Animal Spirits on Steroids: Evidence from Retail Options Trading in India

Vikas Agarwal, Pulak Ghosh, Nagpurnanand Prabhala, and Haibei Zhao*

November 24, 2025

Abstract

We analyze a market-wide panel dataset of retail options trades in India, one of the largest derivatives markets. Retail trades concentrate in index options and are largely short-term, dominated by day trades and short-duration directional bets with escalating volumes as options converge to 0DTE. Traders experience significant losses. An exogenous increase in the supply of short-expiry options increases short-term trading. Traders undo the effects of shocks that increase participation costs through shifts to affordable options but outcomes are worse. The results suggest that while enabling financial market participation increases welfare in canonical household finance models, it can also entrench speculative tastes that are hard to undo.

JEL Codes: D14, D18, G14, G15, G18, G50, G53, O16
Keywords: Options, Retail Options Trading, Speculation, Skewness, Lotteries, Gambling, Addiction, Financial Inclusion, Stock Market Participation

For updates, kindly see https://papers.ssrn.com/sol3/papers.cfm?abstract_id=5430635

*Vikas Agarwal is at the J. Mack Robinson College of Business, Georgia State University. Email: vagarwal@gsu.edu. Pulak Ghosh is from Decision Sciences and Center of Public Policy, Indian Institute of Management Bangalore. Email: pulak.ghosh@iimb.ac.in. Nagpurnanand Prabhala is from Carey Business School, The Johns Hopkins University. Email: prabhala@jhu.edu. Haibei Zhao is from College of Business, Lehigh University. Email: haz816@lehigh.edu. Vikas Agarwal would like to thank the Centre for Financial Research (CFR) in Cologne for their support. We thank Vimal Balasubramaniam, Nicola Fusari, Gerry Gay, Itay Goldstein, Jan Hanousek, Pankaj Jain, Haaris Mateen, Thomas Mosk, Dmitriy Muravyev, Ilaria Piatti, Indira Puri, Davide Tomio, Antoine Uettwiller, Xiaoyan Zhang, seminar participants at the Tsinghua PBC, National University of Singapore, Queen Mary University of London, University of Melbourne, University of Technology Sydney, Deakin University, Lehigh University, University of Memphis, Chinese University of Hong Kong (Shenzhen), City University of Hong Kong, and University of Alabama, and conference participants at the Conference on Financial Economics and Accounting (CFEA), FMA Conference on Derivatives and Volatility, Future Finance Fest (3f), and FMA for valuable comments.

1 Introduction

There has been a significant surge in retail stock options trading in recent years. We present evidence on its nature, drivers, and consequences using a dataset from National Stock Exchange (NSE) of India, which is by some measures the world's largest options market. Our dataset includes trades by all retail investors trading at the NSE with clear markers to identify their trades. Its panel structure lets us characterize typical retail option trading strategies, trader entry and exit, trade performance, and trader responses to three supply-side shocks that increase short-term speculative opportunities or try to curb it by raising participation costs.

We provide a quick summary of the main findings. Retail trades concentrate in options on two stock indexes, viz., NIFTY50 and BANKNIFTY, and represent significant portions of the options market. Option trades are extremely short horizon, dominated by day trading or short duration directional bets. Trading exhibits periodicity. Activity begins to increase starting 5 days before option expiry and surges as options converge zero days to maturity. Traders make significant losses, especially in trades through FinTech brokers, which have a majority market share of trading volume towards the end of our sample period.

We consider three natural experiments, supply-side shocks that alter the opportunities to trade short-term options or the costs of doing so. The first experiment is the introduction of weekly expirations to supplement available monthly expiration cycles. Interestingly, weeklies were offered only for BANKNIFTY index options but not the NIFTY50 options, which sets up a difference-in-difference design within index options. The estimates show that BANKNIFTY options volume increases at both the extensive and intensive margins once weeklies are offered. Thus, increasing the supply of short-term speculative opportunities induces demand.

The second and third experiments sharply increase participation costs in options market. In index options, participation barriers take the form of an increased lot size. In individual options, these costs are imposed through delivery margins applicable for in-the-money options. In both cases, the direct effect that reduces options trading is offset by shifts to more affordable out-of-the-money options. Trader horizons shorten and their trading losses increase. The evidence shows that once speculative habits take root, they seem hard to excise – even if, as in our sample, traders suffer extensive losses.

India's derivatives market is surprisingly big. The notional volume on the NIFTY50 index options has recently surpassed the S&P 500 even in U.S. dollar terms.[1] The Indian options market has also witnessed significant growth in trading volume. Between 2007 and 2021, the time period covered by our dataset, there is 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 notional amount. The seems to be driven at least in part by the entry of new traders unexposed to markets, given that most Indian households lacked even basic bank accounts (Burgess and Pande, 2005, Cole, Giné, Tobacman, Topalova, Townsend and Vickery, 2013). Indeed, the 2024 Indian Economic Survey notes that number of traders grew from 27 million to 92 million between 2019 and 2024.

Our dataset covers all options trades on India's National Stock Exchange (NSE), which accounts for over 99% of all derivatives trading in our sample period. For each individual, the dataset 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 three striking patterns in the data. The first is the significant concentration of retail trading in index options, which account for 75% of the premium and 93% of the notional options volume. Within this universe, two index options, viz., a market wide NIFTY50 index and a bank-specific BANKNIFTY index, constitute 99.9% of the trading volume in our sample period. Given their dominance, we largely focus on index options trading.

A second feature in our dataset is trader short-termism. On average, 87% of a contract's lifetime volume occurs in its last five days. The evidence on short horizons is consistent with patterns in other options datasets (Bryzgalova, Pavlova and Sikorskaya, 2023, Beckmeyer,

[1] See, e.g., 'Retail traders push India stock options volume above S&P 500," (Financial Times, June 7, 2024). According to Futures Industry Association data, Indian markets account for 78% of the 108 billion options contracts traded worldwide in 2023.

Branger and Gayda, 2023, Bogousslavsky and Muravyev, 2024). Attractive features of short-term options include low nominal prices, the quick resolution of uncertainty, and clear payoff structures with high lottery-like skewness. The ultra-short 0DTE (zero days to expiry) options have attracted significant attention in the U.S. market.[2]. Our sample has 0DTE options, but only at monthly or weekly frequencies. These options nevertheless attract significant interest from retail traders, who account for 42% of the expiration day volume. We find other markers of retail trader short-termism. Day trading represents 90% of the volume by the end of our sample period. Thus, retail investors show preference for not only short-maturity options but also short-lived bets. The end-to-end interval between when a position is opened and its close has mean (median) of 2.4 (0) days.

Positions not closed by the end of the day tend to be simple. 78.7% of these are directional positions in options. While simple strategies are not uncommon in the U.S. (Beckmeyer, Branger and Gayda, 2023), their exact magnitude has been debated as retail trades are hard to discern in these data (Han, 2024). We have markers for retail trades. Finally, the traders in our sample sustain significant losses of INR 506 billion ($6.3 billion). Losses continue to mount after our sample period. A report by the securities market regulator in India, Securities and Exchange Board of India (SEBI), finds that losses equal INR 550 billion ($6.9 billion) in 2024 alone.[3]

We consider evidence from three natural experiments, supply-side interventions that increase trading opportunities in short-term options or increase the costs of doing so. The first one is the introduction of short-maturity index options. In May 2016, the NSE introduced weekly option expiry cycles on BANKNIFTY index but not on the NIFTY50 index options, which had only monthly expirations. We find that while both the BANKNIFTY and NIFTY index options display pre-event parallel trends, BANKNIFTY volumes surged once weeklies became available. The growth is at both the extensive and intensive margins.

[2]The CBOE introduced weekly Friday expiration SPX options in 2005, Wednesday and Monday expiries in 2016, and Tuesday and Thursday expiries in 2022. See https://www.cboe.com/insights/posts/the-evolution-of-same-day-options-trading, https://www.cboe.com/insights/posts/0-dt-es-decoded-positioning-trends-and-market-impact/

[3]The report finds that 76% of the option traders have low income, defined as being below INR 0.5 million or about $6,250 per year. See SEBI Report dated September 23, 2024.

At the extensive margin, 68% of traders are new, i.e., have never traded in BANKNIFTY options in the pre-event period. At the intensive margin, we see a volume increase, especially from male traders, younger traders, and those with histories of short-maturity trading. The BANKNIFTY shows a 7.3-fold growth in the notional volume and 2.2-fold growth in the premium volume around the event. We also find negative spillover effects, as the new BANKNIFTY traders reduce their investments in the stock market.

The next two experiments represent efforts to reduce speculative trading in options by increasing participation costs. In August 2015, the regulator SEBI increased the lot size, the smallest possible trading unit, for index options, doubling it for BANKNIFTY and tripling it for NIFTY50 contracts. We assess its effects using a difference-in-differences specification. The treated group comprises small traders trading below the new lot size cutoffs while the control group includes traders who trade in a bandwidth above the new lot size in the pre-event period. The change has the (intended) direct effect: index option trading volumes decrease when traders face greater participation barriers. However, we see an offsetting effect, viz., a shift to affordable alternatives with lower nominal prices. These are options that are more out of the money and have shorter maturity. We find that trading horizons decline, consistent with limited holding capacity of financially constrained investors. Investor returns decline. The results are consistent with the view that speculative habits are hard to shed. Once they take root, traders avenue-shift speculation to alternatives that they can afford and shorten horizons that better accommodate their limited financial resources.

A third experiment occurs in October 2019, when SEBI mandated physical settlements and delivery margins for options on single stocks.[4] This change imposes participation costs, but selectively on open in the money (ITM) positions close to expiry. These options require cash if the position requires taking physical delivery or stock purchases to make delivery as options approach maturity.[5] Our difference-in-difference design exploits the fact that margin requirements apply to ITM options but not out of the money (OTM) options on individual

[4]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.

[5]See, for example, the delivery margin requirements at Zerodha Support Portal, accessed November 2025.

stocks. The results are quite stark. There is a 70% reduction in the volume of ITM options and a 55% increase on OTM options at maturity. Furthermore, the 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.

Of particular interest are "FinTech" brokers, who attract customers by charging lower commissions, offering caveated advice on trading strategies, typically through trading apps. Our dataset identifies trades made through FinTech brokers. This volume expands significantly to over 60% of the retail volume in the final year of our sample. We find that traders using FinTech brokers have greater trading volume and incur greater trading losses. A subsample of traders switches between FinTech and non-FinTech brokers. For these switchers, we can estimate models with trader fixed effects and find that their FinTech broker trades show greater volume and losses relative to their non-FinTech broker trades.

One question is whether traders entering options have successful stock trading histories. This is not the case. In fact, traders who enter options trading have less stock trading experience and exhibit worse prior stock trading performance compared with stock traders who did not enter. Option entrants have historically preferred stocks with greater volatility and lottery-like features. These results are not consistent with the view that option traders are rational learners who extend their span from simpler instruments into more sophisticated instruments. The evidence is more consistent with overconfidence and ability extrapolation (Greenwood and Shleifer, 2014).

In our view, the results indicate significant challenges in curbing speculative behavior in options once it takes root. The supply of short-term contracts induces trading, in particular of a short-horizon speculative nature that seems to have little economic benefit to households. The efforts to undo the new habits result in avenue-shifting to what traders can afford, which are out-of-the-money, short-maturity options traded over shorter horizons if constrained investors have limited capacity to hold positions. There is little reason to expect that these alternatives yield superior performance, nor do we find evidence that they do. The more plausible interpretation is that the premature options participation induces speculative habit that are hard to undo, creating an undesirable path dependence when expanding financial market participation. Speculative losses have psychological or health effects.[6] Our study suggests that such ill-effects and additional manifestations of addiction to speculation are interesting questions for future research.

2 Related Literature

The household finance literature (Badarinza, Campbell and Ramadorai, 2016, Calvet, Campbell and Sodini, 2007) points out that stock market participation benefits individuals by helping them diversify and earning the equity risk premiums. The Indian market has been a success story in this regard. Participation has expanded more than three-fold from 27 million to 92 million individuals in under a half-decade, driven by digitization and simplified onboarding processes. Our study highlights that participation has benefits but can also impose costs. Specifically, our study suggests that tastes for speculation can take root when participation gives households easy access to trade lottery-like instruments with negative consequences for financial (and potentially physical) health. These concerns are by no means unique to the Indian market. In the U.S., the Securities and Exchange Commission (SEC) and FINRA raise concerns about retail participation in unfamiliar products.[7] Xiong and Yu (2011) discuss a related point in the Chinese warrants market. A policy question is how to mitigate these ill-effects. Requiring accreditation limits investor choice. While the argument seems weak when retail traders make consistent losses of large magnitude, designing effective literacy interventions has been challenging (Lusardi and Mitchell, 2014, Cole, Sampson and Zia, 2011).

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 Han (2024).

[6]See Engelberg and Parsons (2016), or press reports from India, e.g., India Today, October 20, 2024 or Livemint, August 23 2024.

[7]See FINRA, August 2022, SEC, June 2024. Press reports, e.g., Wall Street Journal, December 20, 2024 discuss the role of trading apps.

Naranjo, Nimalendran and Wu (2023) and De Silva, So and Smith (2025) 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 (2025) 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 (2025) examine retail order execution in relation to payment for order flows. Lipson, Tomio and Zhang (2023) use Robinhood's introduction of options as a shock to retail trading to assess its impact on retail participation and option prices. Unique features of our data include the availability of market-wide data on all retail option traders, a panel structure, and clear identifiers for retail traders. We characterize the short-termism in retail options trading, its consequences, and its drivers through natural experiments that ease or attempt to rein in speculative behavior.

Bogousslavsky and Muravyev (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 universe of retail option investors in India, including many new to options, their speculative behavior, and natural experiments that speak to the economic drivers of retail option trading.

Several studies assess the manifestation of lottery preferences in stock investments. See Barberis and Huang (2008), Kumar (2009) and Han and Kumar (2013) on lottery stocks and Bali, Cakici and Whitelaw (2011) on a related "high max" portfolio. The concentration of lottery features in very small stocks can create 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 such impressions may be misplaced when considering options. Index options provide ample skewness, as we show in Online Appendix B.[8] More broadly, embedded leverage, nonlinear payoff structures, and variations across maturities, moneyness, and trading horizon offer a variety of bets in options markets that investors seem to recognize. The notional value of options is 86 times the stock volume for individuals trading in both markets.

3 Data

3.1 The Aggregate Indian Options Market

The Indian options market is unusually active. For context, India's 2023 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, according to 2023 Futures Industry Association statistics, the NSE accounts for over 80% of the 137 billion derivatives contracts traded in the world. Derivatives 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) shows that options turnover has increased 35-fold from INR 0.6 trillion to INR 1.52 trillion between 2018 and 2024.[9] Index options dominate options trading in India, constituting 91% of the premium volume. The increase in options volume is not explained by increases in stock index levels, which double over the same period. Nor does the growth in premium volume reflect increased propensity to trade stocks. Option premium volumes increased from 0.4% to a remarkable 70% of the stock market trading volume over this period.[10]

[8]We compute the time-series skewness of the option portfolio returns by maturity and moneyness buckets following Boyer and Vorkink (2014). Skewness is between 1.1 and 3.9 for options with moneyness in [-0.5%, +0.5%] and between 7.5 and 18.1 for out-of-the money options with moneyness below −2%. Lottery stock portfolios have lesser skewness (e.g., 0.219 in Boyer, Mitton and Vorkink (2010) and 1.35 in Bali, Cakici and Whitelaw (2011).

[9]See the Handbook of Statistics, Table 29, available at the SEBI website, accessed on April 11, 2025.

[10]Option premiums are small so notional to premium multipliers tend to be large. For example, a 1-month call on a $100 stock at 20% volatility is priced at $2.49, a 40X notional-to-premium multiplier.

Regulatory oversight of trading vests in the Securities and Exchange Board of India (SEBI). Virtually all options trading in our sample occurs at the National Stock Exchange of India (NSE), an automated electronic trading exchange established in 1992 by India as part of a move towards market reforms and economic liberalization. The NSE introduced derivatives trading beginning in 2000 through 2006 with index futures, single stock futures and options, and index option products. The Bombay Stock Exchange is a traditional open-outcry market in operation since 1875. However, the NSE dominates with 90% of the overall volume and 99.6% of the options volume in India.[11]

3.2 Our Dataset

We have a panel dataset on option trading of all investors on the NSE at the trader-day-contract level from January 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. Because options are in zero net supply, institutions are counterparts for retail trades. Their profits are equal to the aggregate losses of retail traders.

We define retail traders as the ones flagged as "Individual" in the data. We refine the definition 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

[11]See a news report at Bloomberg on an October 21, 2016. As another metric, the NSE reports 2024 revenues of INR 164 billion versus INR 1.62 billion for the BSE.

small in number but with significantly greater activity. We analyze them separately in Online Appendix C, which shows that they are different from other retail traders. We also trim observations in the left tail as it includes "occasional" traders with tiny trading volumes. This bucket has traders whose premium volume is less than 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.

3.3 Key Variables

We consider three metrics of option trading volume, viz., the number of contracts traded, regardless of the option premium or underlying share price, the notional volume (the number of contracts multiplied by the share prices of the underlying), and 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 each investor's trades from the introduction of each options contract to its 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. For completed trades, profits come from 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 based on charges set by a prominent discount broker.[12] The true losses are likely greater as full-service broker commissions are higher. Moreover, if intraday round-trip trades are split, retail traders incur extra commissions that are not captured in our dataset. Appendix A provides detailed variable definitions.

4 Descriptive 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. The significant differences between median and mean reflects the heterogeneity and 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.

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 INR 109,900 or about $1,374, and especially significant for low-income investors with annual earnings below INR 500,000 (US$6,250) who account for 76% of the trading volume according to a 2024 SEBI report (footnote 10). Panel C of Table 1 shows that traders are present for a mean (median) of 548 (147) days in the market. Panel D shows that the mean duration of trades is 2.4 (2.3) days for index calls

[12] This is the fee charged by a major broker Zerodha

(puts). The medians are zero, indicating that the typical trader in options a day trader.

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 with growth elevated in recent years due to universal bank account provision, the establishment of unique digital identity, the spread of mobile phones, and digital payments (Agarwal, Qian, Ren, Tsai and Yeung, 2025, Dubey and Purnanandam, 2025, Ghosh, Vallee and Zeng, 2025) We see similar expansion in the number of contracts traded, notional amounts, and premium volumes. 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.

Profits and Losses Figure 2A plots the monthly profit or loss of all retail options traders. Aggregate retail losses increase as retail trading volume expands, particularly in the recent periods that have witnessed a boom in options trading, and 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 near maturity date on March 26, 2020. These patterns are consistent with the disposition effect in which investors exhibit distaste for realizing losses (Benartzi and Thaler, 1995, Shefrin and Statman, 1985, Barber and Odean, 2000, Dhar and Zhu, 2006, Barberis and Xiong, 2009). This result is remarkable result another reason. The retail investors in our sample typically have net long positions and short horizons, as we 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 D provides more details including the relevant return computations.

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 return is –6.7% if equally weighted across investors and reduces to –1.4% if value weighted. We note that these statistics probably do not do justice to the true economic significance of the losses as they accrue to investors over short horizons of a few days.

Concentration in Index Options Figure 3A shows that index options represent 93% of the total notional volume and 75% of the total premium volume for retail investors.[13] The literature on household finance. See, e.g., (Calvet, Campbell and Sodini, 2007, Badarinza, Campbell and Ramadorai, 2016, Gomes, Haliassos and Ramadorai, 2021) notes that because households are under-diversified, investing in indexes could be welfare-enhancing. However, the case for index options seems less compelling, especially given the short investor horizons we find 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, Pearson and Poteshman, 2007, Bandi, Fusari and Renò, 2023, Bryzgalova, Pavlova and Sikorskaya, 2023, De Silva, So and Smith, 2025). In this market, index options have only one-fifth of the total stock options volume in Chordia, Kurov, Muravyev and Sub-

[13] We omit contract volume because given price differences, comparisons with single stock options are not meaningful.

rahmanyam (2021) and their trading is driven by institutional hedging demand (Lemmon and Ni, 2014). Figure 3B shows that in our sample, the proportion of traders who only trade single stock options in a given month has become increasingly smaller in recent years.[14]

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 with no prior trades in the options. The only 0DTE options in India are options on their expiration dates. Their increased volumes suggest that even when sparsely available, 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

[14]The high proportion of traders trading both calls and puts (Figure 2B) does not indicate that they use straddles, which represent only 4.67% of the open positions, while the remaining 95.33% of option interest comes from simple long call or put positions.

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.[15] 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 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.

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,

[15] 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.

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 (2025) and others.[16]

5 Natural Experiments

5.1 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 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

[16]While institutions are not our focus in this study, we have some data on them. We verify that the aggregate losses borne by retail investors are the aggregate profits of the institutions.

(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 capita 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 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? Do 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. There is little evidence that the introduction of weeklies has been a positive development. Rather, it seems to have induced excess trading and exacerbated retail trader losses.

We have demographic information for a subgroup of investors including gender, age, and investor location. We define three investor groups age18_40 for age between 18 and 40, age41_60 for age between 41 and 60, with the age 60+ as the benchmark omitted category. For geographies, we define Tier 1 as residents of Mumbai, Delhi, Bengaluru, Chennai, Kolkata, Hyderabad, Pune, and Ahmedabad, major urban locations. 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 males trade more (columns 1-3), incur greater losses (column 4), 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). These results are reminiscent of those in Barber and Odean (2001), who discuss overtrading by males as reflecting overconfidence. We find that the results for the young traders resemble those for males. The mixed results for Tier 1 cities indicates that the patterns do not reflect trader locations in Tier 1 cities.

In sum, we have an unusual and significant supply shock that introduces short-term options to retail investors. Volumes spike in the newly available short-term BANKNIFT index options at both the extensive and intensive margins relative to the NIFTY50 options, the other popular option series in which weeklies remain unavailable. An undesirable side-effect is the reduction of stock market participation for those entering options trading. The benefits of short-term trades in index options seem a priori implausible for retail traders. We find that this is the case: losses seem to be exacerbated by increased short-term trading.

5.2 Change in Lot Size

Policy makers and India's stock market regulator, SEBI, have been concerned about retail investor losses from options trading. One approach to curb speculation was to increase lot size. Increasing lot sizes (or requiring greater delivery margins, an experiment we consider later) matter when investors face funding constraints (Kahraman and Tookes, 2017, 2020). If investors are financially 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 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 INR 394,000 on NIFTY and INR 256,000 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 each maturity-moneyness bucket 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 pre-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.[17] 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 less in the money and to shorter-maturity options. The maturity reduction is 1.9 days (column 2), which is meaningful given that active trading picks up around 5 days before maturity. We see a shift to trading 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 is consistent with the fact that OTM and shorter maturity options carry higher relative spreads (Muravyev and Pearson, 2020), greater trading costs, and 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 groups, 47% for the treated versus 53% for the control group, is not significant.

5.3 Physical Settlement

We turn to a rule change that mandated physical settlements for single stock options. Starting from October 2019, traders who keep single stock option positions open at expiry are required to take or make physical deliveries of the underlying stocks. For options in which delivery is anticipated – in the money positions – traders must hold sufficient funds or clear stock holdings, as appropriate. The cash amount, namely the delivery margin requirement, typically increases as contracts approach maturity date.[18] 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

[17]It is also possible that lot size induces option writing over option buying given the increased premium per lot traded. This effect is mitigated by margin requirements on option selling imposed by the NSE.

[18]For example, a prominent broker Upstox requires 10% of contract value on day -4 and 70% at day -1.

even if they are subsequently closed at the end of the day.[19] Positions for which margin requirements are not met are automatically squared off.

We exploit the fact that the delivery margin requirements primarily apply to the in-the-money (ITM) positions as they are subject to actual physical delivery. Certain at-the-money (ATM) positions may be affected as well given their greater likelihood of closing in the money.[20] These requirements apply only to options on individual stocks and not options on the indexes – presumably given the enormous complications associated with index basket delivery and the absence of delivery options in ETFs tracking indexes. Thus, our analysis of this experiment moves us from index options to to options on individual stocks, which represent a small but non-trivial 25% slice of the Indian options market.

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 OTM trade if the premium weighted moneyness is below –5%. These trades are substantially OTM and have little risk of being subject to delivery margin requirements. Figure 10 shows the pre- and post-event trading volumes on ITM and OTM options as options approach maturity.[21] 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 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.

[19]See examples from brokers ICICI Direct and Upstox

[20]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.

[21]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.

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×post×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.[22] In contrast, 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.

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

6 Additional Analyses

6.1 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. In rational learning models in stock trading (Seru, Shumway and Stoffman, 2010, Linnainmaa, 2011), losses temper stock investments, especially in risky stocks. However, the availability of stock options moderates this shift and instead induces risk-taking as a response to losses. Column (2) shows that the variable Highperf reduces probability of participation while Lowperf increases it, in either case with significant economic magnitudes. Given the average value of "entry" is 0.004, the coefficients imply that low (high) performance increase (decrease) entry probability by 50% (25%).

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. Given the positive correlation between return volatility and max returns, we attempt to better identify their individual effects using indicator variables. The variables Highretmax and Highretvol, are indicators for whether the variables are above or below the 75th percentiles and and Highretvol&max is their product. The results in column (4) demonstrate that all three increase the probability of options participation. The remaining variables indicate that individuals with greater volume but short histories enter options markets, consistent with models of overconfidence (Odean (1999), Barber and Odean (2000)). Thus, tastes for speculation and gambling for resurrection motives seem to drive options trading.

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.

6.2 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 open positions taken by traders for single stock options. Long calls and puts are the most popular strategies, followed by short call and put positions, all on one option series. Volatility strategies account for 5.8% of positions, while others such as call or put spreads are about 1% of options activity. Intraday positions follow similar patterns with 94% of them involving simple directional bets, 63% (26%) in a single call (put) option series and 5% involving two option series.

What do single stock options data say about cross-hedging using index options? These bets seem implausible a priori given the differences in volumes across the markets but we 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%, about 56% have bets in stocks and indexes in the same direction and 21% are classifiable as being directionally opposite. Thus, we the lower bound for *not* using index options for cross-hedging is 88.56% (74%+26% $\times$ 56%) while cross-hedging accounts for a small 5.46% (26% $\times$ 21%) portion of the options volume.

What stock options attract retail trader interest? Following Roll, Schwartz and Subrahmanyam (2010) or Johnson and So (2012), we compute the option-to-stock ratio (O/S) by scaling the options volume by the stock volume. Given the settlement rule change discussed in Section 5.3, we focus on data before 2019 for this analysis. 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. Retail investors seem to buy options to lever up capital and gain exposure to high priced stocks. Financial constraints matter: retail investors prefer options with shorter maturity and cheaper nominal prices. Past returns are significant for put buying demand for but not for stocks. Trend chasing does not seem to drive call trading.

6.3 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 in a single shot, akin to what robo-advisory platforms have offered (D'Acunto, Prabhala and Rossi, 2019). We consider the relation between the use of FinTech brokerages and retail options trading.

Our dataset identifies the brokers through which trades are executed. As payments for order flow and execution through dark pools are undeveloped in our sample, the broker identifiers are accurate. Four FinTech brokers are identified in our sample. Figure 11 shows their growth, which accelerated around January 2020 when the first Covid cases were reported in India. By June 2020, the volume through FinTech brokers exceeds that for all other brokers put together. The combined market share of FinTech brokers ends up at over 60%.

Our dataset allows us to identify investor-broker pairings. Approximately 2 million traders ever used FinTech brokers. Of these 155,000 traders switch from traditional to FinTech brokers permanently while 52,000 do the reverse, and 418,000 traders use both types of brokers. Panel A of Table 8 depicts daily premium volume for an interesting set of traders who use both traditional and FinTech brokers. Switches to FinTech brokers are elevate trading volumes by 55% while there is a 17% reduction for switches from FinTech to traditional brokers. Finally, for the 418,000 investors who use both traditional and FinTech brokers, the volume is 31% more in trades using FinTech brokers. The growth in FinTech broker volumes do not merely reflect increasing participation through these brokers.

We consider trades conducted via FinTech and traditional brokers in Panels B and C of Table 8, which are regression estimates without and with trader fixed effects, respectively, with the latter exploiting the panel structure of our data that provides individual identifiers. The variables are scaled by the number of months with participation. We find that volumes and losses are greater for FinTech broker trades with greater economic magnitudes when we include trader fixed effects (Panel C). For example, premium volume via FinTech brokers is greater by INR 0.51 million per month, which is economically significant given the sample mean is 0.53 INR million per month. The losses in trades through FinTech brokers are lower by 1.69%. The net effect of increased volume and lower but still negative losses translates into greater losses of INR 5,146 more per month FinTech broker trades for switchers.[23]

7 Concluding Remarks

Our study examines retail participation in the options market from India, one of the largest derivatives markets. 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.

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 index options, a feature now being observed in other markets. In the Indian markets, retail

[23]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.

volume also constitutes a large fraction of the aggregate market volumes, reaching 42% for options with zero days to expiry (0DTE) 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. The first experiment 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, especially low-in come individuals, to sophisticated institutions. This issue has attracted considerable attention in the press and is under investigation by India's securities regulator, SEBI.[24] While the household finance

[24]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 Jane Street Group from trading and impounded 500$millionoutofestimatedprofitsofover$4 billion from such arbitrage activities.

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.

References

Agarwal, Sumit, Wenlan Qian, Yuan Ren, Hsin-Tien Tsai, and Bernard Yeung. 2025. "The real impact of FinTech: Evidence from mobile payment technology." *Management Science*. Forthcoming.

Badarinza, Cristian, John Y. Campbell, and Tarun Ramadorai. 2016. "International comparative household finance." *Annual Review of Financial Economics*, 8: 111–144.

Bali, Turan G., Nusret Cakici, and Robert F. Whitelaw. 2011. "Maxing out: Stocks as lotteries and the cross-section of expected returns." *Journal of Financial Economics*, 99: 427–446.

Bandi, Federico, Nicola Fusari, and Roberto Renò. 2023. "0DTE option pricing." Working Paper.

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

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

Barberis, Nicholas, and Wei Xiong. 2009. "What drives the disposition effect? An analysis of a long-standing preference-based explanation." *Journal of Finance*, 64: 751–2100.

Beckmeyer, Heiner, Nicole Branger, and Leander Gayda. 2023. "Retail traders love 0DTE options... but should they?" Working Paper.

Benartzi, Shlomo, and Richard Thaler. 1995. "Myopic loss aversion and the equity premium puzzle." *Quarterly Journal of Economics*, 110: 75–92.

Bogousslavsky, Vincent, and Dmitriy Muravyev. 2024. "An anatomy of retail option trading." Working Paper.

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

Boyer, Brian H., Todd Mitton, and Keith Vorkink. 2010. "Expected idiosyncratic skewness." *Review of Financial Studies*, 23: 169–202.

Bryzgalova, Svetlana, Anna Pavlova, and Tatyana Sikorskaya. 2023. "Retail trading in options and the rise of the big three wholesalers." *Journal of Finance*, 78: 3465–3514.

Burgess, Robin, and Rohini Pande. 2005. "Do rural banks matter? Evidence from the Indian social banking experiment." *American Economic Review*, 95: 780–795.

Calvet, Laurent E., John Y. Campbell, and Paolo Sodini. 2007. "Down or out: Assessing the welfare costs of household investment mistakes." *Journal of Political Economy*, 115: 707–747.

Chordia, Tarun, Alexander Kurov, Dmitriy Muravyev, and Avanidhar Subrahmanyam. 2021. "Index option trading activity and market returns." *Management Science*, 67: 1758–1778.

Cole, Shawn, Thomas Sampson, and Bilal Zia. 2011. "Prices or Knowledge? What Drives Demand for Financial Services in Emerging Markets?" *Journal of Finance*, 66: 1933–1967.

Cole, Shawn, Xavier Giné, Jeremy Tobacman, Petia Topalova, Robert Townsend, and James Vickery. 2013. "Barriers to household risk management: Evidence from India." *American Economic Journal: Applied Economics*, 5: 104–135.

D'Acunto, Francesco, Nagpurnanand Prabhala, and Alberto Rossi. 2019. "The Promises and Pitfalls of Robo-Advising." *Review of Financial Studies*, 32: 1983–2020.

De Silva, T., Eric C. So, and K. Smith. 2025. "Losing is optional: Retail option trading and expected announcement volatility." Working Paper.

Dhar, Ravi, and Ning Zhu. 2006. "Up close and personal: An individual level analysis of the disposition effect." *Management Science*, 52: 726–740.

Dubey, T. S., and Amiyatosh Purnanandam. 2025. "Can cashless payments spur economic growth?" Working Paper.

Eaton, Gregory, T. Clifton Green, Brian Roseman, and Yanbin Wu. 2025. "Retail option traders and the implied volatility surface." *Journal of Financial Economics*. Forthcoming.

Engelberg, Joseph, and Christopher Parsons. 2016. "Worrying about the Stock Market: Evidence from Hospital Admissions." *Journal of Finance*, 71: 1227–1250.

Ernst, Thomas, and Chester Spatt. 2023. "Payment for order flow and option internalization." Working Paper.

Ghosh, Pulak, Boris Vallee, and Yao Zeng. 2025. "FinTech lending and cashless payments." *Journal of Finance*. Forthcoming.

Gomes, Francisco, Michael Haliassos, and Tarun Ramadorai. 2021. "Household finance." *Journal of Economic Literature*, 59: 919–1000.

Greenwood, Robin, and Andrei Shleifer. 2014. "Expectations of returns and expected returns." *Review of Financial Studies*, 27: 714–746.

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

Han, S. 2024. "Unveiling the sophistication: Understanding retail investors' trading behavior in the U.S. options market." CBOE Working Paper.

Hendershott, Terrence, S. Khan, and Ryan Riordan. 2022. "Option auctions." Working Paper.

Hu, Jianfeng, Antonia Kirilova, Seongkyu Park, and Doojin Ryu. 2023. "Who profits from trading options?" *Management Science*, 70: 4742–4761.

Huang, X., Philippe Jorion, and Christopher Schwarz. 2025. "Some anonymous options trades are more equal than others." Working Paper.

Johnson, Travis L., and Eric C. So. 2012. "The option to stock volume ratio and future returns." *Journal of Financial Economics*, 106: 262–286.

Kahraman, Bige, and Heather Tookes. 2017. "Trader leverage and liquidity." *Journal of Finance*, 72: 1567–1610.

Kahraman, Bige, and Heather Tookes. 2020. "Margin trading and comovement during crises." *Review of Finance*, 24: 813–846.

Kumar, Alok. 2009. "Who gambles in the stock market?" *Journal of Finance*, 64: 1889–1933.

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

Lemmon, Michael, and Sophie X. Ni. 2014. "Differences in trading and pricing between stock and index options." *Management Science*, 60: 1985–2001.

Linnainmaa, Juhani T. 2011. "Why do (some) households trade so much?" *Review of Financial Studies*, 24: 1630–1666.

Lipson, Marc C., Daniele Tomio, and J. Zhang. 2023. "A real cost of free trades: Retail option trading increases the volatility of underlying securities." Working Paper.

Lusardi, Annamaria, and Olivia Mitchell. 2014. "The economic importance of financial literacy: Theory and evidence." *Journal of Economic Literature*, 52: 5–44.

Muravyev, Dmitriy, and Neil D. Pearson. 2020. "Options trading costs are lower than you think." *Review of Financial Studies*, 33: 4973–5014.

Naranjo, Andy, Mahendrarajah Nimalendran, and Y. Wu. 2023. "Betting on elusive returns: Retail trading in complex options." Working Paper.

Odean, Terrance. 1999. "Do investors trade too much?" *American Economic Review*, 89: 1279–1298.

Roll, Richard, Eduardo Schwartz, and Avanidhar Subrahmanyam. 2010. “O/S: The relative trading activity in options and stock.” *Journal of Financial Economics*, 96: 1–17.

Seru, Amit, Tyler Shumway, and Noah Stoffman. 2010. “Learning by trading.” *Review of Financial Studies*, 23: 705–739.

Shefrin, Hersh, and Meir Statman. 1985. “The disposition to sell winners too early and ride losers too long.” *Journal of Finance*, 40: 777–790.

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

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.

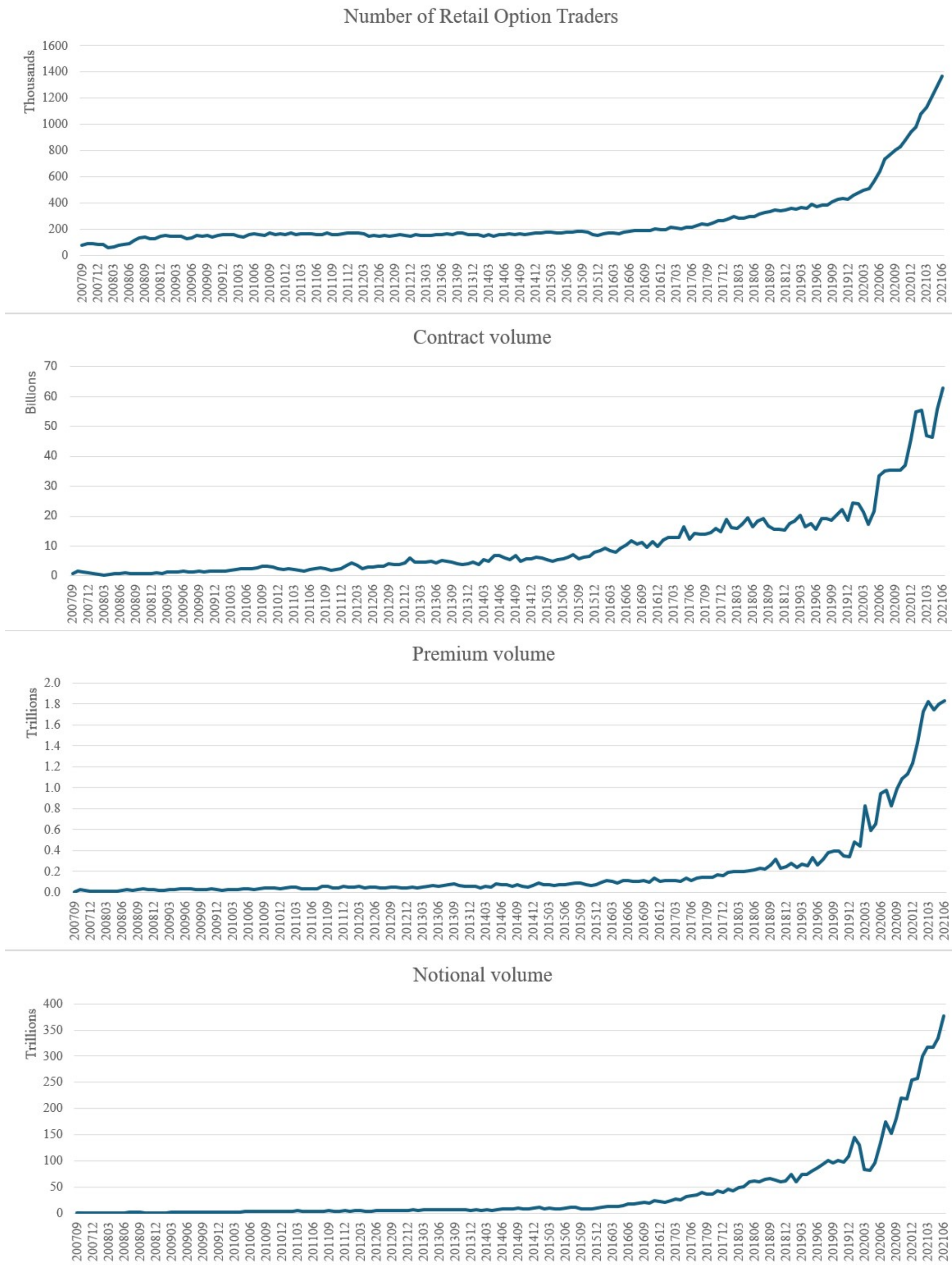
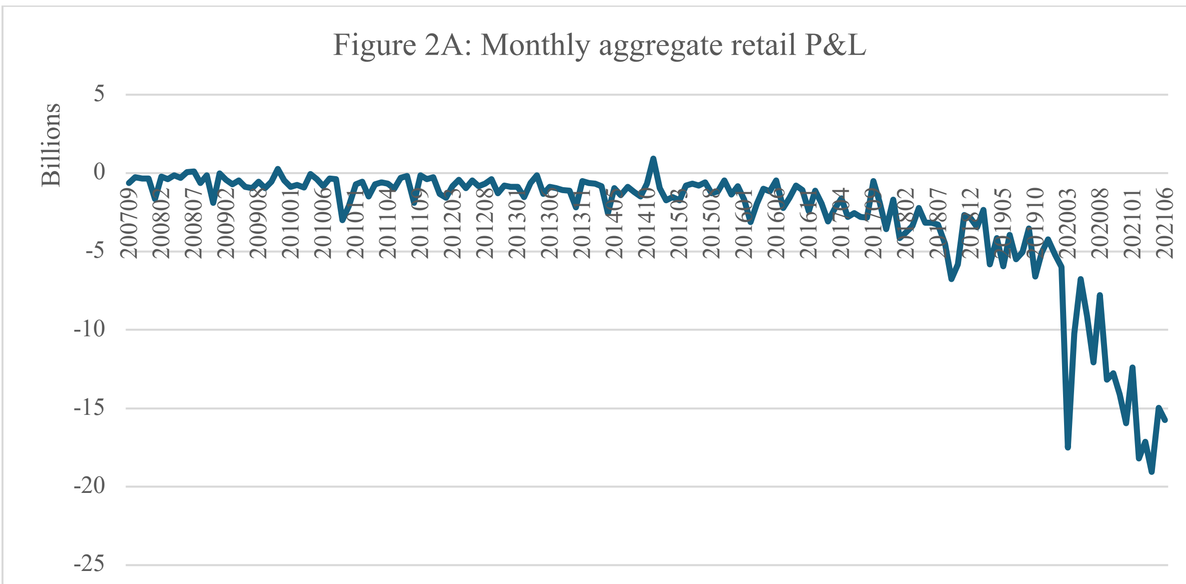


Figure 2: Trading Profits and Losses and returns

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.



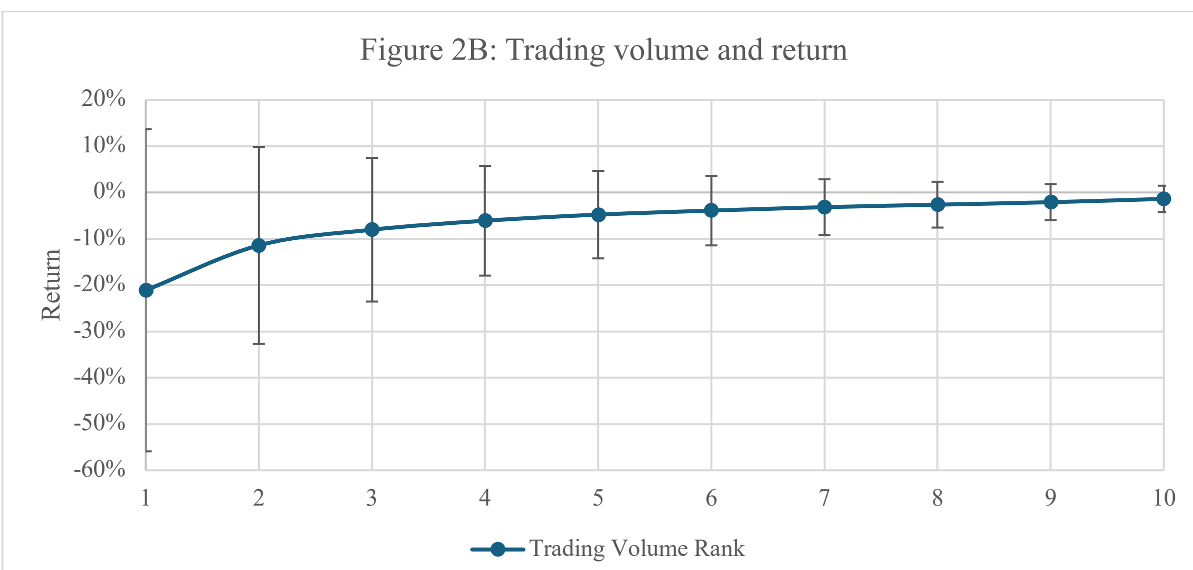
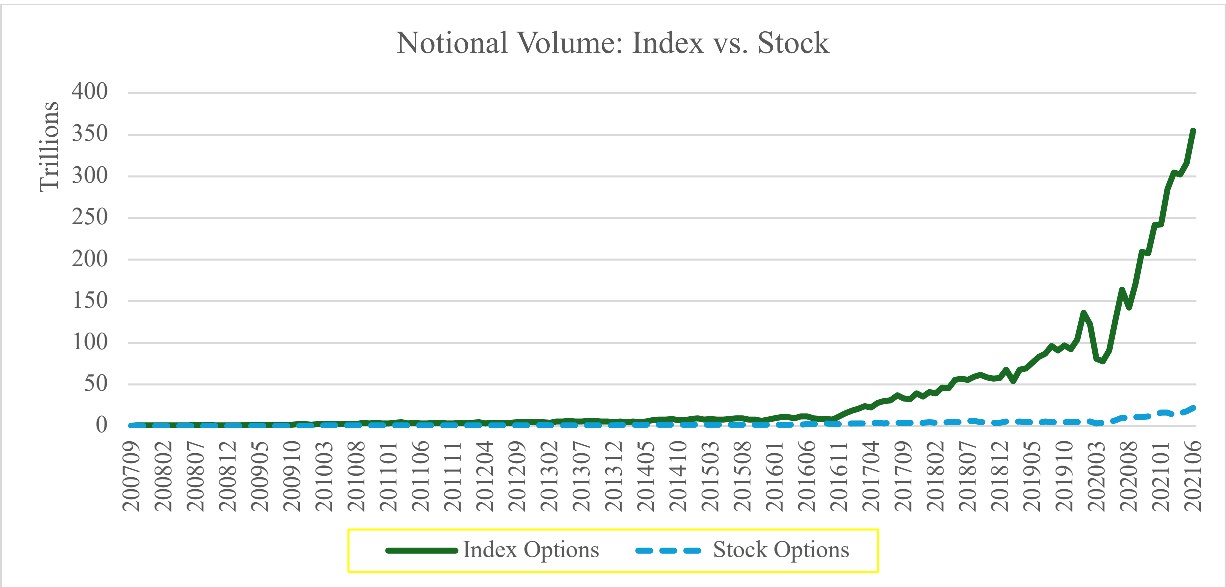
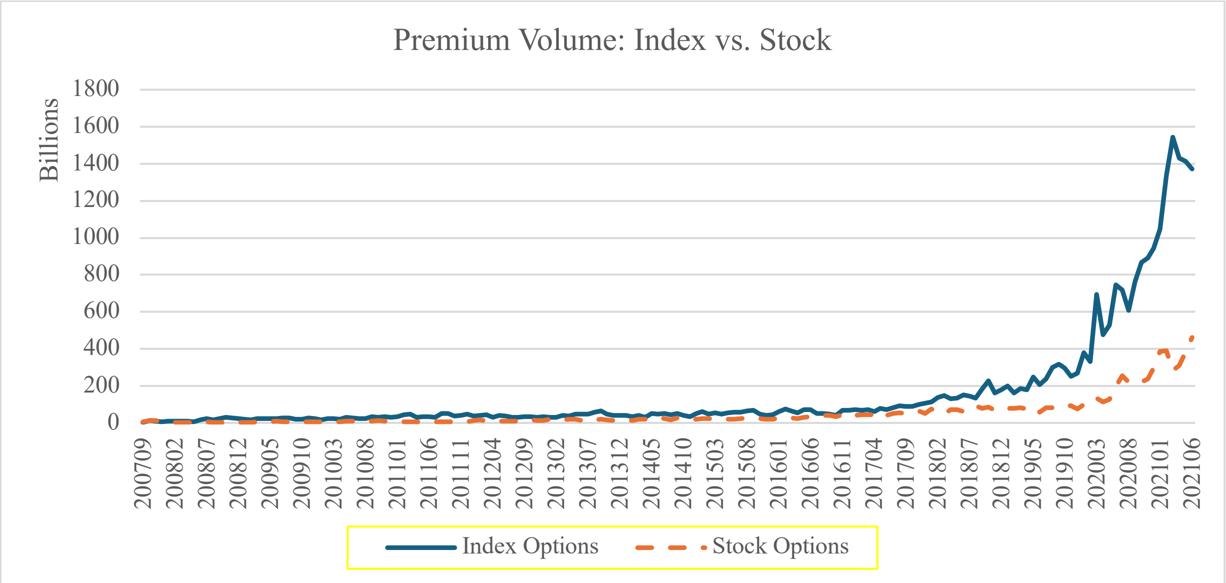


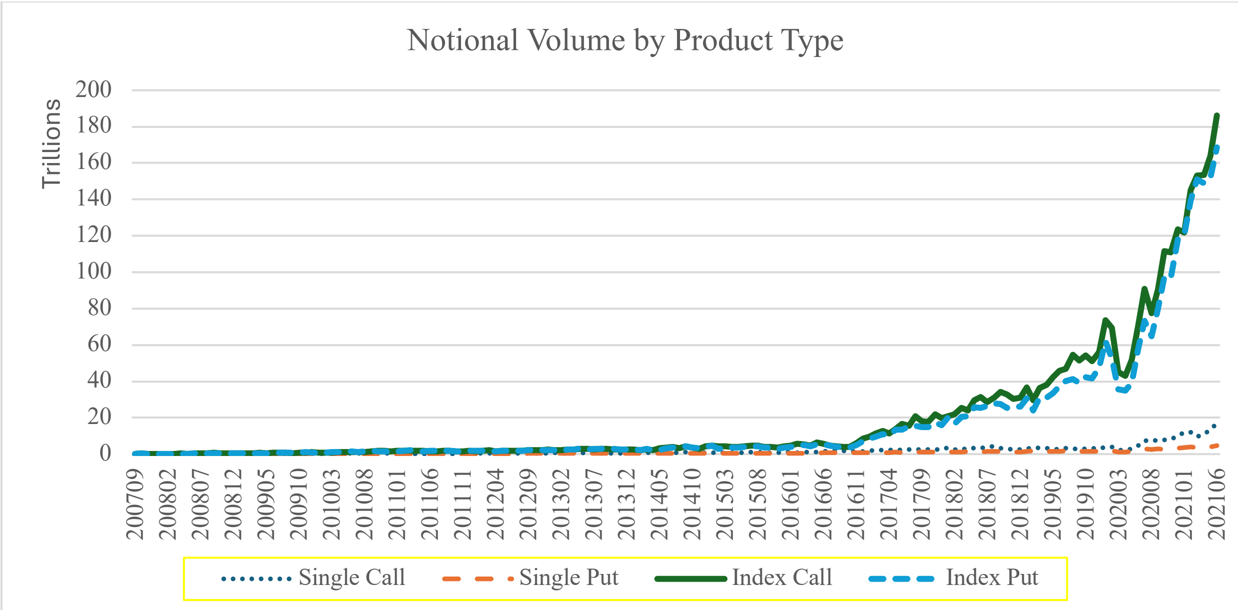
Figure 3: Trading volume on index and single stock options

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
201802
201807
201812
201905
201910
202003
202008
202101
202106
Single Call
Single Put
Index Call
Index Put

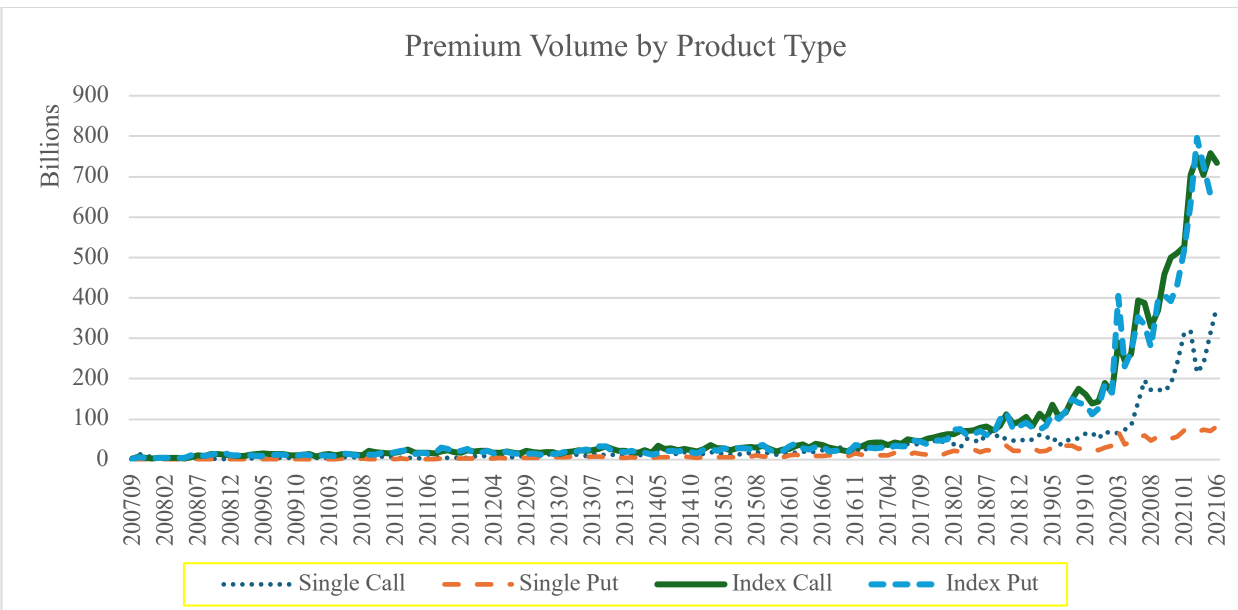
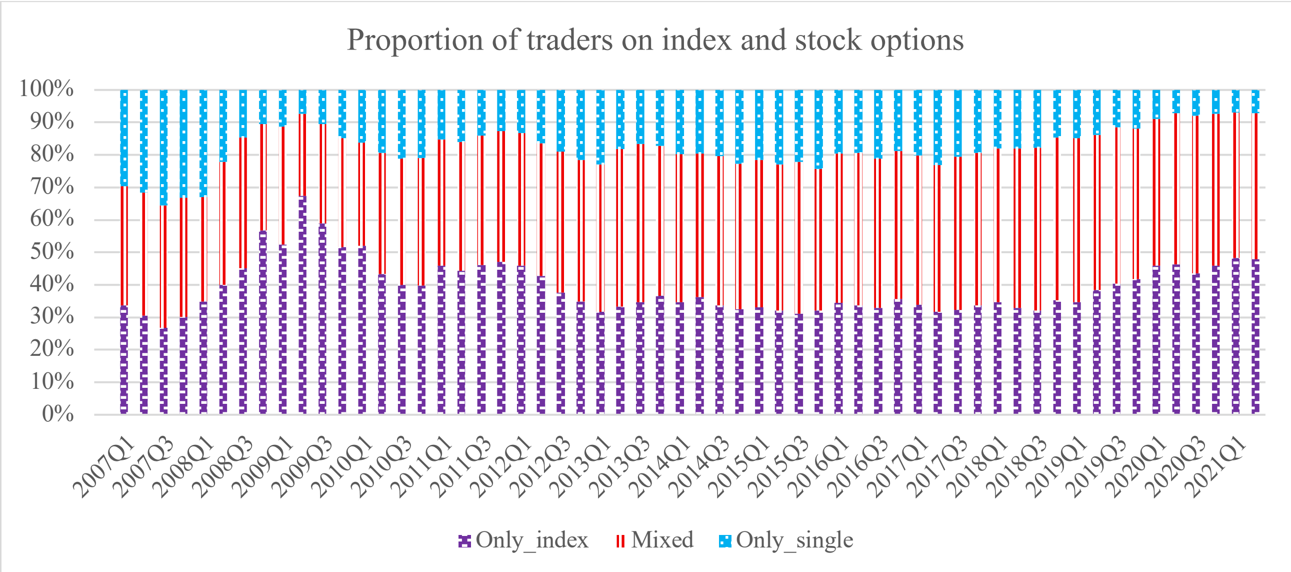

Premium Volume by Product Type
Billions
900
800
700
600
500
400
300
200
100
0
200709
200802
200807
200812
200905
200910
201003
201008
201101
201106
201111
201204
201209
201302
201307
201312
201405
201410
201503
201508
201601
201606
201611
201704
201709
201802
201807
201812
201905
201910
202003
202008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

Figure 3B: Fraction of traders on different products



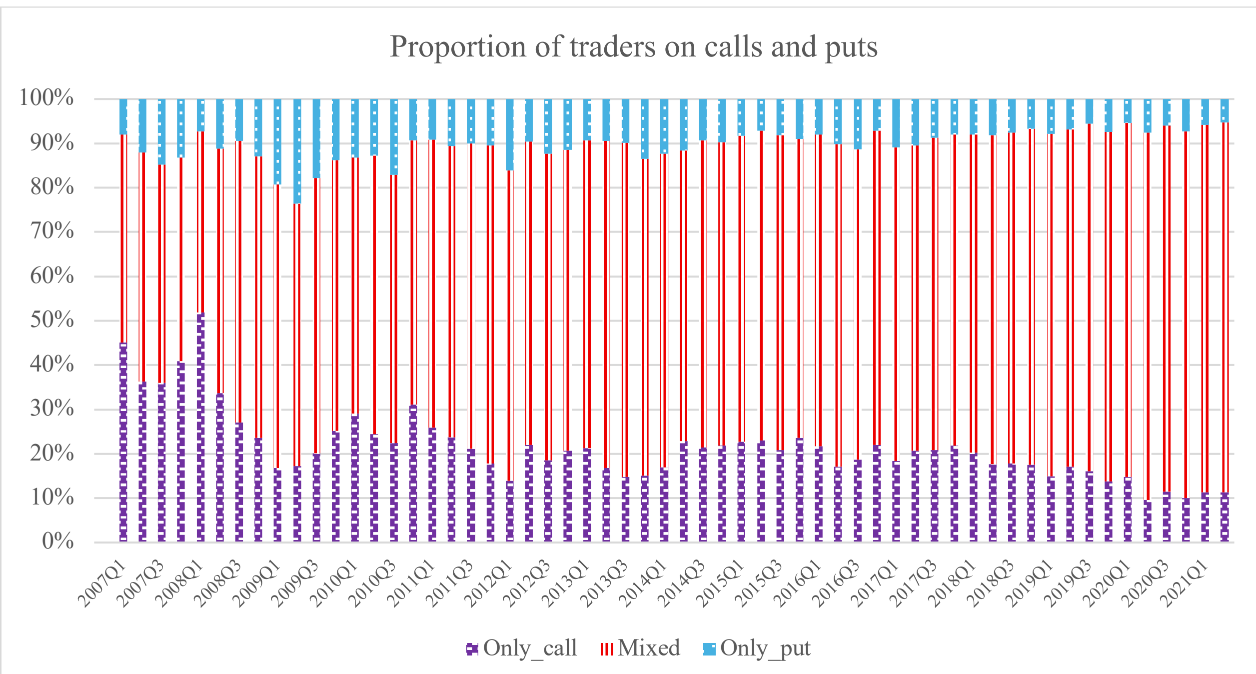


Figure 4: Time to maturity and trading behavior

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

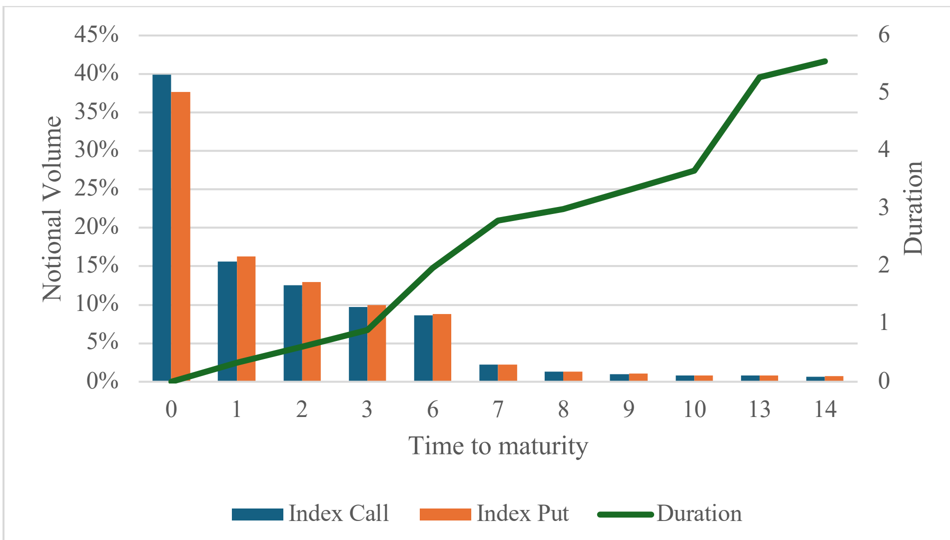
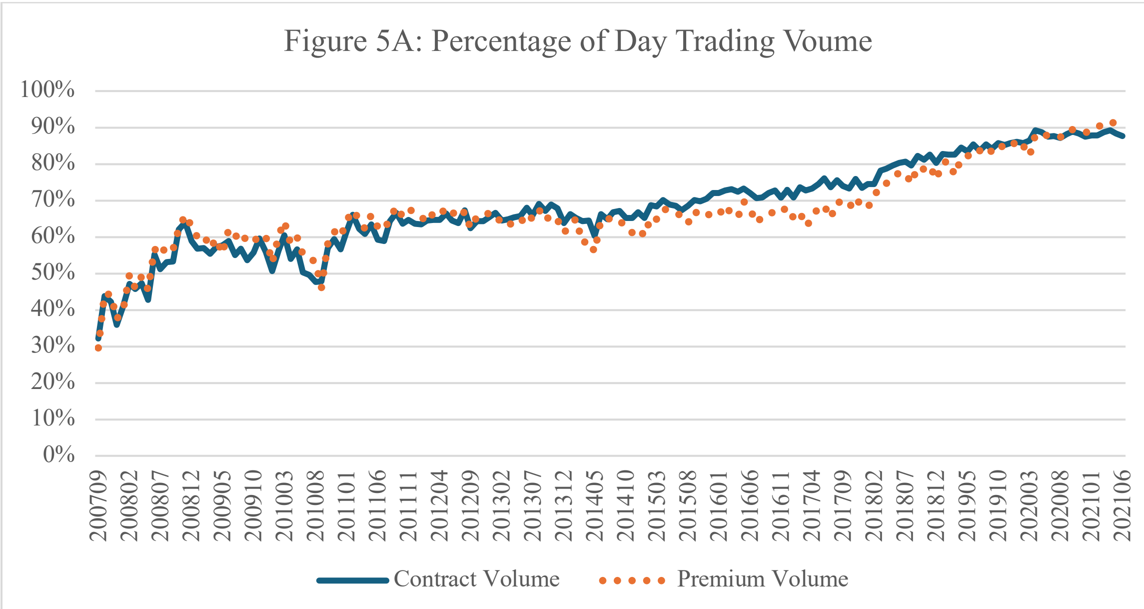
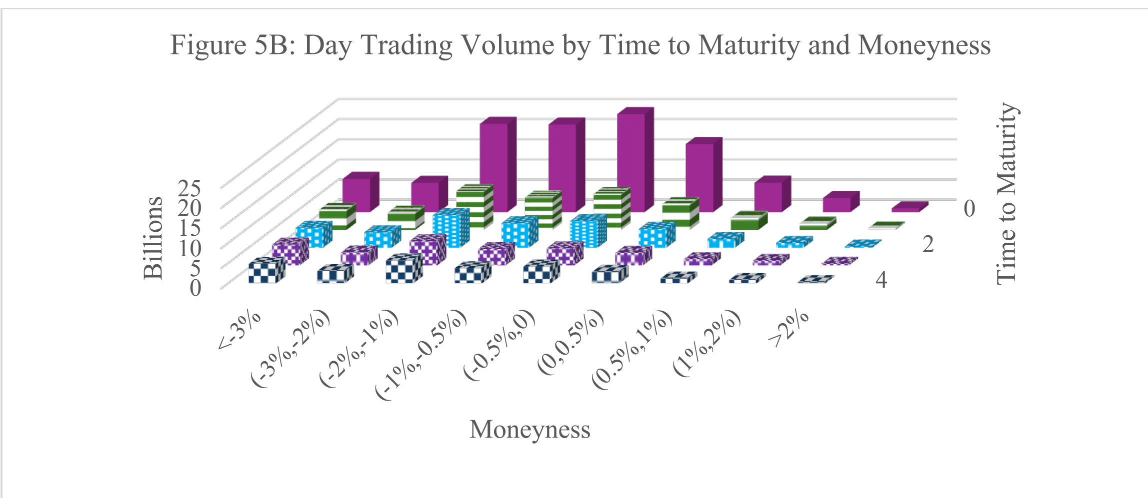


Figure 4B: Volume by new and old traders

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.





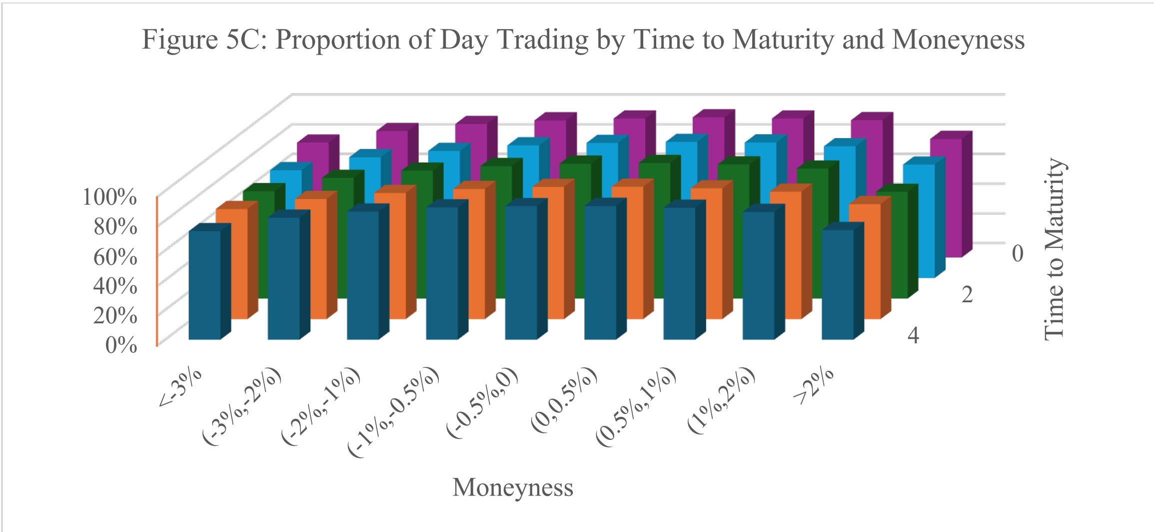
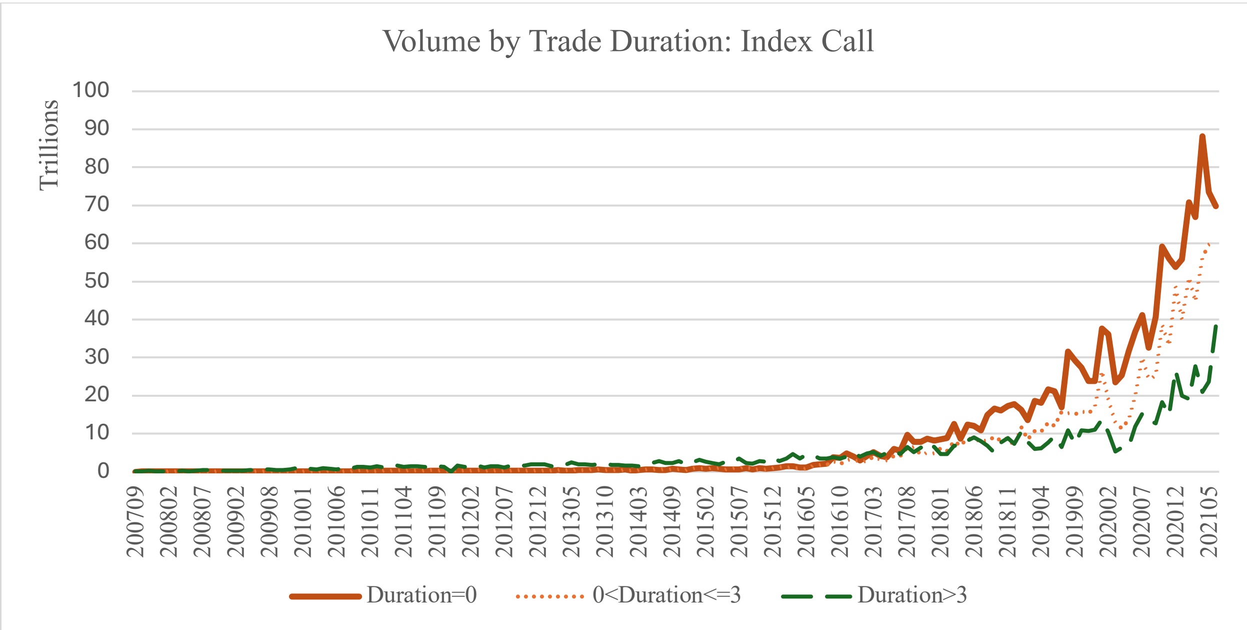


Figure 5C: Proportion of Day Trading by Time to Maturity and Moneyness
100%
80%
60%
40%
20%
0%
<-3%
(-3%,-2%)
(-2%,-1%)
(-1%,-0.5%)
(-0.5%,0)
(0,0.5%)
(0.5%,1%)
(1%,2%)
>2%
Moneyness
0
2
4
Time to Maturity

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.



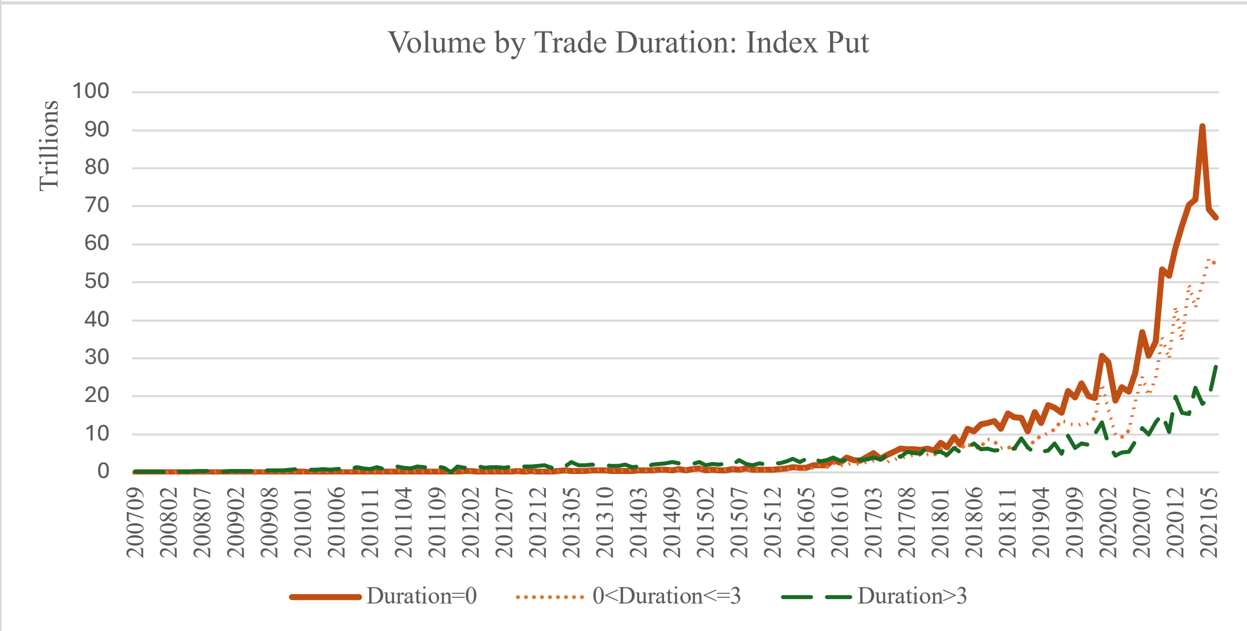
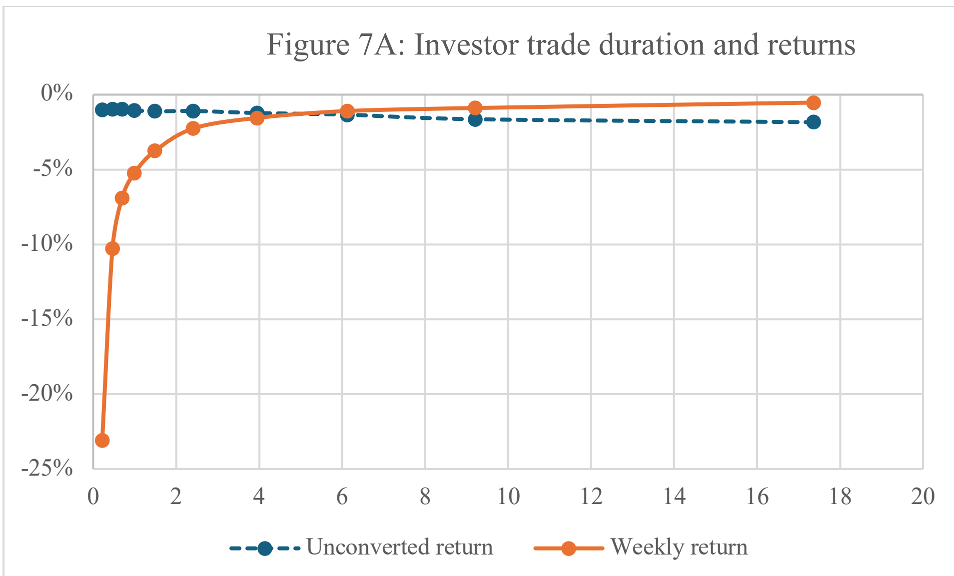


Figure 7: Trader duration and returns

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.



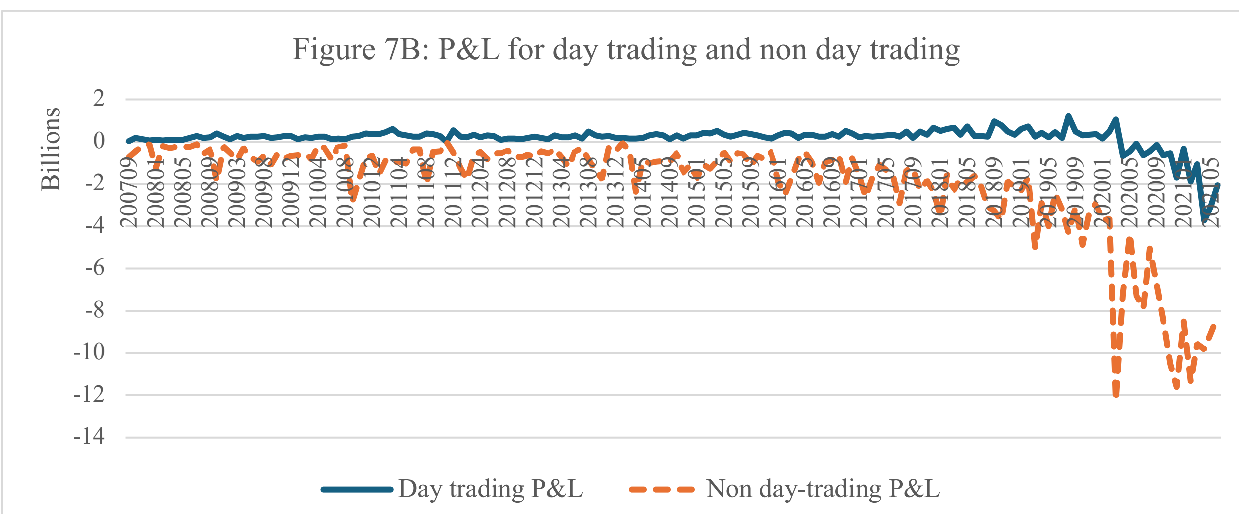
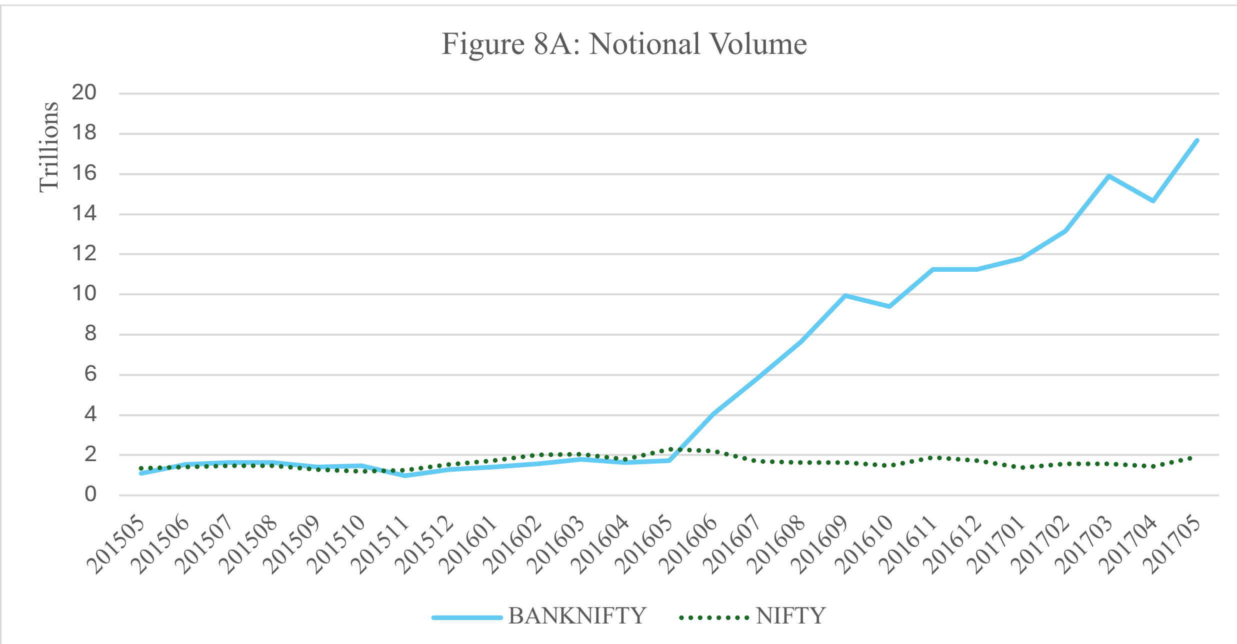


Figure 8: Introduction of weekly BANKNIFTY

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.



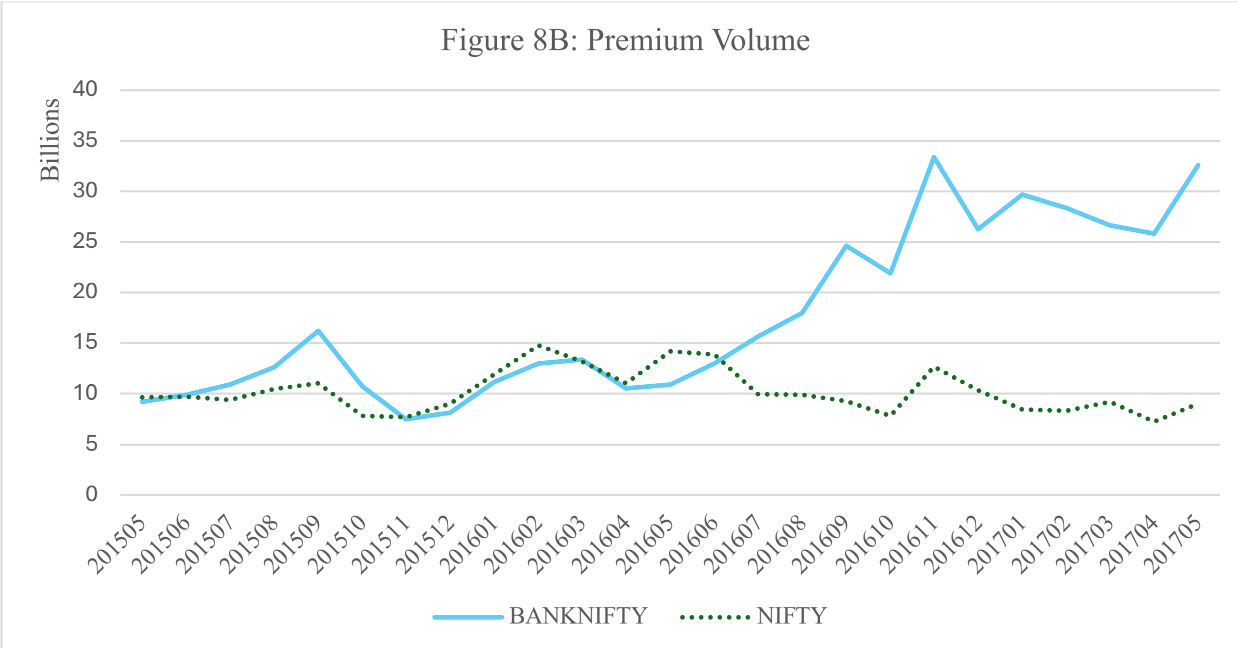


Figure 8B: Premium Volume
Billions
40
35
30
25
20
15
10
5
0
201505
201506
201507
201508
201509
201510
201511
201512
201601
201602
201603
201604
201605
201606
201607
201608
201609
201610
201611
201612
201701
201702
201703
201704
201705
BANKNIFTY
NIFTY

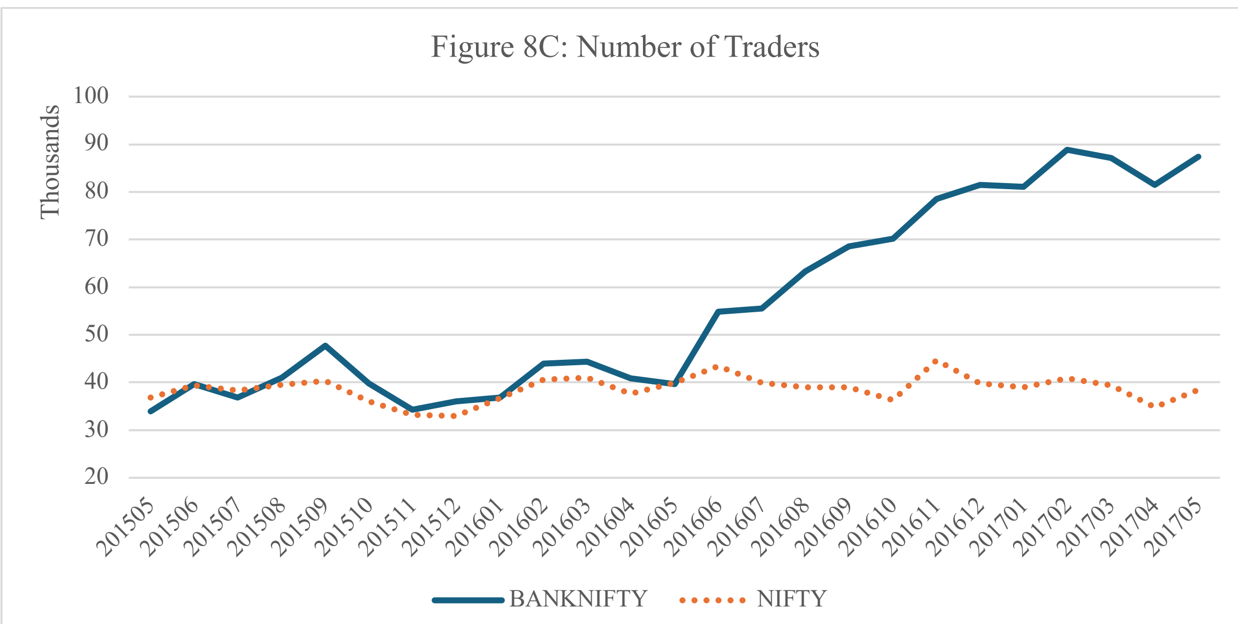


Figure 8C: Number of Traders
Thousands
100
90
80
70
60
50
40
30
20
201505
201506
201507
201508
201509
201510
201511
201512
201601
201602
201603
201604
201605
201606
201607
201608
201609
201610
201611
201612
201701
201702
201703
201704
201705
BANKNIFTY
NIFTY

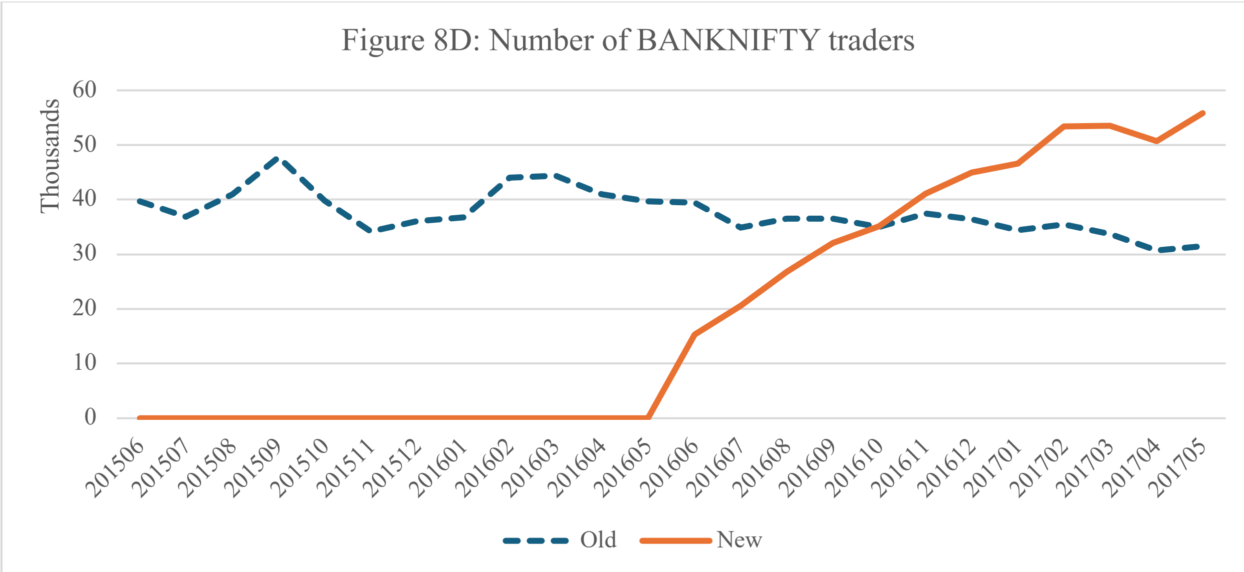


Figure 8D: Number of BANKNIFTY traders
Thousands
60
50
40
30
20
10
0
201506
201507
201508
201509
201510
201511
201512
201601
201602
201603
201604
201605
201606
201607
201608
201609
201610
201611
201612
201701
201702
201703
201704
201705
Old
New

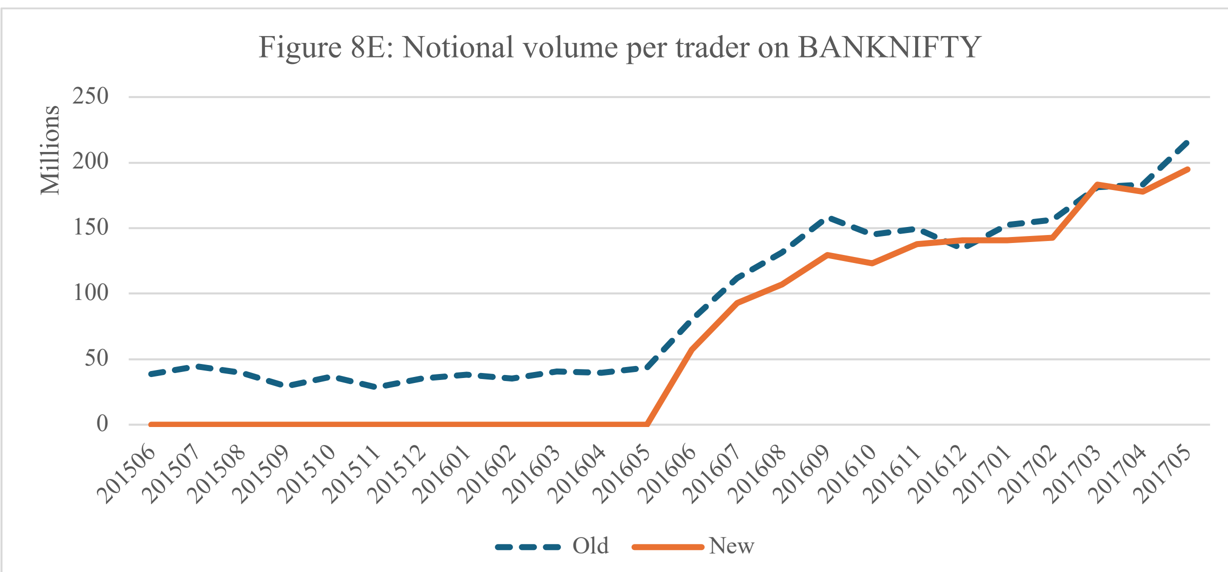


Figure 8E: Notional volume per trader on BANKNIFTY
Millions
250
200
150
100
50
0
201506
201507
201508
201509
201510
201511
201512
201601
201602
201603
201604
201605
201606
201607
201608
201609
201610
201611
201612
201701
201702
201703
201704
201705
Old
New

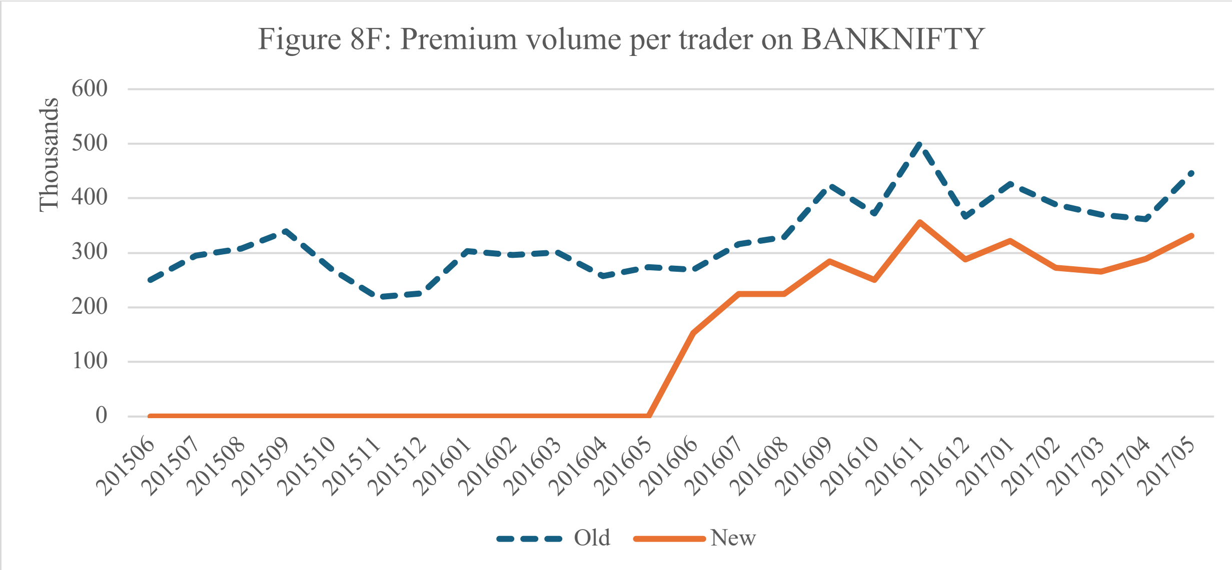


Figure 8F: Premium volume per trader on BANKNIFTY
Thousands
600
500
400
300
200
100
0
201506
201507
201508
201509
201510
201511
201512
201601
201602
201603
201604
201605
201606
201607
201608
201609
201610
201611
201612
201701
201702
201703
201704
201705
Old
New

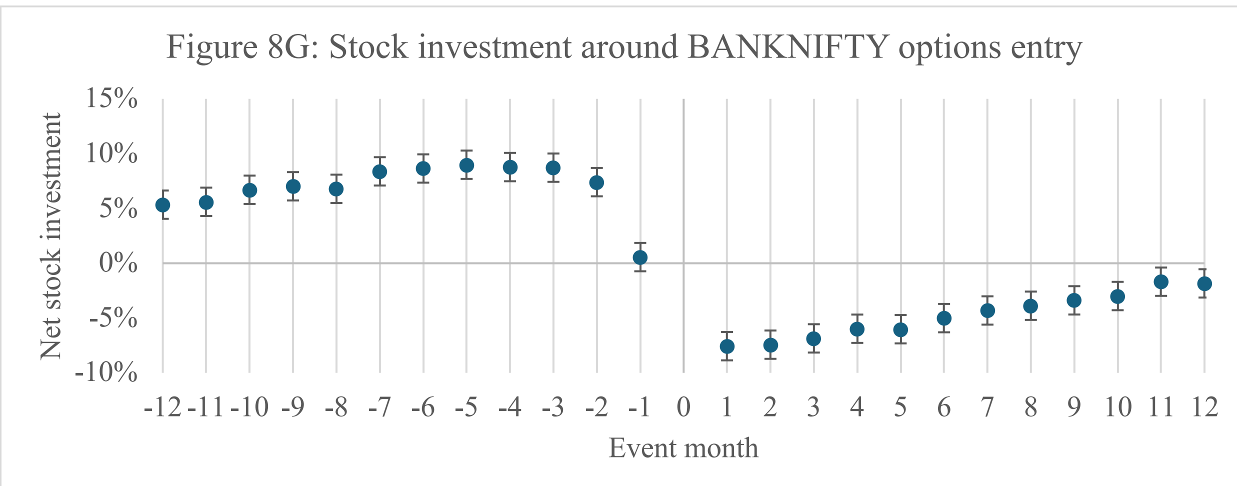
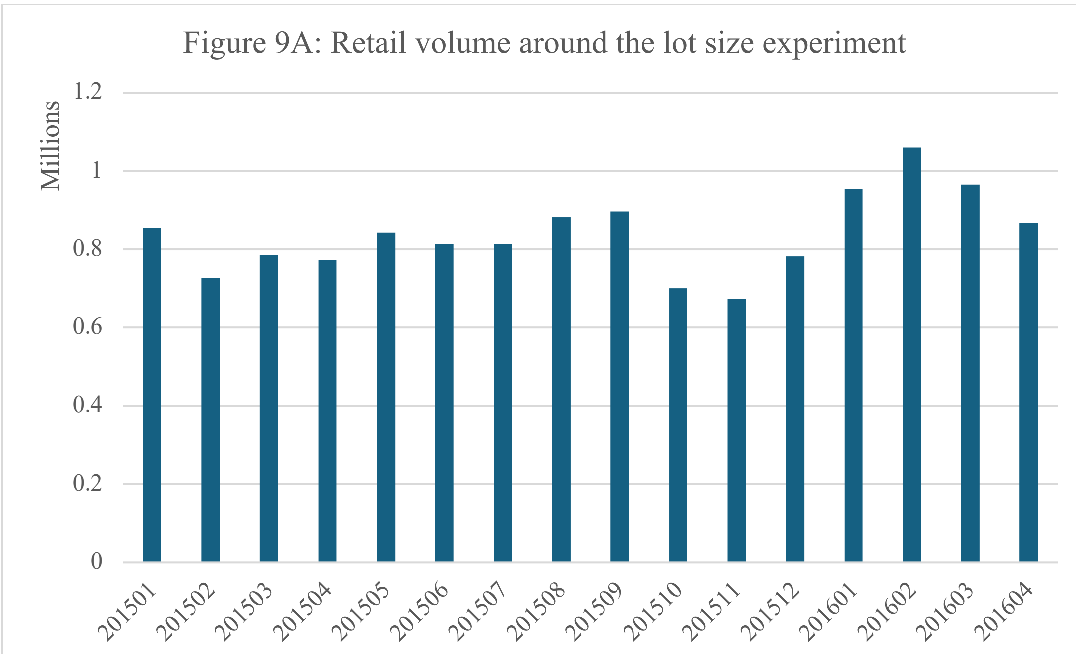


Figure 8G: Stock investment around BANKNIFTY options entry
Net stock investment
15%
10%
5%
0%
-5%
-10%
-12 -11 -10 -9 -8 -7 -6 -5 -4 -3 -2 -1 0 1 2 3 4 5 6 7 8 9 10 11 12
Event month

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 bucket. The maturity buckets are 0, 1, 2, 3, and 6 days to maturity, corresponding to Thursday, Wednesday, Tuesday, Monday, and the prior Friday. The moneyness buckets are below −2%, [−2%,−1%], [−1%,0], [0,1%], and over 1%. 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.



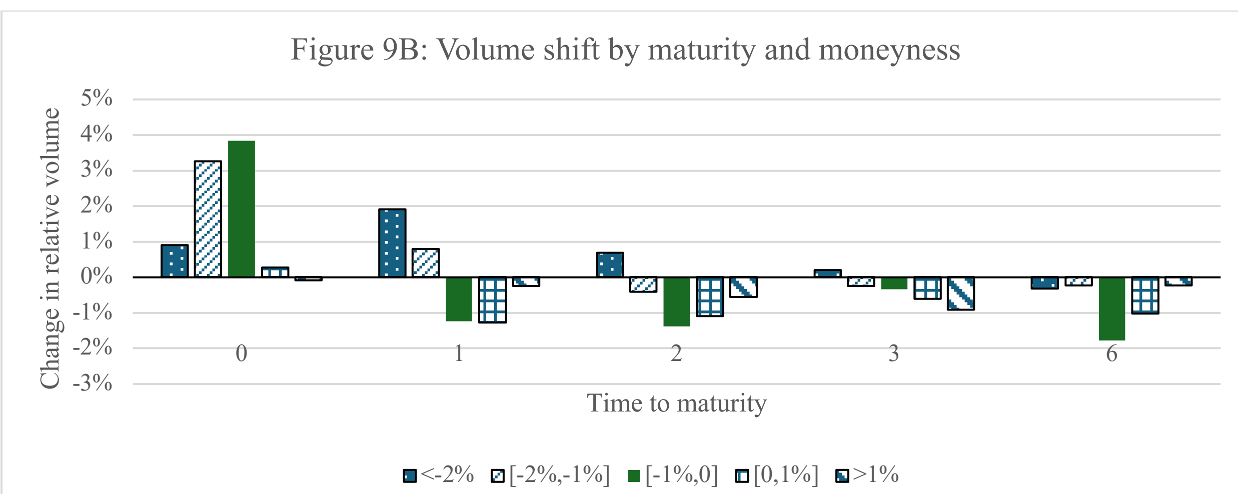
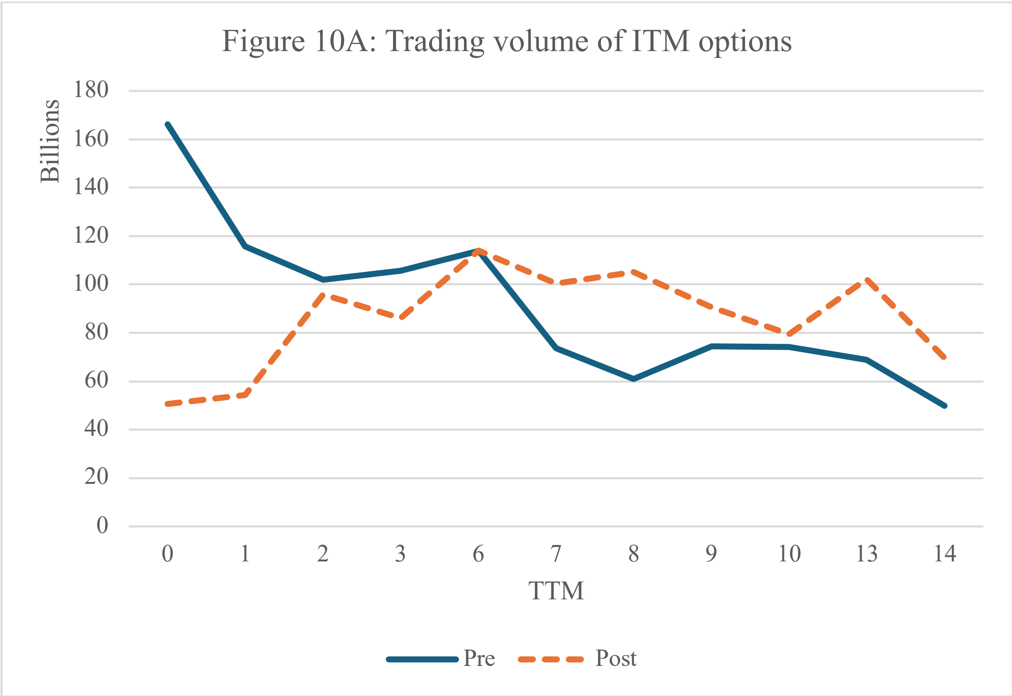


Figure 10: Physical settlement and trading on ITM and OTM single stock options

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%.



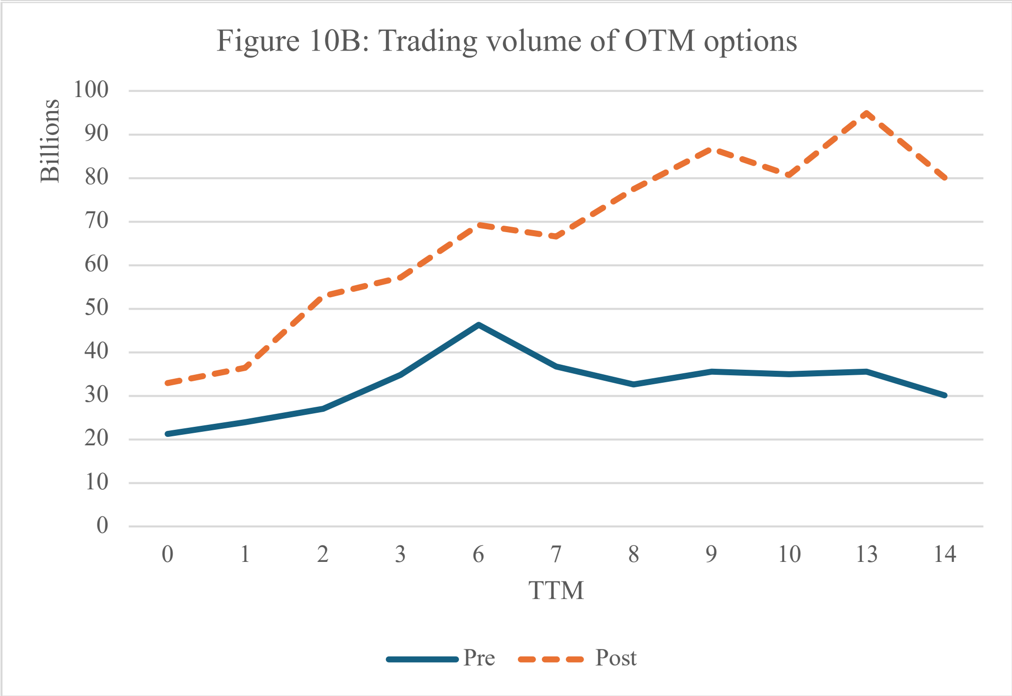


Figure 11: FinTech brokers

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.

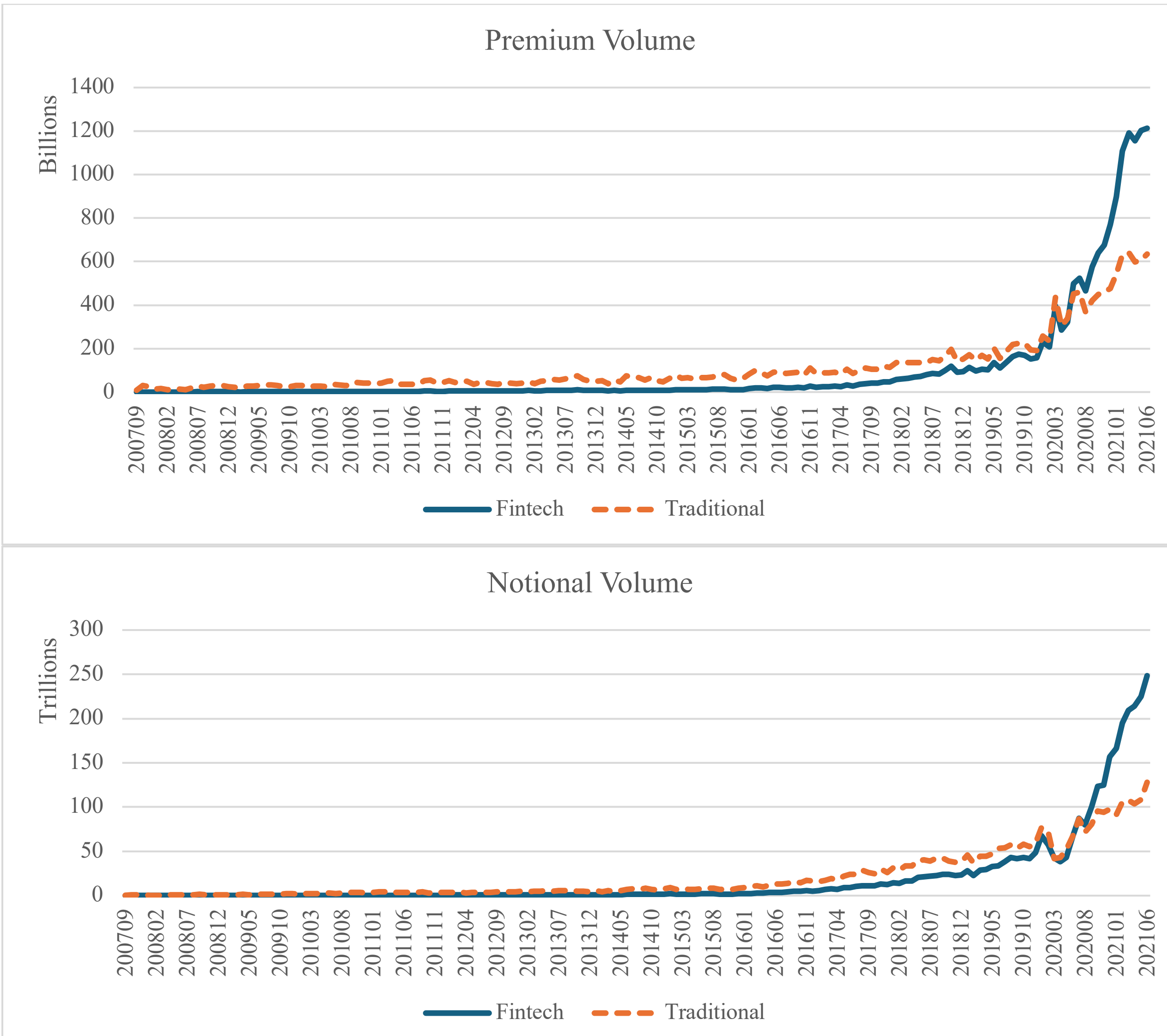


Table 1: Summary statistics

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)	(2)	(3)	(4)
	premvol	*undervol*	*contravol*	*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)	(2)	(3)	(4)
	numactiveweek	*avg_premvol*	*avg_undervol*	*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) *entry*	(2) *entry*	(3) *entry*	(4) *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 90^{th} 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, scaled by the number of months traded. The premium 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	0.44***	89.71***	9.04***	1.74***	−4,789***
	(367.08)	(378.80)	(226.57)	(133.89)	(−229.30)
Trader FEs	N	N	N	N	N
Observations	5,307,463	5,307,272	5,307,463	5,286,924	5,307,463
Adjusted R^2	0.03	0.03	0.01	0.00	0.01

Panel C: Trading volume and performance: switchers

	(1) *premvol*	(2) *contravol*	(3) *undervol*	(4) *%Return*	(5) *P&L*
finbroker	0.51***	89.65***	12.37***	1.69***	−5,146***
	(226.09)	(200.53)	(173.71)	(80.18)	(−140.39)
Trader FEs	Y	Y	Y	Y	Y
Observations	1,551,196	1,551,156	1,551,196	1,539,159	1,551,196
Adjusted R^2	0.286	0.283	0.284	0.0827	0.251

ONLINE APPENDIX

Appendix A. Variable Definitions

Variable	Definition
<u>Options trading</u>	
contravol	Number of option contracts traded, irrespective of option premium or underlying share price.
undervol	Number of contracts multiplied by the underlying asset's share price. Represents the local currency equivalent of trades.
premvol	Option premium per contract multiplied by the number of contracts traded.
ContraPrice	Price per option contract.
%moneyness	Previous day's closing price of the underlying index, scaled by the strike price.
P&L	For each trader and contract, equal to total dollar proceeds from selling, minus total dollar paid through purchasing, plus settlement payoffs for contracts held to maturity, defined as net position size × $\max(S_T - K, 0)$ for calls or $\max(K - S_T, 0)$ for puts, where S_T is the expiration-day closing price and K is the strike. Brokerage fee of ₹20 is subtracted for each trader-contract-day transaction.
P&L (trader)	Aggregated *P&L* across all contracts for a given trader.
numactiveweek	Number of expiries during which the investor traded in either the pre- or post-event periods.
avg_premvol	Average weekly premium volume per trader, conditional on participation.
avg_undervol	Average weekly notional volume per trader, conditional on participation.
avg_contravol	Average weekly contract volume per trader, conditional on participation.
Day Trading	For positions fully closed within a day, 100% of contract volume is attributed to day trading. For partial closes, only the smaller of shares bought or sold counts toward day trading. Measured by contract volume to mitigate index price effects.
0dte	Trades executed on the contract's maturity date (zero days to expiration).
Duration	Number of days a trader holds a position in a given contract: from first to last trading day if closed before maturity, or until expiration if not closed.
%Return	Computed following Bryzgalova, Pavlova, and Sikorskaya (2023): assumes proceeds from short positions are fully posted as collateral at zero interest (no netting). %Return = P&L / total dollar trading volume of buys and sells, plus the absolute value of settlement payoffs.

Variable	Definition
OTM	Indicator equal to 1 if the premium-weighted moneyness across all trading days on a contract is below −5%, and 0 otherwise.
TTM	Time to maturity, measured in days.
moneyness	Percentage moneyness: (Stock price − strike price)/stock price for calls, reversed for puts.
Demographics	
male	Indicator for male investors.
age18_40	Indicator for investors aged 18–40 years.
age41_60	Indicator for investors aged 41–60 years.
tier1	Indicator for investors located in Tier 1 cities: Mumbai, Delhi, Bengaluru, Chennai, Kolkata, Hyderabad, Pune, and Ahmedabad.
Stock trading	
Performance	Trader's stock trading performance during the past three months, calculated as the volume-weighted market-adjusted stock returns, measured from each trading day until the beginning of the current month.
Highperf	Indicator for traders in the top decile of *Performance* during a given month.
Lowperf	Indicator for traders in the bottom decile of *Performance* during a given month.
Retvol	Volume-weighted stock return volatility for all stocks traded during the past three months.
Maxret	Volume-weighted maximum daily return of stocks traded during the past three months.
Stockvol	Logarithm of past three months of stock trading volume (or past month, depending on specification).
Experience	Number of months since a trader first started trading stocks in the sample.
Highretvol	Indicator for *Retvol* above the 75th percentile and *Maxret* below the 75th percentile.
Highretmax	Indicator for *Maxret* above the 75th percentile and *Retvol* below the 75th percentile.
Highretvol&max	Indicator for both *Retvol* and *Maxret* above the 75th percentile.

Variable	Definition
entry	Indicator equal to 1 for the month a trader initiates options trading, and 0 for all months prior. Observations after entry month are dropped. Equals 0 if a stock trader never initiates options trading.
O/S	Option-to-Stock ratio constructed following Roll, Schwartz, and Subrahmanyam (2010) and Johnson and So (2010). For each day and option contract, O/S = dollar notional amount of retail options volume ÷ dollar stock volume on the same day. Scaled by 1,000 for expositional convenience.
highprice	Indicator equal to 1 if the stock's price per share is above the 90th percentile on the previous day, and 0 otherwise.
lagret	Lagged daily stock return.
mktcap	Logarithm of the stock's market capitalization.

Appendix B: 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 B.1.[29]

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 report the skewness estimates for each maturity-moneyness bin for NIFTY and BANKNIFTY options, respectively. We find that option skewness is inversely related to both

[29] 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.

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 B.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 Vorkink (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 C: 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 C.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 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 C.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 C.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 C.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 C.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.

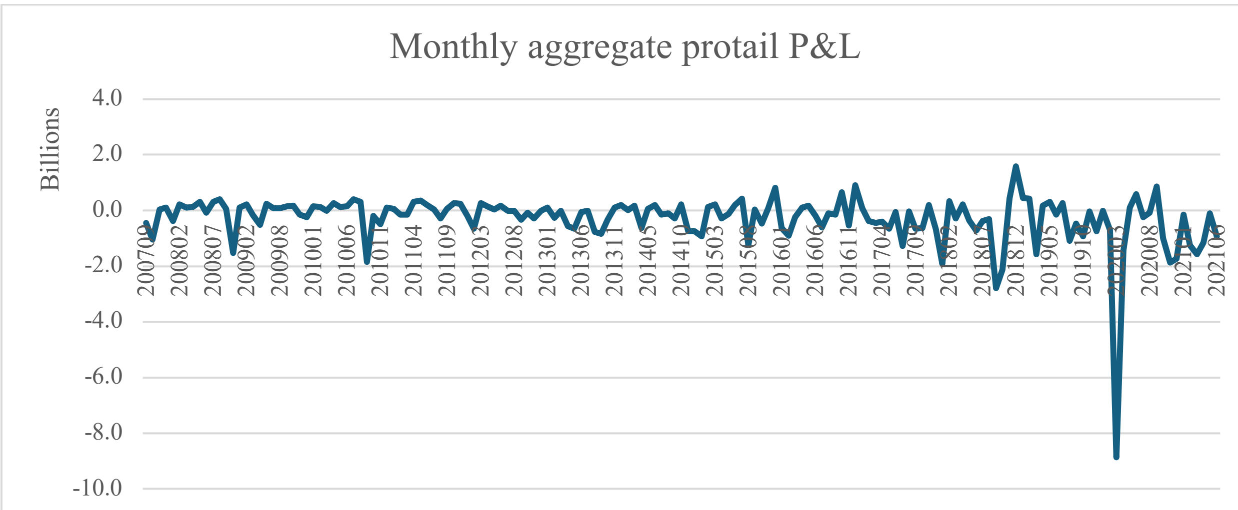
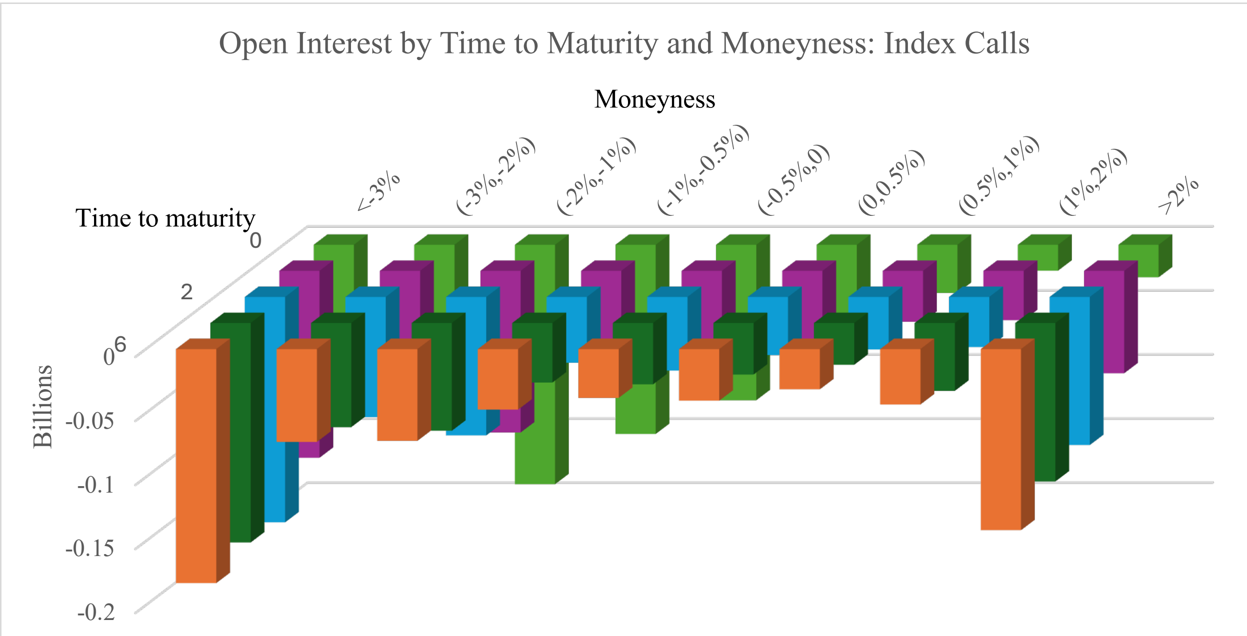
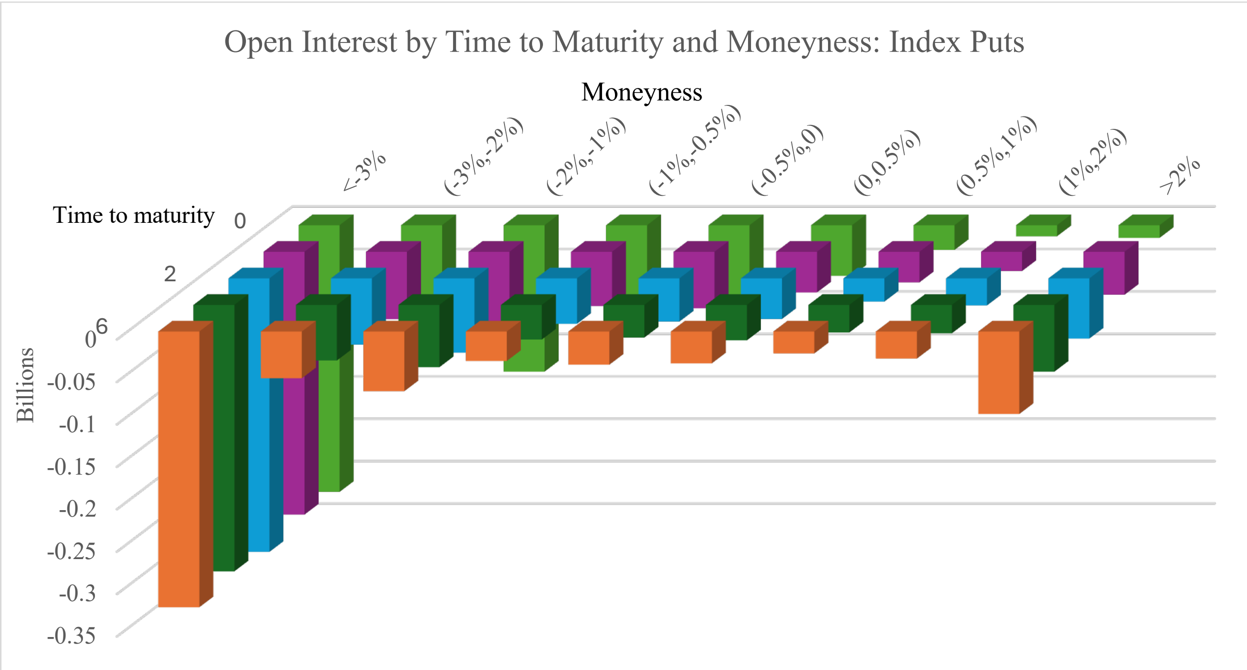


Figure C.2: Aggregate retail open interest of protail investors

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 D: 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 D.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.

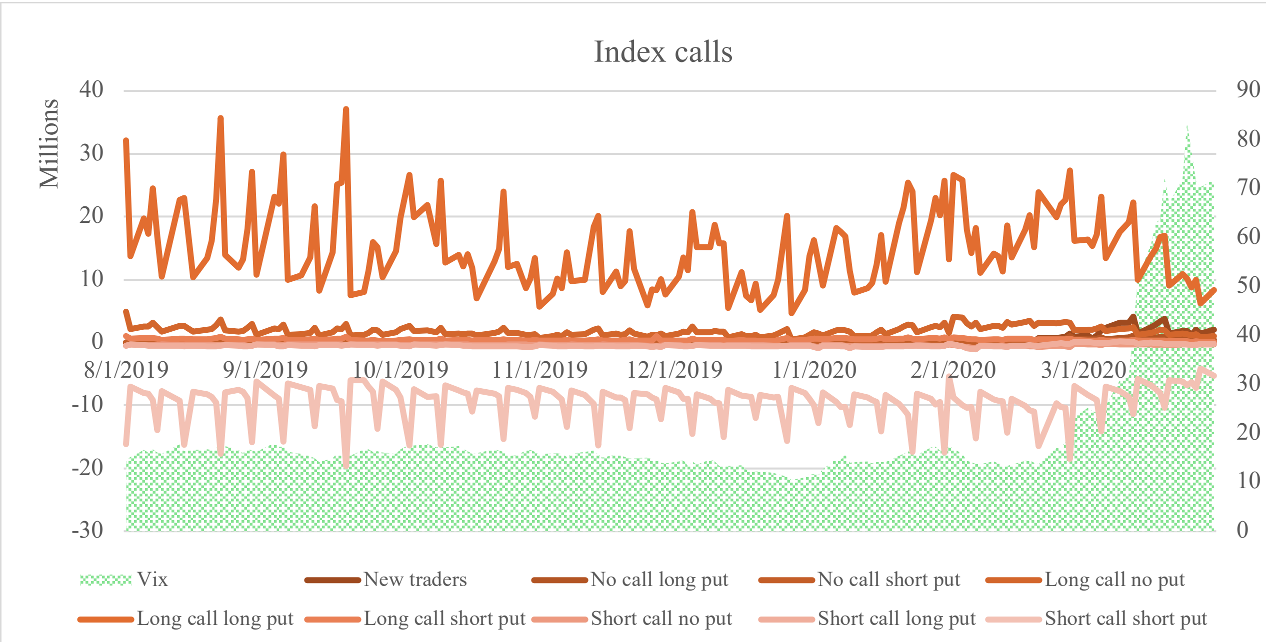
The first part of Figure D.2 displays the profits or losses by investor groups on the March 2020 expiry contract. The retail losses come almost exclusively from the short investors (mainly put writers) and represent most of the losses in March 2020 of all traders in Figure 2. In Figure B2, we find that 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 D.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 D.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.



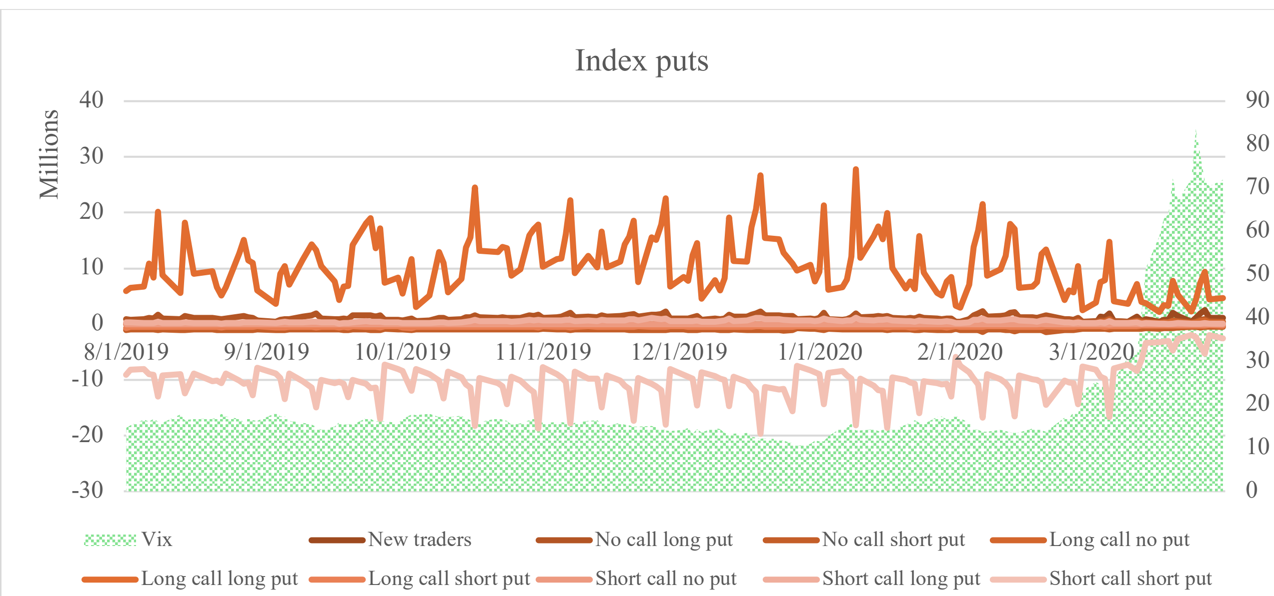
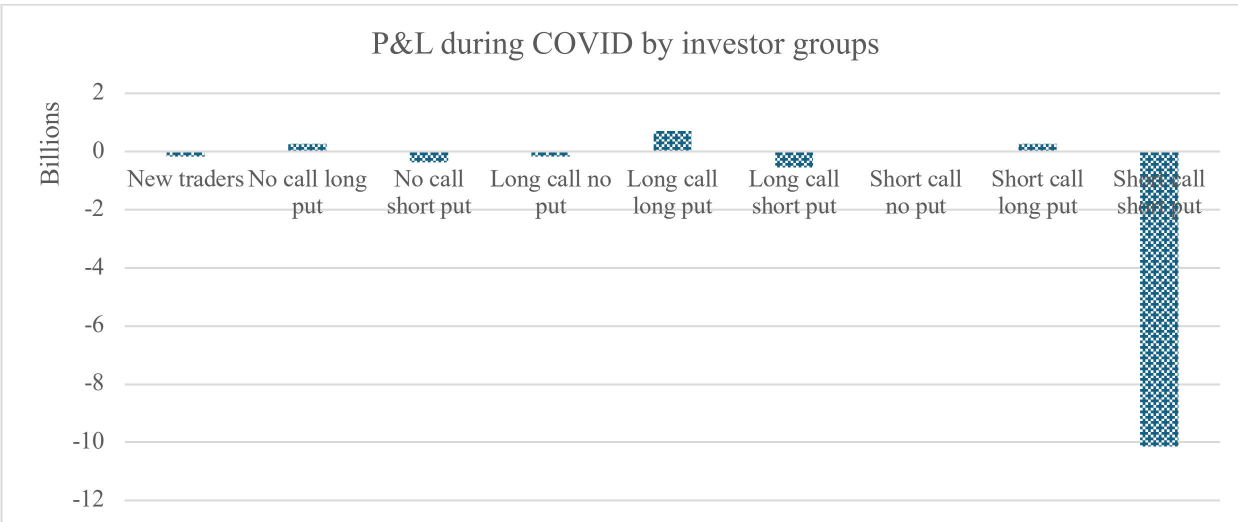


Figure D.2: Open interest by investor groups around COVID-19

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.



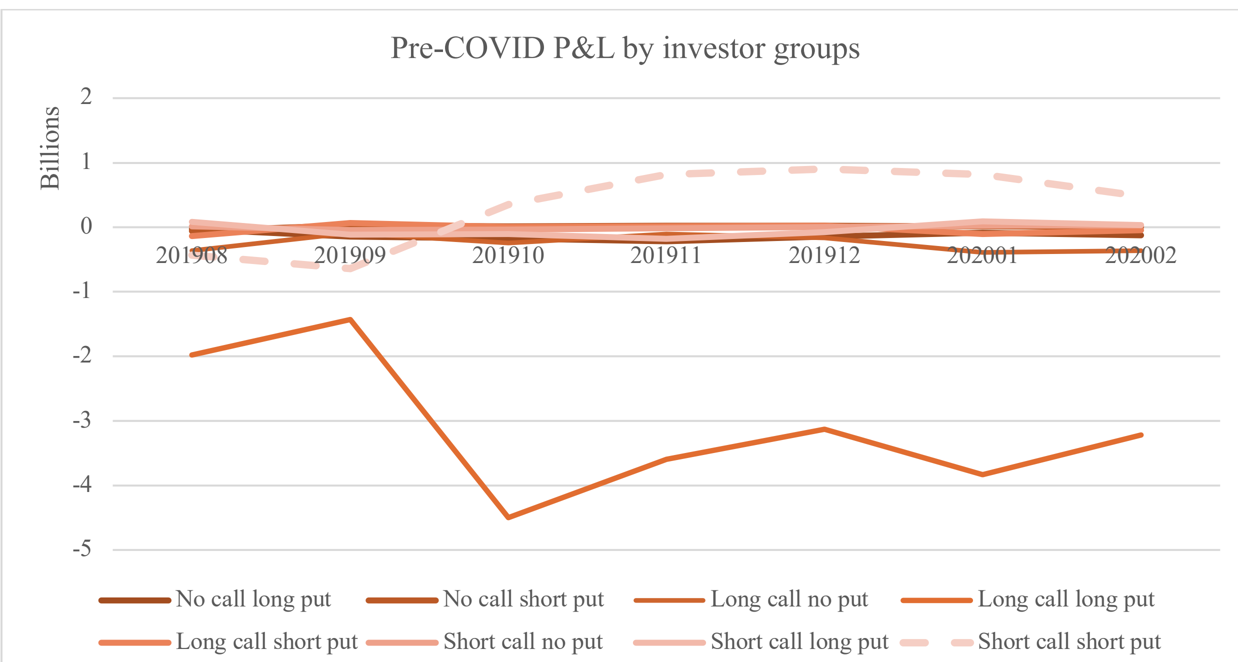


Figure D.3: Trader exit

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.