFTY and BANKNIFTY options from the archival files on the National Stock Exchange, including end-of-day closing prices, open interest, daily trading volume, and underlying index values. The data period spans between September 2008 and October 2004. We exclude options with option interests below 100 contracts or daily trading volume below 25 contracts. As discussed in the main text, index options typically expire on Thursdays, with trading activity concentrated within the six calendar days prior to expiration. We thereby form option portfolios 6, 3, 2, and 1 calendar day(s) before the expiration dates. For each of these time to maturity category, we further sort options into different moneyness buckets, as shown in Appendix Table A.1.[34]

For each expiration day and its corresponding time to maturity-moneyness bin, we form equal-weight option portfolios and hold them till the expiration day. This procedure generates a time series of option portfolio returns for each time to maturity-moneyness bin. We then compute the time-series skewness for a given maturity-moneyness bin as the skewness of the time series of portfolio returns. Our methodology follows the approach of Boyer and Vorkink (2014), who estimate time-series skewness for single-stock options. In contrast, our analysis focuses on index options.

Panels A and B of Appendix Table A.1 report the skewness estimates for each maturity-moneyness bin for NIFTY and BANKNIFTY options, respectively. We find that option skewness

[34] Option moneyness is computed based on option strike prices and the closing underlying index values 6, 3, 2, and 1 day(s) before the maturity date, and we eliminate options that are more than 10% in the money and -10% out of the money.

is inversely related to both the time to maturity and option moneyness. This pattern provides a potential explanation for the observed preference among retail traders for short-term options and stronger preference for out-of-the-money positions than in the money ones. While Boyer and Vorkink (2014) focus on a different market context—namely, single-stock options in the U.S. with different underlying characteristics and maturities—the skewness estimates observed in our index option sample are comparable to, and in some cases exceed, those reported for individual equity options in their study, especially for options with 1 day to maturity. For convenient comparisons, we reproduce their results in Panel C. The last rows of Panels A and B indicate that the option skewness is not driven by the skewness of underlying index returns, where the indexes are held over the same periods as the option portfolios.

Next, we estimate the return skewness of lottery stocks, defined as those with high maximum daily returns in the past month (Bali, Cakici, and Whitelaw, 2011). We form decile portfolios at the beginning of each investment period, i.e., six days before each option expiration day in our sample, by ranking stocks based on their maximum daily return during the past month. Stocks in the top decile, which exhibit the highest maximum returns, are classified as lottery stocks. We then construct equal-weighted portfolios for each decile and calculate holding-period returns across different time-to-maturity (TTM) intervals, aligning these with the option portfolios. For example, for TTM = 3, we compute the equal-weighted return assuming the portfolio is held from three days before expiration until the expiration date. This procedure ensures that the holding periods of the stock portfolios match those of the corresponding option portfolios.

Panel D presents the skewness estimates for each stock portfolio across the corresponding holding periods. Notably, the skewness measures are negative even for the lottery stock portfolios due to the short investment horizons. Moreover, these skewness values are significantly lower than those observed in the option return portfolios. This result underscores a key distinction between stock and option investments: options provide investors with concentrated exposure to highly skewed payoffs over short horizons, a feature that is difficult to obtain through stock investments.

Appendix Table A.1: Skewness of realized returns

This table reports the skewness of realized stock and option returns. Panels A and B show the realized skewness of BANKNIFTY and NIFTY options. Options are sorted into moneyness and maturity buckets 1, 2, 3 and 6 days before maturity, and then held to expiration. For each of the option portfolio in the corresponding maturity−moneyness bucket, we compute the time-series skewness of the option portfolio returns. The last row reports the skewness of the underlying index returns, assuming the same holding horizon as the option portfolios. Panel C reproduces the estimation results in Boyer and Virkink (2014) for portfolios of single stock options. Panel D reports the skewness of stock portfolios based on their past maximum returns. Decile portfolios are formed six days before each option expiration day based on the stocks' maximum daily return during the past month. The portfolios are then held until the expiration days to match the holding periods of option portfolios in Panel A and Panel B.

Panel A: BANKNIFTY options

		TTM (call)				TTM (put)			
		1	2	3	6	1	2	3	6
Moneyness	(-10%,-2%)	18.1	12.8	8.9	9.3	13.0	10.3	9.4	8.2
	(-2%,-1%)	11.5	5.7	4.6	6.5	10.0	7.1	6.3	3.5
	(-1%,-0.5%)	5.1	3.2	2.8	3.9	6.3	3.9	3.4	2.4
	(-0.5%,0)	2.8	2.4	2.0	1.9	3.9	2.7	2.6	2.5
	(0,0.5%)	1.9	1.3	1.5	1.3	2.6	1.8	1.8	1.4
	(0.5%,1%)	1.0	1.1	0.9	1.5	1.9	1.3	1.2	1.3
	(1%,10%)	0.4	0.4	0.5	0.8	0.8	0.6	0.9	1.0
Skewness of underlying		−0.9	0.1	−0.6	0.1				

Panel B: NIFTY options

		TTM (call)				TTM (put)			
		1	2	3	6	1	2	3	6
Moneyness	(-10%,-2%)	10.1	9.3	7.5	8.6	13.8	13.1	8.6	11.6
	(-2%,-1%)	5.8	7.3	5.0	3.7	10.8	6.7	5.2	4.3
	(-1%,-0.5%)	4.4	3.4	3.0	1.9	5.2	3.6	3.5	2.6
	(-0.5%,0)	2.2	1.8	2.2	1.6	3.5	2.5	2.5	2.4
	(0,0.5%)	1.3	1.1	1.4	1.5	2.6	1.8	2.3	1.8
	(0.5%,1%)	0.7	1.0	0.9	1.1	2.0	1.4	1.6	1.6
	(1%,10%)	0.0	0.6	0.5	1.1	0.8	0.5	0.6	0.8
Skewness of underlying		−1.4	0.3	−0.6	−0.8				

Panel C: Boyer and Vorkink (2014)

	call			put		
	7	18	48	7	18	48
Low	0.07	-0.3	0.38	0.38	0.62	1.28
2	0.57	0.16	0.76	0.77	1.2	1.86
3	1.09	0.71	0.96	1.35	1.76	2.8
4	1.82	1.37	1.17	2.09	2.7	3.94
High	2.68	1.64	1.48	2.71	4.55	7.01

Panel D: stock portfolios

	Holding period			
	1	2	3	6
1 (low max return)	-1.62	-0.34	-0.87	-0.65
2	-1.79	-0.39	-0.67	-0.64
3	-1.83	-0.47	-0.73	-0.52
4	-1.78	-0.42	-0.46	-0.21
5	-1.43	-0.50	-0.59	-0.31
6	-1.57	-0.41	-0.28	-0.16
7	-1.32	-0.31	-0.62	-0.47
8	-1.90	-0.47	-0.61	-0.36
9	-1.92	-0.33	-0.57	-0.35
10 (high max return)	-1.95	-0.46	-0.47	-0.20

Appendix B: Protail Investors

We show that a small sliver of highly active "protail" traders is quite different from the remaining retail options traders. We define investors in the top 1% of past 6-month trading volume as protail investors. Panel A of Table B.1 shows that this small group is significantly different from 99% of the retail investors. For example, the median notional volume of protail on index calls is ₹4,342 million, or 482 times the median notional volume of retail investors shown in Table 1 (₹9 million). The mean notional volume of protail on index calls is ₹34,686 million, or 42 times the mean notional volume of retail investors (₹821 million). The differences in premium volume are as great. For example, volume of index call options has a mean of ₹181,008K for protail traders or 53 times the mean premium volume of retail investors (₹3,443K). The relative differences in notional and premiums indicates that protail investors have lower propensities to trade low-denomination or "cheap" options.

Panel B of Table B.1 shows that protail investors lose less when profits are scaled by trading volume. For example, the protail lose 16 times the loss of an average retail investor although the premium volume, as discussed above, is 53 times greater. Protail investors report profits from single stock call options.

Figure B.1 shows the number of profit-generating months. Retail investors seem have net zero profits in only 4 out of the 169 months, protail investors generate profits in 72 out of the 169 months in our sample. In untabulated results, we show that protail investors have longer trade duration and more active trading days than the retail population.

Figure B.2 shows that the aggregate open interest of protail investors. Protail investors are net sellers of both index calls and puts but the magnitude of the open interests is substantially lower than that of retail investors. Institutions are the major counterparts to retail options trader positions.

The statistics highlight the asymmetries between protail and retail investors and the importance of excluding the former in drawing inferences about the latter.

Table B.1: Summary statistics

This table reports the descriptive statistics of protail options trading. Panel A shows the trading volume for each investor measured by the total premium, number of contracts, and total notional amount. The notional amounts are scaled by 1,000,000 and the premium and contract volume are scaled by 1,000 for expositional convenience. Panel B shows the statistics of trading profits and losses at the investor level in thousand Rupees. For each trader trading each option contract, the gross profit or loss is equal to the total premium received from selling options, minus total premium paid for buying options, plus the final settlement amount. Profits and losses at the investor-contract level are then aggregated to the investor level, with ₹20 brokerage fees being subtracted for each buy or sell activity on each contract, to reach the net profit or loss for each investor.

Panel A: Trading volume

	Type		Mean	25th	Median	75th
Premium volume	Single	Call	41,042	266	1,657	10,221
		Put	18,357	145	753	4,210
	Index	Call	181,008	7,281	30,735	110,858
		Put	168,497	6,597	28,277	104,015
Contract volume	Single	Call	9,586	21	143	937
		Put	2,957	11	62	387
	Index	Call	2,332	72	287	1,057
		Put	2,164	67	276	1,027
Notional volume	Single	Call	1,993	11	68	408
		Put	859	7	35	186
	Index	Call	34,686	878	4,342	16,978
		Put	31,692	826	4,163	16,208

Panel B: Trader performance

Type		Mean	10th	25th	Median	75th	90th
Single	Call	121	−550	−106	−8	9	192
	Put	−237	−319	−53	−4	6	104
Index	Call	−698	−2,023	−587	−110	11	495
	Put	−206	−1,945	−560	−106	12	603
Overall		−936	−3,991	−1,284	−302	−9	796

Figure B.1: Aggregate trading loss by protail investors

This figure shows the monthly aggregate profit and loss for protail option traders. For each trader on each contract, the profit or loss is the total sale price minus the total purchase price if the positions are completely closed out before maturity, or if not completely closed out, plus the settlement P&L. The profits and losses of all retail investors on all contracts expiring in each month are then aggregated to compute the monthly profit or loss figures for a given expiry month.

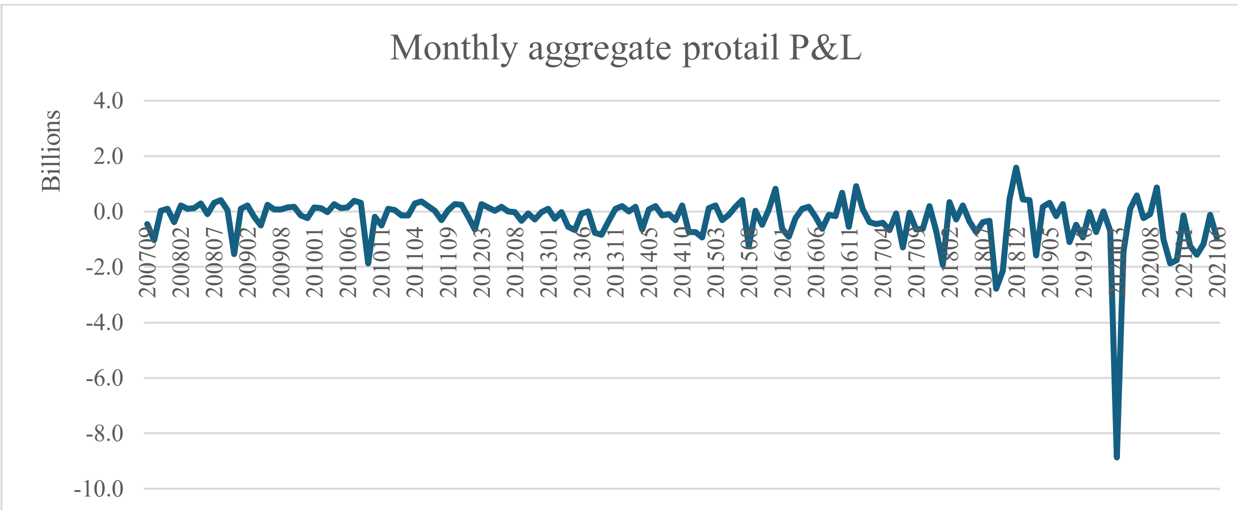
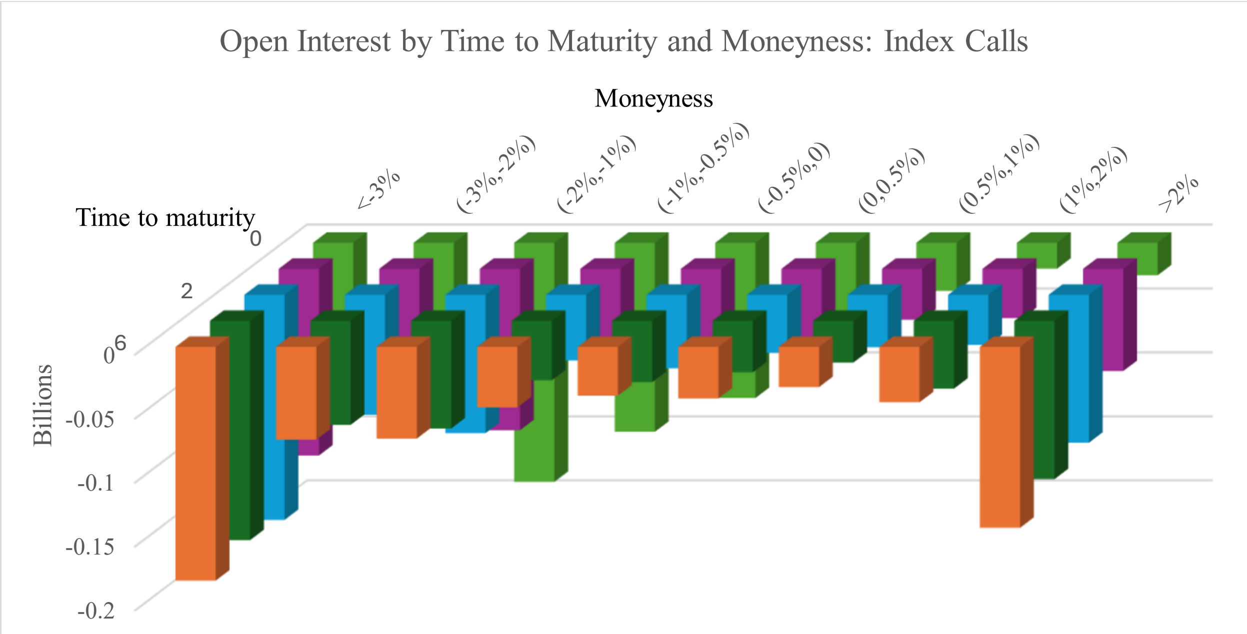
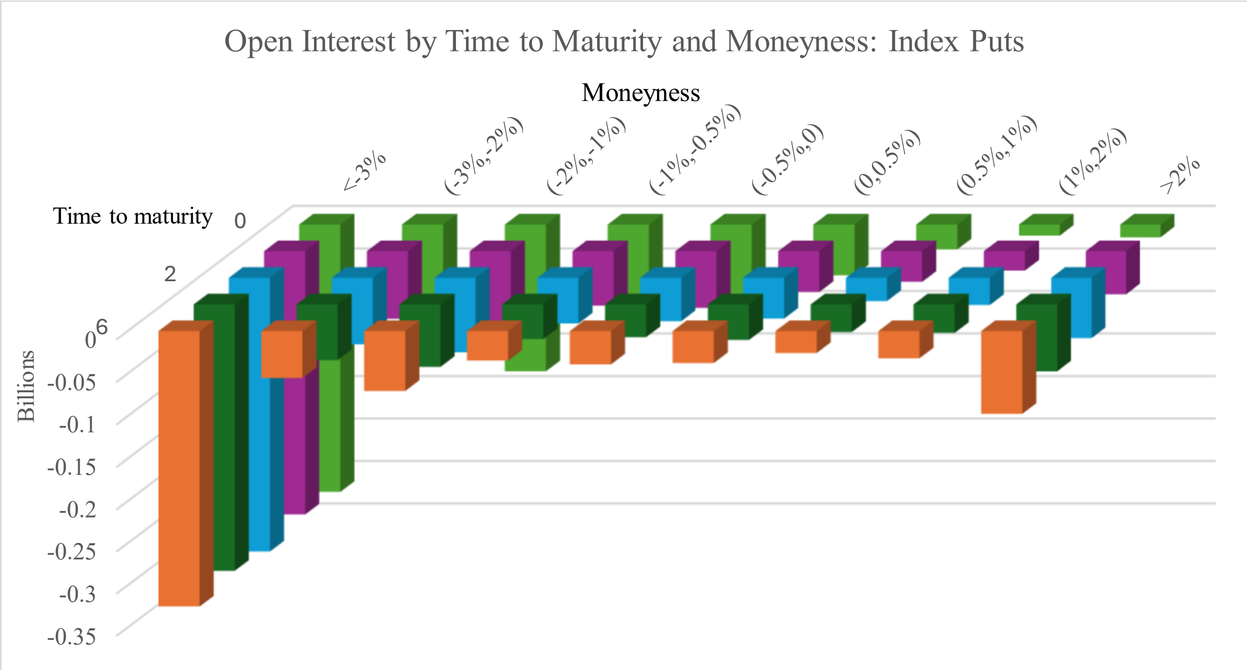


Figure B.2: Aggregate retail open interest of protail investors

This figure plots the aggregate protail open interest on index calls and puts. The daily net open interest for each trader on each contract is the aggregate protail net position after netting out all the previously opened and closed long and short positions before the end of the trading day. The daily net open interests are then aggregated for each time to maturity level and moneyness intervals.





Appendix C: Pandemic Trading

In this appendix, we report investor trading as the Covid-19 pandemic unfolded for the March 2020 expiry contracts (Figure 2). Retail traders lost heavily during this period with 60% of the losses due to index options (40% on NIFTY50 and 20% on BANKNIFTY).

We classify all traders based on their overall positions for the 6 months before Covid from August 2019 to January 2020. For each trader, we compute daily end-of-the-day positions for each options contract. Based on this data, we classify traders into no call and long put, no call and short put, long call and no put, long call and long put, long call and short put, short call and no put, short call and long put, and short call and short put. Some investors have no trades. About 5.9% of the traders are net sellers of both calls and puts, 87.7% of the traders are net buyers of calls and puts.

The shaded area of Figure C.1 shows the daily India VIX and the solid lines show the open interests of different groups of investors. The VIX starts to increase from the end of February of February and reaches a peak on March 23, 2020, three days before the expiration date of the monthly index options on March 26, 2020. The open interest of the long call-long put group is significantly positive both before and during the event period, on both index calls and index puts. In contrast, the open interest of the short call-short put group is significantly negative both before and during the event period, also on both calls and puts, indicating that the major division of the groups is into long-only and short-only strategies. The open interest of the rest is relatively small. While the long investors show positive open interest on both calls and puts as a group, each trader typically has a simple strategy of being long in either calls or puts. The short investors are more likely to follow complex strategies involving both types of options.

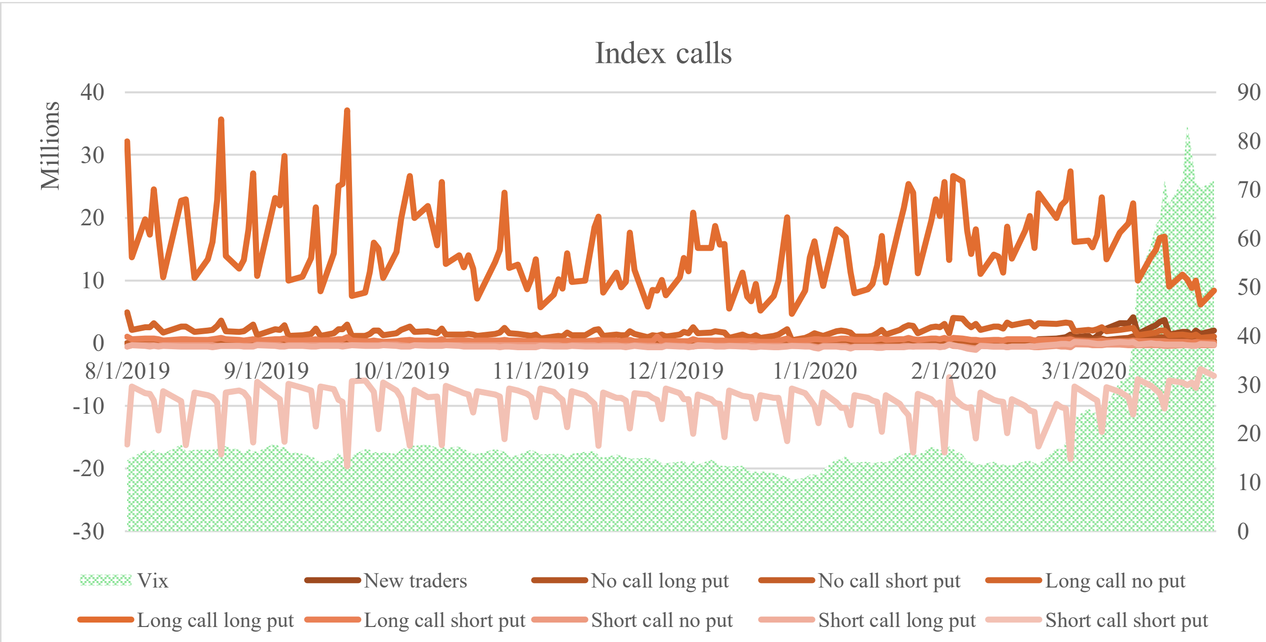
The first part of Figure C.2 displays the profits or losses by investor groups on the March 2020 expiry contract. The retail losses come almost exclusively from the short investors (mainly put writers) and represent most of the losses in March 2020 of all traders in Figure 2. In Figure B2, we find that short sellers profit substantially from short volatility strategies during the pre-event period and on the February 2020 contracts. Thus, selling volatility produces profits during normal times, reflecting a volatility risk premium, and losses during market downturns.

We turn our attention to the monthly options expiring on March 26, 2020. Within the group of short investors, Figure C.3 shows the last time that they hold any open interest on the March 26, 2020, contracts. Most traders hold positions until expiration or the day before. Trading losses are attributable to these two groups of traders with sticky strategies at least partially held to maturity.

Overall, these results suggest that option sellers sell volatility during normal times and profit from the volatility risk premium. They rebalance but close more short puts than short calls after adverse market movements but do not turn into buyers of puts, perhaps reflecting the unwillingness to realize losses, the disposition effect. The resulting stickiness combines with leverage embedded in options to generate large losses. That is, options have a multiplier effect on the delayed loss-taking in ways that make the bias consequences more severe than in stock trading.

Figure C.1: Open interest by investor groups around COVID-19

Traders are classified into different groups based on their total positions held during the pre-event period from August 1, 2019, to January 31, 2020. Traders who did not trade during the pre-event period are classified as new traders. The shaded areas denote the India VIX (right y-axis), and the solid lines of different shades denote open interests (left y-axis) by investor groups.



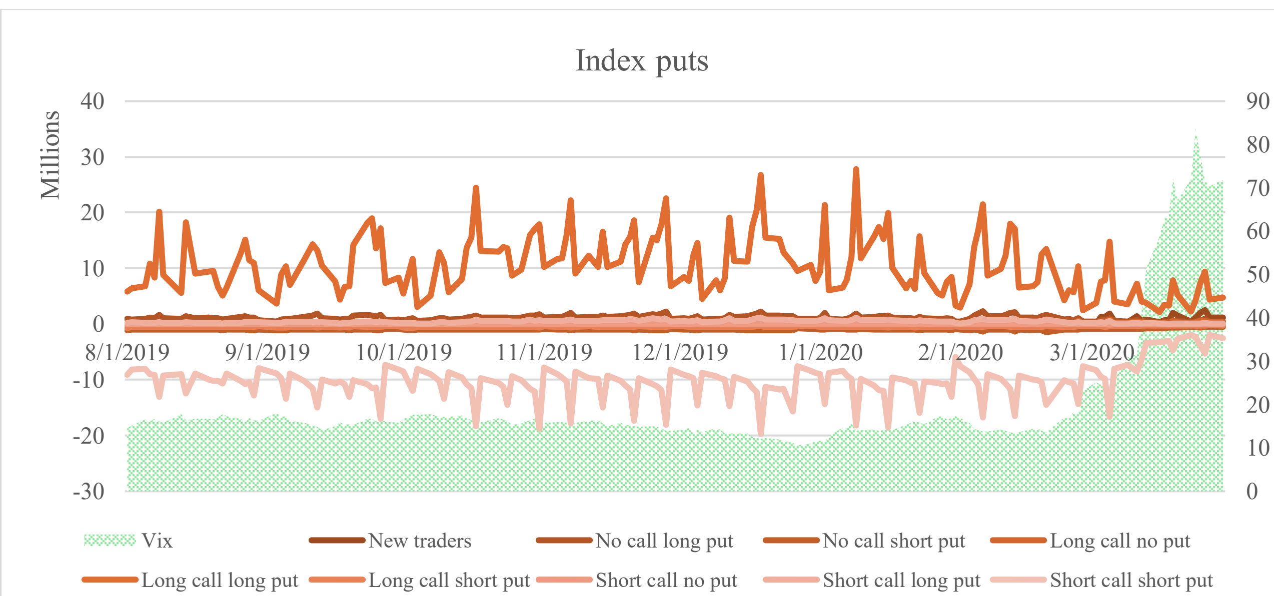
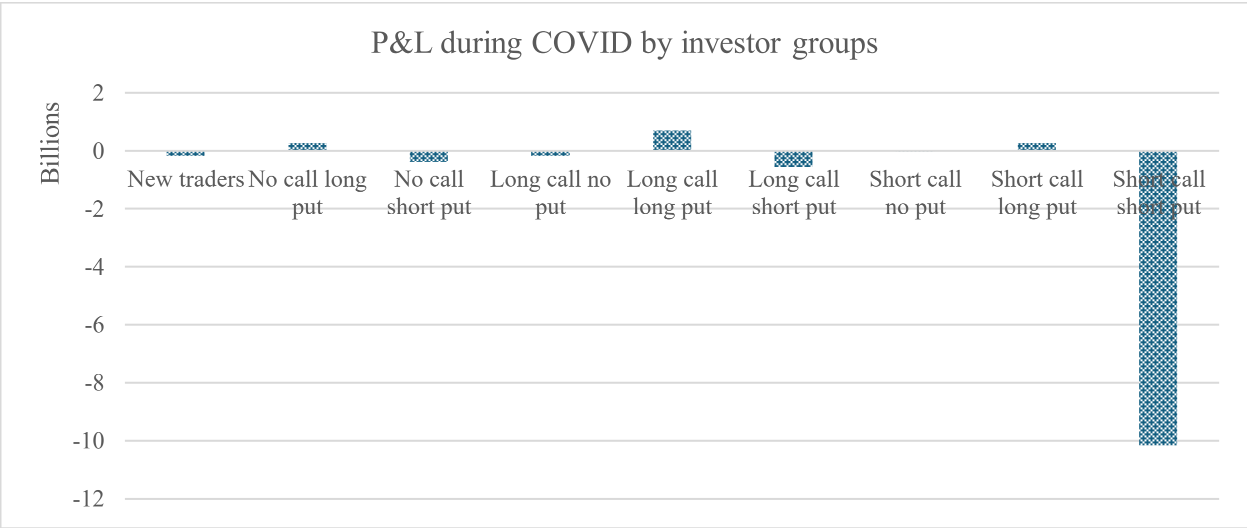


Figure C.2: Open interest by investor groups around COVID-19

Traders are classified into different groups based on their net positions held during the pre-event period from August 1, 2019, to January 31, 2020. Traders who did not trade during the pre-event period are classified as new traders. In the first subplot, the bars denote the total P&L of each group of investors on the March 26, 2020, expiry contracts. In the second subplot, the lines denote the total P&L of each group of investors on contracts expired for the seven months before March 2020.



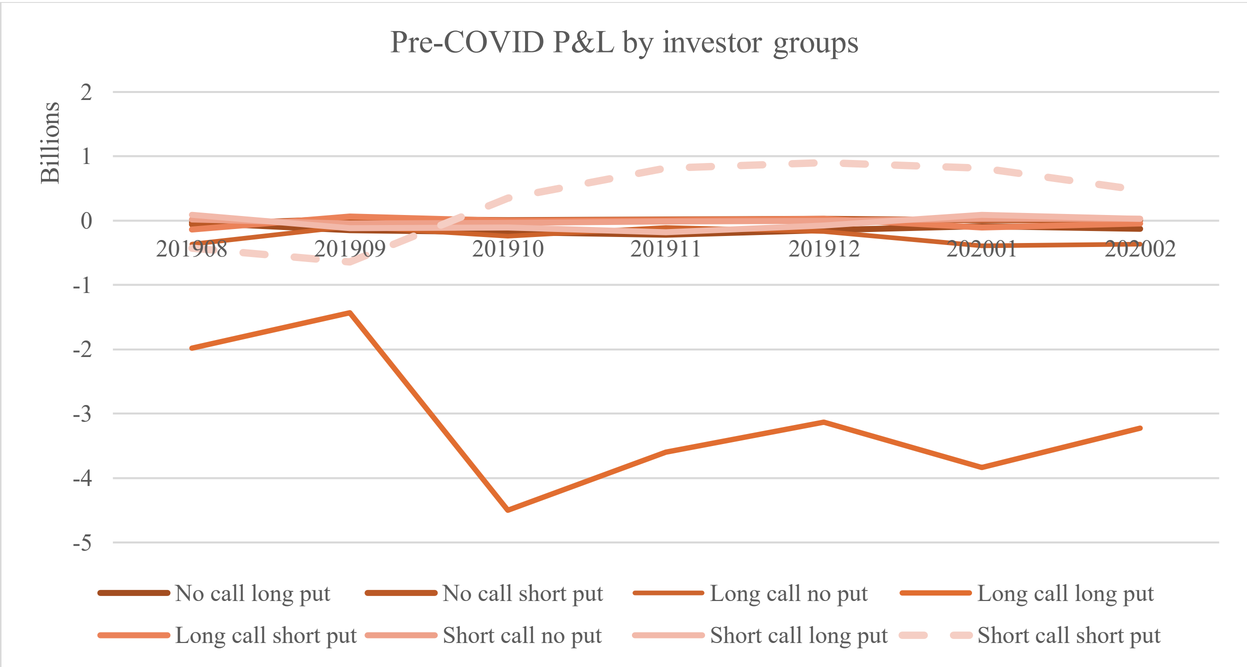
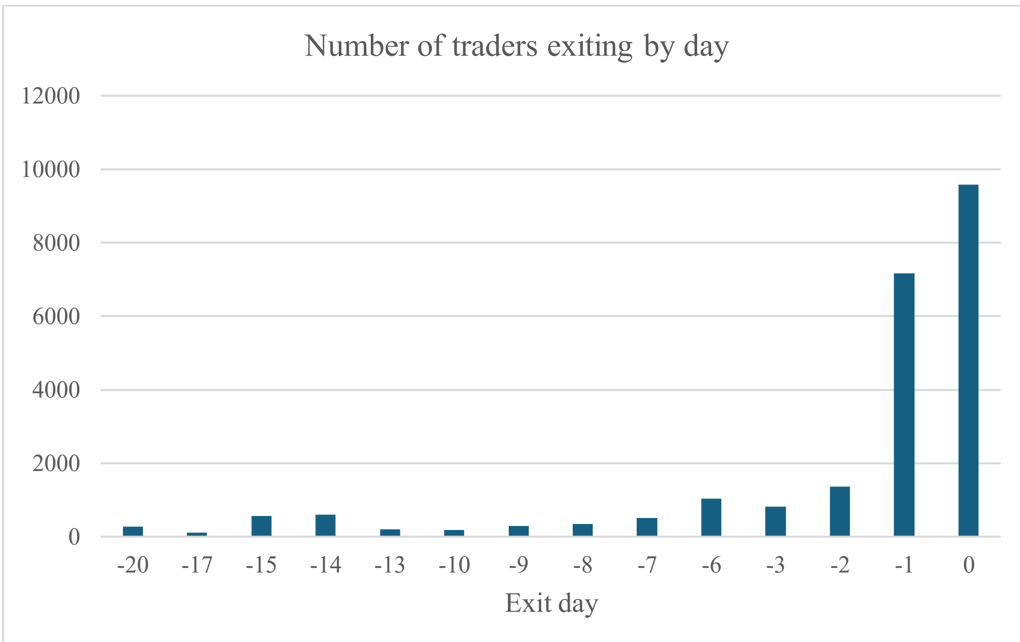
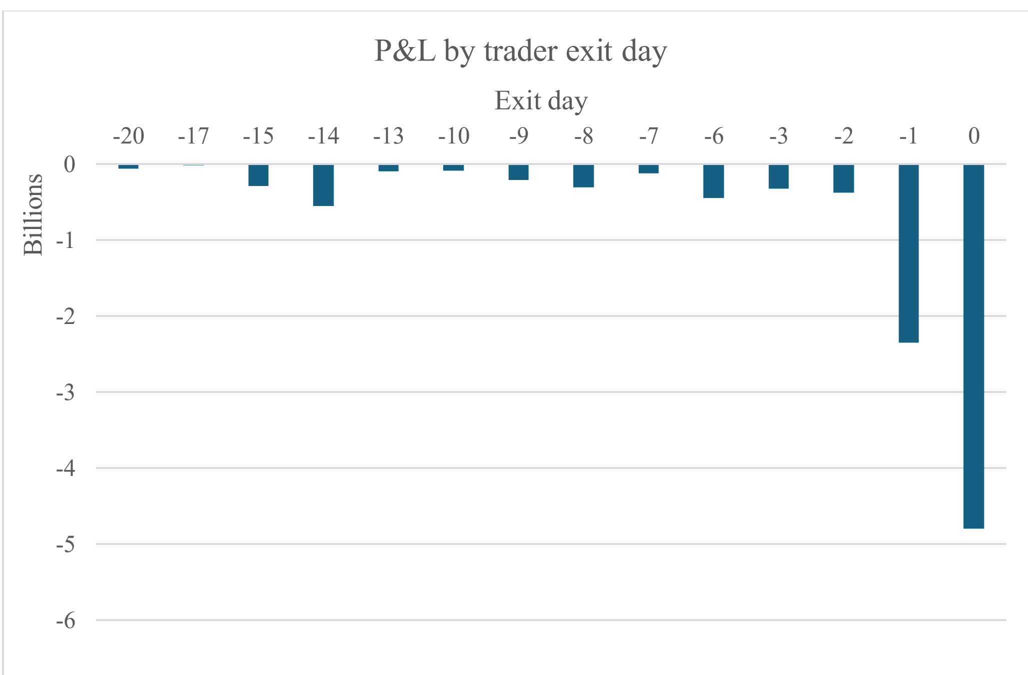


Figure C.3: Trader exit

Investors who are net sellers of both call and put options between August 1, 2019, and January 31, 2020, are classified into different categories based on the last day that they traded the March 26, 2020 contract. The exit day denotes the number of days before March 26, 2020. The first subplot shows the number of traders exiting every day up to 20 days before March 26, 2020. The second subplot shows the aggregate P&L for traders exiting on different days.





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