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

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Abstract

We study retail options trading using a comprehensive dataset from India, one of the world's largest options markets. Retail trading volumes are high, concentrate in index options, and feature extreme short-termism and significant wealth losses. We consider three natural experiments, supply-side interventions that facilitate or deter short-term trading. Increasing the supply of short-term options induces trading while increasing participation costs venue-shifts trades to cheaper alternatives. Losses increase in each case. The results suggest that premature financial inclusion imposes costs on small investors by facilitating tastes for speculative trading that are difficult to reverse even if they generate wealth losses.

JEL Codes: D14, D18, G14, G15, G18, G50, G53, O16

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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 comprehensive dataset of retail options trades from the National Stock Exchange of India (NSE).

Our sample and analysis are of interest from three main viewpoints. First, the NSE is a large options exchange and in fact by some measures the world's largest options market. The 15-year sample period from 2007 to 2021 witnessed a 15-fold growth in the number of retail traders, many unexposed to financial markets due to decades of financial exclusion during which households lacked even basic bank accounts (Burgess and Pande, 2005, Cole, Giné, Tobacman, Topalova, Townsend and Vickery, 2013). There is a 53-, 86- and 358-fold growth in contracts traded, premium turnover, and notional amount, respectively. Towards the end of our sample period, the monthly retail volume reached 63 billion contracts, or more than US$4 trillion in notional amount. The notional volume on the NIFTY50 index options has recently surpassed the S&P500 even in U.S. dollar terms.

A second feature of interest is that the NSE data explicitly identify retail trades at the individual account level. The data let us overcome a key challenge in studying retail trading, particularly in the U.S., that retail trades are not explicitly marked and must be inferred using proxies or algorithms. We can thus track individual trader entry, exit, and performance, and in particular trader responses to three natural experiments, which represent a third point of interest in our study. As we discuss shortly, these experiments include one that expands the supply of short-term options favored by investors and two that try to curb options trading by increasing participation costs. The first induces extra retail options trading, while investors offset the latter two efforts to curb trading through shifts in the locus of speculative habitats, worsening outcomes in each case. The results show that once speculative habits take root, they seem hard to excise – even if, as in our sample, traders suffer extensive losses.

We briefly describe the analysis and results next. Our dataset covers all options trades on the NSE, which accounts for more than 99% of all derivatives trading in India within our sample period. For each individual and trading day, we observe the number of contracts traded and the average price paid for purchases or sales of each contract, as well as the name of the underlying stock or index.

We observe three striking patterns in the data. The first is the significant concentration of retail trades in index options, which account for 75% of their premium and 93% of the notional volume in the options market. Within this universe, two index options, viz., a market wide NIFTY50 index and a bank-specific BANKNIFTY index, constitute 99.9% of the index option volume. A second feature is trader short-termism, consistent with other options datasets (Bryzgalova, Pavlova and Sikorskaya, 2023, Beckmeyer, Branger and Gayda, 2023, Bogousslavsky and Muravyev, 2024). On average, 87% of the index option's lifetime volume occurs in its last five days. While index investing can be welfare-enhancing for under-diversified households (Calvet, Campbell and Sodini, 2007, Badarinza, Campbell and Ramadorai, 2016, Gomes, Haliassos and Ramadorai, 2021), it is difficult to make this case for short-term trading of index options.

A third feature is the spike in retail traders activity in the ultra-short 0DTE (zero days to expiry) options. We note that the 0DTE options in our sample are available only at monthly frequencies – except for weekly expiration cycles introduced for BANKNIFTY index options in 2016, as discussed below. Nevertheless, the retail interest in 0DTE options increases over time, both at the extensive and intensive margins, reaching a substantial 42% of the market volume on 0DTEs at the end of our sample. The shift is greater after both past gains and past losses, consistent with overconfidence, loss-chasing, and gambling-for-resurrection motives, and is amplified by exogenous increases in the supply of short-maturity contracts. Collectively, traders in our sample sustain significant losses of ₹506 billion ($6.3 billion).[1]

We consider evidence from three natural experiments, supply-side interventions that

[1] 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. 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.

expand trading opportunities in short-term options or increase participation costs. The first experiment is a selective introduction of weekly expiration cycles. Prior to May 2016, both the BANKNIFTY and the NIFTY50 options had one option expiration date per month. However, in May 2016, the NSE introduced weekly expiry cycles on the BANKNIFTY but not the NIFTY50. We find that BANKNIFTY volumes surged once weeklies became available, reflecting growth at both the extensive and intensive margins. At the extensive margin, 68% of the traders are new, i.e., have never traded in BANKNIFTY options in the pre-event period. At the intensive margin, we see an increase in volume, especially from male traders, younger traders, and those with histories of short-maturity trading. The BANKNIFTY shows a 7.3-fold growth in notional volume and a 2.2-fold growth in the premium volume around the event, while the NIFTY volumes remain essentially flat. 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 options speculation by increasing participation costs. In August 2015, SEBI, India's financial market regulator, doubled the minimum lot size for BANKNIFTY options and tripled it for NIFTY50 options. We assess its effects using a difference-in-differences specification. The treated group comprises small traders whose pre-event trades are below the new lot size cutoffs. The control group includes traders with pre-event trades in a bandwidth above the new lot size. We find the intended direct effect: increasing participation barriers lowers trading volumes. However, there is an unintended offsetting effect. Traders shift to affordable shorter maturity and out-of-the-money options with lower expected returns. The results suggest that speculative habits are difficult to shed. Once they take root, traders avenue-shift speculation to affordable alternatives and shorten horizons that fit budget constraints.

A third experiment occurs in 2019, when SEBI mandated physical settlements and delivery margins for options on single stocks.[2] This change imposes participation costs on positions close to expiry: long traders must post cash margins in anticipation of taking

[2]The rule does not apply to index options, presumably reflecting difficulties with multiple fractional and odd lot settlements of the underlying stocks for one options lot.

delivery and short sellers must hold stocks to make delivery.[3] The margin requirements apply to in-the-money (ITM) but not out-of-the-money (OTM) options as they are not subject to physical delivery. We observe a pronounced shift from ITM to OTM options among short-term investors, those who demonstrated a preference for short maturities prior to the shock and are thus more likely to be affected by the rule change. However, these investors also shifted more aggressively toward OTM options, resulting in a greater annual loss of ₹9,324 per capita after the shock.

We report other results. Of particular interest is the role of "FinTech" brokers, trades through whom are identified in our dataset. FinTech volume grows significantly, expanding to more than 60% of the retail volume in the final year of our sample. We find that traders using FinTech brokers have shorter duration, greater day trading intensity, higher trading volume, and more losses. In an interesting subsample of traders who use both FinTech and non-FinTech brokers, models with trader fixed effects again show that within the same trader, their FinTech broker trades have shorter horizons, larger volumes, and greater losses than their non-FinTech broker trades.

We also provide evidence on the behavioral dynamics underlying retail options trading. Entry into options is more likely following poor stock market performance and prior exposure to volatile, lottery-like stocks, pointing to speculative rather than rational learning from experience. After entry into options, past winners are less likely to exit, even though their past gains turn into future losses. Taken together, these results suggest that retail options trading reflects a process of behavioral reinforcement, such as gambling-for-resurrection and skill extrapolation.

In sum, our results indicate significant challenges in curbing speculative behavior in options once it takes root. The supply of short-term contracts induces short-horizon speculative trading that seems to have little economic benefit to households. The efforts to undo the habits result in avenue-shifting to what traders can afford, i.e., out-of-the-money and short-maturity options. There is little reason to expect these alternatives to deliver superior performance, nor do we find evidence that they do. The more plausible

[3] See, for example, the delivery margin requirements at Zerodha Brokerage, accessed November 2025.

interpretation is that the massive options participation induces speculative habits that are hard to undo, creating an undesirable path dependence when expanding financial market participation, and losses that can have psychological or health effects.[4] Such ill-effects and additional manifestations of the addiction to speculation are interesting questions for future research.

2 Related Literature

The household finance literature points out that stock market participation benefits individuals by helping them diversify and earning the equity risk premiums (Badarinza, Campbell and Ramadorai, 2016, Calvet, Campbell and Sodini, 2007). The Indian market has been a success story in this regard. Stock participation has expanded more than three-fold from 27 million to 92 million individuals in less than a half-decade, driven by digitization and simplified onboarding processes. Our study highlights that financial participation has benefits, but can also impose costs. Specifically, 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.[5] 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 choices. Although the argument seems weak when retail traders make consistent losses of a 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,

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

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

2024). Due to data limitations, prior studies rely on indirect measures such as markers for non-professional customers provided by the exchange, single-leg price improvement flag in the Options Price Reporting Authority (OPRA) data, small-sized trades, and trades through Robinhood (see, e.g., Beckmeyer, Branger and Gayda (2023), Bryzgalova, Pavlova and Sikorskaya (2023), De Silva, So and Smith (2025), Naranjo, Nimalendran and Wu (2023), Lipson, Tomio and Zhang (2023), Eaton, Green, Roseman and Wu (2025), Huang, Jorion and Schwarz (2025)). Exceptions include Bogousslavsky and Muravyev (2024) who analyze a retail cohort using data from a trading journal in the U.S., and Hu, Kirilova, Park and Ryu (2023) who focus on the use of complex option strategies by Korean retail investors. Unique features of our data include the entire universe of option participants on the National Stock Exchange of India, a panel structure, and clear identifiers for retail traders. Our data allows us to track the behavior of the "average" investor, including millions of novice traders new to the market. Furthermore, we move beyond descriptive evidence to provide causal identification through three supply-side natural experiments. These shocks allow us to identify the economic drivers of participation and document the emergence of speculative habit formation.

Several studies assess the manifestation of lottery preferences in stock investments, including 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 return" portfolio. The concentration of lottery features in small-cap stocks can create the misimpression that lottery preferences are not economically substantial.[6] Our study suggests that such impressions may be misplaced when considering options. Options provide ample skewness, as we show in Online Appendix B.[7] More broadly, embedded leverage, nonlinear payoff structures, and variations across maturities, moneyness, and trading horizon offer a variety of bets in options that investors seem to recognize. In our data, the notional value of options is 86 times the stock volume for individuals trading in both markets.

[6]For example, the "high max" portfolio in Bali, Cakici and Whitelaw (2011) has mainly small stocks that cover 1.44% of the market capitalization.

[7]We compute the skewness of option portfolio returns following Boyer and Vorkink (2014). Skewness is between 1.1 and 3.9 for short maturity options with moneyness in [–0.5%, 0.5%] and between 7.5 and 18.1 for options with moneyness below –2%, far exceeding the skewness of lottery stocks (e.g., 0.219 in Boyer, Mitton and Vorkink (2010) and 1.35 in Bali, Cakici and Whitelaw (2011)).

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 approximately 5% of the global market (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 more than 100% from 2018 to 2024 in terms of notional amounts, culminating in 2024 notional volume of ₹79,927 trillion ($999 trillion).[8]

Virtually all options trading in India during our sample period was on the National Stock Exchange of India (NSE), an automated electronic trading exchange established in 1992 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 over 99% of the options volume in India during our sample period.[9]

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 September 2007 to June 2021.[10] Each trader in our dataset is assigned a unique and masked identifier based on a 10-digit permanent account number (PAN) that corresponds to a unique tax ID. The exchange aggregates daily transaction

[8]For data from the regulator, Securities and Exchange Board of India (SEBI), see the Handbook of Statistics, Table 29, available at the SEBI website, accessed on April 11, 2025.

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

[10]The NSE discontinued access to account-level trading data after June 2021, preventing us from extending the sample to more recent periods when the retail participation exploded even further.

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, the number of contracts purchased or sold, the average premium paid or received, and option features such as the name of the underlying, call or put, 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 have zero net supply, institutions are counterparts to retail trades. Therefore, aggregate losses of retail traders should equal the aggregate profits of institutions, which we verify through institutional account-level data also available to us.

We refine the definition of retail investors in two ways. The first draws on the observation by Bryzgalova, Pavlova and Sikorskaya (2023) that individual traders include a right tail of "protail" investors, professionals small in number in the population, but with significantly greater activity. We analyze them separately in Online Appendix C, which shows that they differ substantially 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 ₹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. For a small number of tests, we extract firm characteristics from the COMPUSTAT Global database. We match COMPUSTAT firm identifiers with NSE data using a ticker–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 premium amount or underlying share price, the notional volume corresponding to the number of contracts multiplied by the share prices of the underlying, and the premium volume that equals 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 that one option 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 contracts. To illustrate, suppose that the lot size on NIFTY50 index options is 75. A trader buys 2 lots at ₹20 per contract, sells one lot next day at ₹19, and lets the other lot settle on the expiration day at ₹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 $150 \times 20 + 75 \times 19 + 75 \times 8 =$ ₹5,025. The notional volume equals $(150 \times 30{,}000) + (75 \times 30{,}100) + (75 \times 30{,}200) =$ ₹9,022,500 and represents the local currency equivalent of the options trades.

We track each investor's trades from the introduction of each option 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 trades in the NSE data, profits come from execution prices and thus reflect bid-ask spreads but not fees charged by brokerage companies. We deduct a nominal ₹20 for each trader-contract-day trade based on charges set by a prominent discount broker.[11] The true commission fees are likely greater as full-service broker commissions are higher, and commissions on multiple intraday trades are only counted once (as we only have data at the daily frequency). Finally, we do not account for costs associated with maintaining margin requirements that are unobservable to us, as well as various taxes such as the Securities Transaction Tax (STT) and Goods and Services Tax (GST).[12] Online Appendix A provides detailed variable definitions.

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

[12]Brokerage-level data shows that the transaction costs account for approximately 20% of retail trader losses. See SEBI Report dated September 23, 2024.

4 Descriptive Statistics

Intensive and Extensive Margins in Volume Figure 1 presents time series evidence on retail option trading. During 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 large expansions in the number of contracts traded (53-fold), premium volumes (86-fold), and notional amounts (358-fold). The greater growth in the notional amount relative to premiums indicates that investors gravitate towards "cheaper" contracts over time, i.e., options that are closer to maturity or more out of the money. Such options offer pronounced skewness (Online Appendix B), suggesting a demand for skewness rather than mere leverage, as futures trading — an alternative source of leverage — remained flat throughout the sample period (untabulated).

Profits and Losses Figure 2A plots the cumulative retail losses, aggregated from the beginning of our sample period up to each subsequent month. Cumulative losses increase as retail trading volume expands, and accelerate in recent periods that have witnessed a boom in options trading, totaling an uncompounded amount of ₹506 billion (about $6.3 billion) by the end of the sample period. The imputed commission fees (₹20 per trader per trading day on a contract) constitute 6% of the total losses. While data on the bid-ask spreads is unavailable to us, a back-of-the-envelope calculation suggests that spread costs account for 48% of the total losses on index options.[13]

Not all investors incur losses. Figure 2B shows that in a given month, the losses incurred by loss makers are partially captured by the profit makers, creating a wealth redistribution effect. The redistribution widens as the trading volume rises in the later

[13]This estimate is based on the 1.25% spread of NIFTY 50 options reported in Bhat, Pandey and Rao (2024). In untabulated results, we also compute percentage return as the net dollar profitability divided by the premium volume plus settlement. Returns decrease monotonically as we move to the group of lowest volume traders. We do not focus on returns in our subsequent analysis because premium volume may not equal to the actual capital invested that is unobservable in our data.

part of the sample.

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. Some retail investors who adopted short volatility strategies prior to this period suffered losses as VIX started to rise in early March. These investors reduced but did not fully close short put positions as their contracts approach the maturity date on March 26, 2020. These patterns are consistent with the disposition effect in which investors exhibit distaste for realizing losses (Benartzi and Thaler, 1995, Shefrin and Statman, 1985, Barber and Odean, 2000, Dhar and Zhu, 2006, Barberis and Xiong, 2009). Online Appendix D provides more details.

Concentration in Index Options Figure 3 shows that index options represent 93% of the total notional volume and 75% of the total premium volume for retail investors.[14] 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 options market volume (Chordia, Kurov, Muravyev and Subrahmanyam, 2021) and their trading is driven by institutional hedging demand (Lemmon and Ni, 2014). The literature on household finance (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 as we illustrate later.

Index options offer several unique features. First, index options have weekly expiries in the latter part of our sample, while stock options only have monthly cycles. Attractive features of short-term options include low nominal prices and quick resolution of uncertainty. Second, for short maturity options, the skewness of option returns is in fact

[14] We do not compare contract volume because given large price differences, comparisons with single stock options are not meaningful.

inversely related to the return volatility of the underlying (Boyer and Vorkink, 2014). Index returns in general have lower volatility than returns of single stocks, and cheap index options can offer highly leveraged bets. Third, index options are more liquid and are less subject to adverse selection risks. These features help explain the popularity among retail investors.

Tastes For Short Maturities and Short Horizons Figure 4A tracks the volume of option trading by time to maturity. Investors exhibit preference for shorter maturities: 87% of the notional volume occurs 6 days prior to maturity. The expiration day alone accounts for around 38% of the volume. We consider another metric of investor horizon, the length of time that traders hold positions. Figure 4A also shows trade duration for each time-to-maturity bucket in the right axis. 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.

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 comes from new traders with no prior trades in the options. The only 0DTE options in India are weekly or monthly options on their expiration dates. Their increased volumes suggest that even when sparsely available, retail investors exhibit a preference for ultra-short options. These options are characterized by low cost, high leverage, and lottery-like payoffs, making them attractive for retail traders.

Day trading is quite significant in our sample. Figure 5A plots the day trading volume as a proportion of the total volume of index options over time. Specifically, 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 that results are not driven by underlying index prices, we also measure day trading activities by contract volume. 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 moneyness at different levels in Figure 5B. 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 option skews and smiles can make the options more expensive in implied volatility terms and trading costs are greater in a proportional sense.

Trader Level Statistics Panel A of Table 1 displays the trading volume by contract type at the individual level, and again reveal clear evidence of index options dominance: an average of ₹821 million notional volume on index calls and ₹742 million on index puts, significantly exceeding the average volume on single name calls (₹110 million) and puts (₹60 million). Index levels far exceed individual stock prices, which explains the lower contract volume but higher notional volume on index options. Average premium volumes are also higher for index options. Although the differences are less stark than those in notional volume, index option traders outnumber stock option traders (untabulated).

Panel B of Table 1 reports the distribution of losses at the individual trader level by contract type. The average overall loss per investor is ₹109,900, exceeding India's per capita GDP of ₹100,032 in 2021. While we do not have data on individual-level income or wealth, according to a 2024 SEBI Report, 76% of the option traders are low-income and 18% are mid-income investors. Consistent with the graphical evidence, Panel C shows that the mean duration of trades is 2.4 (2.3) days for index calls (puts). The medians are zero, indicating that the typical trader in index options is a day trader.

In the aggregate, retail investors trade both index calls and puts (Panel A) and incur comparable losses on both (Panel B). This symmetry is initially puzzling, as the Indian stock market experienced substantial growth during our sample period (a cumulative 250% increase in the NIFTY 50 index from 2007 to 2021). However, retail activity is concentrated in short-duration bets rather than multi-year LEAP options. A 250% gain over 15 years translates to a daily return of only 0.0331%. The long-term equity risk premium therefore account for a negligible fraction to the index's short-term fluctuations.

Trading Strategies Although the majority of retail activities is day trading, traders do leave certain positions open after the trading day. We perform a recursive inventory calculation at the trader-contract-day level by aggregating all the historical trades up to the end of each trading day. We then aggregate the positions to the trader-day-underlying level to examine which option or combination of options is held as open positions for the same underlying name.

Directional unhedged positions are single leg positions or split strike strategies. Directional hedged positions are where the trader takes a directional bet along with an opposite position to hedge losses. Such strategies include covered call, protective put, as well as bull and bear spreads. A third category includes volatility strategies such as straddles, strangles, and butterfly spreads. Panel A of Table 2 shows the statistics of directional unhedged, directional hedged, and volatility strategies. Panel B gives a more detailed breakdown of each of the three categories. Most trades are directional unhedged positions. For example, 90.8% of the day-end open positions on single stock options and 78.7% on index options are directional, unhedged strategies, more than the 56.8% found in South Korean markets (Hu, Kirilova, Park and Ryu, 2023) and in line with data for individual stock options noted in Eaton, Green, Roseman and Wu (2025) and others.[15]

At the trader-day-underlying name-option class level, only 25% of the open positions are net short positions of calls or puts. Given the well-documented negative variance risk premium (VRP), a natural question is why retail investors do not use option selling as their dominant strategy as the VRP is also present in the India market (Bhat, Pandey and Rao, 2024). However, option selling involves hefty margin requirements that automatically preclude the participation of many small, financially constrained investors.[16]

[15]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.

[16]The total margin includes SPAN (Standard Portfolio Analysis of Risk) margin and extreme loss margin that usually far exceed the option premium collected. For example, selling one lot of ITM 3DTE NIFTY calls (puts) on March 20, 2026 requires ₹180,000 (₹184,000), close to the annual GDP per capita

In fact, 90% of the short positions are held by a small fraction (1.3%) of the traders (untabulated). Interestingly, retail option selling yields a cumulative profit of ₹3 billion during normal times, but a significant loss of ₹11 billion during COVID wiped out all the cumulative gains from options writing. The analyses in Online Appendix D suggest that even option sellers who are less financially constrained are not net beneficiaries of the VRP due to behavioral biases.

5 Natural Experiments

This section exploits a sequence of regulatory and product-design changes in the Indian options market that generate plausibly exogenous variation in retail investors' access to short-term speculative opportunities. Importantly, these shocks differ in intent. One expands opportunities for short-horizon trading, while the other two attempt to curb speculation by raising participation costs. These variations allow us to assess not only the immediate effects of market access, but also whether and how retail trading behavior adjusts when speculative opportunities are restricted. Together, they allow us to study how retail traders respond along both the extensive margin (entry and participation) and the intensive margin (trading intensity, contract choice, and performance).

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. The NSE circulars pertaining the introduction are FAOP32329 and CMPT32338, although the economic rationale for introducing the weeklies was not given in the official documents. [17]

in India, and significantly larger than the premium amount of ₹14,000 (₹15,000).

[17] A private letter from the NSE to the brokers suggests that weeklies offer cheaper and more precise hedging against economic data releases and RBI announcements. A copy of the letter is available at https://www.dropbox.com/scl/fi/fimy78tpl0yxihc6wrdv4/Weekly-Options-on-Nifty-Bank-Index-v2.pdf?rlkey=e5v0rdp1foau98jlxu4f96agc&e=1&dl=0.

Before this date, both the NIFTY50 and the BANKNIFTY options had one expiration date per month, viz., the last Thursday of each month. The weekly options introduced by the NSE 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 (treatment group), and NIFTY options that only have monthly expiries before and after (control group) to facilitate comparison.

Figure 6A shows the notional 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 figure scales the NIFTY50 volume by a factor of 5 to facilitate comparison. The trading volumes for 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 only one year after the shock, whereas the post-event volume on NIFTY50 options is only 1.03 of its pre-event level. 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.[18]

The panel nature of our data allows us to 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 6B shows a growing number of investors trading the BANKNIFTY options in each post-event month, while the number of NIFTY50 option traders is virtually constant. How many of these investors are new? Figure 6C shows a steady growth in the number of new traders, defined as those who did not have any BANKNIFTY trading experience in the pre-event period. Overall, 68% of weekly BANKNIFTY options traders had no pre-event trading in the contract, and 46% of the weekly traders did not have any experience with trading options in the pre-event period.

[18] The premium volume numbers are omitted for brevity. The post-event premium volume on BANKNIFTY is 2.2-fold of its pre-event level, while the premium volume on NIFTY50 is only 89% of its pre-event level.

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 BANKNIFTY traders have a comparable per capita notional volume as the old traders, but significantly lower premium volume (untabulated), consistent with a preference for cheaper options.

Next, we consider the intensive margin. For each trader every month, we separate their trading volume into those on BANKNIFTY and NIFTY50. Figure 6D plots the monthly treatment effect estimates from a dynamic DiD panel using 12 months before and after the shock with trader and month fixed effects (results not shown in tables). The pre-event DiD coefficients are insignificantly different from zero, confirming the parallel trend in trading volume on BANKNIFTY and NIFTY50 options.[19] In contrast, the monthly DiD coefficients after the shock exhibit a secular increasing trend that is significant. Panel A of Table 3 presents the DiD regression results of all measures of trading volume and performance. For the same trader, the premium volume on BANKNIFTY increased by ₹91,020 per month and the notional by ₹65.56 million per month compared with their volumes on NIFTY50. BANKNIFTY trading results in greater dollar losses of ₹2,352 per month during the post-event period, an expected result as shorter maturity options have lower expected returns (Boyer and Vorkink, 2014). 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.

Because short maturity trading constitutes most of the index options volume, the introduction of weeklies expands investors' trading opportunity set from a single expiration week in a month to all four weeks. In untabulated results, we find that traders increase both the frequency of participation during the expiration week, and the trading intensity conditional on participation.

We also have demographic information for a subgroup of investors, including gender, age, and location. We define three investor groups: *age18_40* for the age between 18 and 40, *age41_60* for the age between 41 and 60, with the ages above 60 as the benchmark

[19] In all the DiD tests, the treatment and controls are entropy-balanced to maintain parallel pre-trends.

omitted category. For geographies, we define Tier 1 as residents of major urban locations including Mumbai, Delhi, Bengaluru, Chennai, Kolkata, Hyderabad, Pune, and Ahmedabad. The first four columns of Panel B of Table 3 reports the changes in trading behavior for different demographic groups around the introduction of weekly NIFTY options, and the last four columns further controls for trader fixed effects. We find that males trade more and incur greater losses, reminiscent of those in Barber and Odean (2001) who discuss excessive trading by males as reflecting overconfidence. Results for young traders resemble those for males. Traders located in Tier 1 cities show larger increase in volume, although the P&L results are inconclusive.

Finally, we investigate whether options participation impacts stock market participation. Options trading may promote financial inclusion that helps build stock investment, or encourage short-term speculative behavior that crowds out long-term investment activities. We consider new options market entrants induced by the introduction of weekly BANKNIFTY options, i.e., those who never traded options before but began BANKNIFTY options trading shortly after the shock (May 2016 to May 2018). For each trader, we calculate their monthly net stock investment, defined as the net shares purchased scaled by the average of shares purchases and sales, around their entry month into BANKNIFTY. With a different entry time for each trader, we have a staggered difference-in-differences model in which the not-yet-treated investors serve as the controls. Figure 6E shows the monthly dynamic treatment effects where the month before entry serves as a benchmark. Before entering options, traders show positive net investments averaging 4.8% per month, i.e., a net buy of 4.8 shares per 100 shares traded. Net investment in stocks turns negative after starting options trading, averaging –6.2% for the one-year period after entry. Thus, entry into the options market coincides with withdrawal from stocks and foregone equity risk premium.

In sum, we study an unusual and significant supply shock that introduces short-term options to retail investors. Volumes spike in the newly available short-term BANKNIFTY index options at both 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 the options market. The benefits of short-term trades in index options seem a priori implausible for retail traders. We find that this is indeed 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 the significant losses of retail investors from trading options. One step they took to curb speculation was to increase the 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, an increase in the lot size 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 NIFTY50 from 25 to 75 contracts per lot and doubled that for BANKNIFTY options from 15 to 30 contracts. These changes were made effective from the November 2015 expiration contracts. At the contract closing prices on November 26, 2015, this amounts to an increase in the notional amount of ₹394,000 on NIFTY and ₹256,000 on the BANKNIFTY contracts. This increase in lot size is designed to impose a participation burden on retail investors, especially those who are financially constrained.

Figure 7A 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 in May 2016. Trader volumes exhibit an upward trend before the shock and then decline, particularly in the last quarter of 2015. However, Figure 7B 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 OTM 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 NIFTY50 and below 30 on BANKNIFTY during the pre-event period. These investors are directly affected 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 those 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 the NIFTY50 options and [30, 90] for the BANKNIFTY options. The treatment and control groups consist of 36,885 and 7,650 traders, respectively.

Figure 7C displays the monthly treatment effect estimates around the lot size experiment from a dynamic DiD panel with trader and month fixed effects (results not shown in tables). While the treatment and controls exhibit parallel trends in their volume before the shock, the treatment group experiences a reduction in volume following the shock, suggesting that the increased lot sizes constitute a stronger binding constraint for the smaller-lot group.

We next turn to the regression results of trading behavior and performance in Table 4, where *post* is an indicator set to one for NIFTY50 (BANKNIFTY) contracts after the rule change with a new lot size of 75 (30), and zero if the lot size is 25 (15).[20] Panel A confirms that the trading volume for the smaller-lot group is significantly reduced after the shock relative to the control group. This reduction is as intended by the policy. An interesting result is presented 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 have lower nominal prices. Columns (2) and (3) reveal that treated small-lot investors shift to more out-of-the-money and shorter maturity options. The reduction in moneyness is

[20] 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.

0.26%, or approximately 21 index points in late 2015.[21] The reduction in maturity is 0.65 days, which is also meaningful given that active trading picks up around 5 days before maturity. Trading OTM options over a short duration carries higher spreads (Muravyev and Pearson, 2020), higher trading costs, and lower returns (Boyer and Vorkink, 2014). Column (4) shows that the combined impact of reduced volume but shifts to options with higher transaction costs and lower expected returns yield a negative, although statistically insignificant, effect on dollar profits. This result suggests that the regulatory effort failed to achieve the intended effect of mitigating retail trading losses. Finally, we note that the difference in the attrition rate between the treated and control groups, 47% for the treated versus 53% for the control group, is not significant, i.e., the policy did not drive more trader exit (not tabulated).

In sum, the lot size experiment reduces the trading mechanically but does not discipline speculative behavior. Financially constrained investors respond by shifting toward low-priced, out-of-the-money, and short maturity options with higher transaction costs. The lack of a meaningful increase in exit rates among retail traders suggests that once speculative trading habits take root, raising participation costs does not eliminate speculation, but instead pushes it into more fragile and loss-prone trading behavior. In this sense, the policy inadvertently amplifies the very short-termism and gambling-like behavior it aims to restrain.

5.3 Physical Settlement

Finally, we turn to the last experiment related to a rule change that mandated physical settlements in 2019. The rule applies only to options on individual stocks and not options on the indexes – presumably given the significant 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 options on individual

[21]Assuming a implied volatility of 20%, risk-free rate of 6%, and an index level of 8,000, a 21 index points increase in strike prices from 8,000 to 8,021 would reduce the call option premium by 28% for options with 1 day to maturity.

stocks, which represent a small but non-trivial 25% slice of the Indian options market. The rule was introduced in three phases: the bottom 50 stocks by market capitalization transitioned to physical settlement in April 2019, the next 50 stocks in July 2019, and the remaining large cap stocks in October 2019.

The physical delivery rule mandates that traders who keep long or short option positions until expiration 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 stock holdings, as appropriate. The cash amount, namely the delivery margin requirement, typically starts four trading days before maturity, and increases to the full notional amount on the maturity date.[22] Brokers would block the margin at the beginning of the trading, thus affecting intraday orders even if they are subsequently closed at the end of the day.[23] Positions for which margin requirements are not met are automatically squared off. Crucially, the delivery margin requirements apply to the in-the-money (ITM) positions, as they are subject to actual physical deliveries and certain at-the-money (ATM) positions, as they are likely to close in the money, but not OTM options.[24]

Our test focuses on trader heterogeneity. 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 that are more likely to be affected by the rule change. These traders primarily traded shorter maturity options before the rule change, perhaps reflecting the unavailability of funds or the unwillingness to deploy them due to self-imposed constraints on longer-maturity positions. Since the rule change applied in three phases, we estimate a staggard DiD panel where the event month corresponds to the month when a stock option switch to physical delivery.[25]

[22]For example, a prominent broker Upstox requires 10% of contract value on day -4 up to 70% on day -1, and the full contract value on the expiration day.

[23]See examples from brokers ICICI Direct and Upstox.

[24]For example, the broker Zerodha considers strikes close to the last traded price and up to three OTM strikes from the last traded price.

[25]For example, Yes Bank switched to physical delivery in July 2019 and HDFC bank in October 2019. If a trader traded options of both banks in September 2019, the trades on options of Yes Bank would

Figure 8 displays the dynamic DiD estimates of the proportion of short maturity volume between treated and controls by event months. For each trader every month, the proportion of short maturity volume is the trading volume in single stock options with less than one week to maturity, scaled by the total monthly volume. The figure shows a parallel trend of short maturity trading, while after the shock, the treated investors who had a preferred habitat of trading short maturity options exhibit a pronounced decline in short maturity trading. Column (1) in Panel A, Table 5 confirms this result in a regression framework: the treated investors reduce their trading in short maturity options by ₹79.03 million of notional after the shock compared with controls, and increase trading in longer maturity options by ₹78.11 million. An interesting result emerges in Columns (3) and (4), which show that the treated group now shifts their volume to OTM options: ₹56.43 million reduction in ITM options in Column (3) but ₹58.87 million increase in OTM options in Column (4).[26] The opposing effects of less trading in short maturity options but more in OTM options yield a greater dollar losses by ₹777 per month for the treated investors after the shock (Column (5)).

Our post-event period includes the COVID era when the volatility shock may increase the demand for OTM options. However, Panel B excludes the COVID period and shows that the results are virtually unchanged.

Faced with new regulatory changes that aim to reduce speculation in short maturity options, we observe that investors shift speculative activities to deeper OTM options and place more bets. Constraints matter: they alter the nature of speculative activity of traders but cannot alter their addiction to such activity.

5.4 FinTech Brokers

As in the U.S., India has also witnessed rapid growth of discount brokers based on "Fin-Tech" that facilitate trades through low commissions, the ability to execute complex strategies with a single click and mobile-centered platforms. For example, Zerodha, a

have an event month of 2 and on HDFC bank the event month is -1.

[26]In results not tabulated, we find that the treated investors also shift to cheaper index options.

FinTech broker, provides a "Kite Connect" API to build, back test, and execute algorithmic trades in a single shot, similar to what robo-advisory platforms have offered (D'Acunto, Prabhala and Rossi, 2019). We consider the relation between the use of FinTech brokerages and options trading by retail investors.

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 9 shows their growth, which accelerated around January 2020 when the first cases of COVID 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. Panel A of Table 6 shows the summary statistics of trades through FinTech and traditional brokers at the trader-month level.[27] FinTech users display significantly lower trade duration of 1.8 days, compared with 3.7 days for non-Fintech users. As high as 74.0% of the FinTech trades are day trading, while only 50.6% of the trades via traditional brokers are day trades. The premium and notional volumes of FinTech users are 72% and 95% greater than those of non-FinTech users. These results are consistent with the fact that FinTech apps offer push notifications that induce more trading, and cellphones provide convenient and continuous access to trading.[28] Finally, FinTech users lose ₹9,671 per month versus a loss of ₹6,278 for non-FinTech users.

Approximately 2 million traders have used FinTech brokers. A subset of these traders also use traditional brokers: 155,000 traders switch from traditional to FinTech brokers permanently, while 52,000 do the reverse, and 418,000 traders use both types of broker. Panel B presents regression estimates with trader fixed effects by exploiting the

[27]We again focus on index options in this section, although the results are qualitatively the same if we include single stock trades. The contract volume is omitted for brevity.

[28]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.

panel structure of our data that provides individual identifiers. For the subset of traders who have used both traditional and FinTech brokers, we again observe shorter duration, greater day trading, more volume, and more losses for their FinTech broker trades after controlling for trader-level heterogeneity. Even for the same trader, the dollar loss on their FinTech trades is ₹2,791 higher per month. Finally, Panel C shows a breakdown of trading volume for 3 groups of switchers. Switchers from traditional to FinTech brokers increase their volumes by 212% from a notional of ₹60.7 million to ₹189.4 per month. For those who use both traditional and FinTech brokers, the volume is 70% higher in trades using FinTech brokers. Finally, even though the last group of traders switch from FinTech to traditional brokers, their volume does not show a decrease but a slight increase from ₹120.5 million to ₹130.2 million after they forgo the convenience of trading, another indicator of addictive behavior.

6 Additional Analysis

We begin by examining the growing concentration in zero-days-to-expiration (0DTE) trading and how past trading outcomes determine risk-taking at the intensive margin. We then turn to entry into and exit from options trading to understand which investors are drawn into options markets in the first place, how prior stock market experience influences this transition, and whether losses discipline participation or instead encourage further speculation. Finally, we study trading in single stock options to assess whether retail activity reflects hedging or cross-hedging motives, or instead represents stand-alone speculative bets similar to those observed in index options. Together, our analysis covers the evolution of options trading from entry into the options market to the escalation of speculative behavior over time. We provide evidence on behavioral and economic channels that include leverage, short-termism, and speculation, which seem to motivate retail investors to trade options rather than use them for risk management.

6.1 Convergence to 0DTE trading

We examine whether retail traders converge toward 0DTE trading over time, shedding light on the intensive-margin dynamics underlying the growth in short-term trading documented earlier. Specifically, we relate the share of 0DTE trading in an investor's monthly volume to their past experience, cumulative gains and losses, and previous trading intensity. Because the analysis includes trader fixed effects, the estimates capture changes in trading behavior within the same investor over time, rather than differences across traders.

We define 0DTE trading as trading activity that occurs on the expiration day of an option contract, excluding trades used solely to close positions carried over from previous sessions, which may reflect intentional holding to expiration date or inattention rather than active short-term speculation. Specifically, we begin with all trades executed on option expiration dates. For traders who enter the expiration day without any open position, all trades are classified as 0DTE trading. When traders carry positions until the expiration day, we classify only the portion of the trading that represents new intraday exposure as 0DTE, excluding the volume required to liquidate prior positions. This approach provides a lower bound on 0DTE participation and ensures that our results are driven by active short-horizon trading rather than mechanical unwinding of positions.

Table 7 reports the estimation results. Column (1) shows that the proportion of 0DTE trading increases strongly with trading experience, indicating that the aggregate rise in 0DTE activity reflects not only the entry of new traders but also the convergence of existing traders toward even shorter maturities. Both cumulative profits and cumulative losses are associated with a higher share of 0DTE trading, while a higher cumulative trading volume predicts a lower share of 0DTE trading, consistent with more diversified activity among larger traders. Columns (2) and (3) divide the sample around the introduction of weekly BANKNIFTY options. The coefficients on experience, cumulative profits, and cumulative losses increase substantially in the post-introduction period, suggesting that the exogenous expansion in the supply of short-dated options amplifies the tendency of traders to concentrate activity in 0DTE contracts.

Columns (4) through (6) include both trader and time fixed effects, isolating within-trader responses to experience and past performance. Although experience is absorbed by time fixed effects, the effects of both gains and losses remain economically and statistically significant, indicating that the same trader increases reliance on 0DTE trading following both positive and negative outcomes. This pattern is consistent with extrapolation after gains and loss-chasing after losses and suggests that extreme short-term trading is reinforced rather than disciplined by prior experience. Column (7) replaces trader fixed effects with demographic controls and shows that younger and male traders are more likely to concentrate trading in 0DTE options, while traders located in Tier 1 cities exhibit a lower 0DTE intensity. Taken together, these results show that experience and past outcomes can induce retail trading in increasingly short-horizon, high-risk contracts, reinforcing speculative behavior over time.

6.2 Trader Entry into and Exit from Options

We examine the propensity of retail investors to initiate options trading. In particular, we are interested in whether investors gather experience in the stock market before trading options and if so, what type of formative experience is likely to drive entry into options. We combine the account-level options trading data for every individual with their stock account data. Taking into account the large size of the combined sample, the results are based on a random 10% sample of 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 performance of each retail investor in trading stocks. 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, namely, $Highperf$ 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 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 estimate the 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-weighting the volatilities by the investor's trading volume in the stocks. *Stockvol* is the logarithm of the stock trading volume over the past three months. 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 measures are set to zero. Our results are robust after excluding no-trade observations. The dependent variable, *Entry*, is an indicator 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 8 reports the results of the estimation 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 the participation of retail traders in the options market: 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 that 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 stocks with lottery-like payoffs ($Maxret$ in column (3)) are significantly more likely to initiate option trading. Because return volatility and maximum returns are positively correlated, we disentangle their effects by introducing indicator variables. *Highmaxret* and *Highretvol* denote whether these measures exceed the 75th percentile in a given month, and *Highretvol&max* captures their interaction. Column (4) shows that each of these indicators independently increases the likelihood of participation in the options market. Traders are more likely to enter options markets when they have experience with highly volatile stocks, stocks with extreme payoffs, or both. The remaining controls suggest that traders with higher trading volume but shorter market experience are more likely to enter options markets, consistent with models of overconfidence (Odean (1999), Barber and Odean (2000)). Overall, the evidence points to speculative and gambling-related motives rather than risk management as key drivers of retail entry into options trading.

At first glance, the determinants of entry into options markets and the determinants of 0DTE trading intensity appear to differ. Entry from the stock market into the options market is primarily driven by prior losses and is attenuated by gains, whereas among active options traders, both cumulative gains and cumulative losses predict more 0DTE trading. However, these patterns are not necessarily contradictory. Rather, they reflect distinct behavioral mechanisms that operate at different margins of participation. Losses motivate investors to initiate options trading, consistent with gambling-for-resurrection motives, while gains reduce the demand for leverage at the entry stage. However, conditional on participation, both gains and losses are associated with short-horizon speculative trading—because of overconfidence following gains and loss chasing following setbacks. Together, these results show that losses draw investors into options markets and subsequent extreme outcomes, positive or negative, push them toward extreme short-termism.

We next examine trader exit from the options market. In each month, traders are independently sorted into quartiles based on premium volume and realized returns, resulting in 16 groups, as shown in the top panel of Panel B of Table 8. We then estimate the probability that a trader remains active in the options market in the following month. The middle panel reports attrition rates across these groups and shows a strong relation with past performance: traders with higher recent returns are significantly more likely to continue, while those with poor performance are more likely to exit. Importantly, the bottom panel shows that continuation is not associated with superior subsequent performance. Traders who remain active do not earn higher future returns, indicating that traders extrapolate their ability from their past successes without any evidence of persistence in skill.

6.3 Single Stock Options

Single stock options constitute a relatively small segment of the Indian options market, accounting for less than 25% of total premium volume. As reported in Table 2, retail participation in single stock options is dominated by simple directional strategies: long calls and long puts are the most common positions, followed by short calls and short puts, typically involving a single option series. More complex strategies are rare. Volatility strategies account for only 5.8% of positions, while spreads and other multi-leg strategies represent about 1% of activity. Intraday trading exhibits similar patterns, with 94% of positions reflecting directional bets, 63% (26%) involving a single call (put) option, and only 5% spanning two option series.

We next assess whether single stock options are used for cross-hedging with index options. Although such strategies appear implausible given the large differences in trading volumes, we directly evaluate this possibility. We find that 74% of single stock option positions have no end-of-day open interest in index options. Among the remaining 26%, 56% involve positions in stocks and indexes that move in the same direction, 21% are directionally opposite, and the remaining in mixed directions. Taken together, these figures imply that at least 88.56% (74%+26%×56%) of single stock option trades do not involve cross-hedging.

We then examine which stock options attract retail trading interest. Following Roll, Schwartz and Subrahmanyam (2010) and Johnson and So (2012), we compute the option-to-stock ratio (O/S) by scaling options volume by the trading volume in the underlying stock. Focusing on the pre-2019 period to avoid confounding effects of settlement rule change discussed in Section 5.3, Table 9 reports the results. The coefficient of the high stock price indicator, *highprice*, is significantly positive, indicating greater trading in 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. Negative past stock returns are significant for put buying demand, but do not seem to drive call trading. Overall, the evidence from Table 9 reinforces the view that retail participation in single stock options is primarily motivated by leverage and speculative payoffs rather than hedging or risk management considerations.

7 Concluding Remarks

We study retail participation in options markets using comprehensive investor-level data from India, one of the world's largest derivatives markets and a setting characterized by rapid, digitally driven financial inclusion. Although much of the population historically lacked access to formal financial markets, recent technological and regulatory changes have enabled large-scale retail entry into complex derivative products. Retail trading quickly concentrates in short-dated index options and accounts for a substantial share of market activity, reaching 42% of the market volume in zero-days-to-expiry contracts at the end of our sample. Trading is dominated by short-term, directional bets, and retail investors incur persistent and economically significant losses. Exploiting a sequence of supply-side shocks, we show that expanding access to short-maturity options induces entry and intensifies trading, while attempts to curb speculation by raising participation costs do not lead to exit or longer horizons. Instead, traders substitute for cheaper, riskier contracts and suffer additional losses. Together, the evidence suggests that premature financial inclusion through access to highly leveraged short-term instruments can foster addictive speculative behavior that persists even in the face of financial harm.

Our study suggests avenues for future research. One side effect is the issue of wealth redistribution. The high speculative volume of retail traders creates excess liquidity in the options market and opens the door to profitable arbitrage trades between options and the underlying and wealth transfers from retail investors, especially low-income individuals, to sophisticated institutions. This issue has attracted considerable attention in the press and is under investigation by India's securities regulator, SEBI.[29] While the household finance literature has examined the portfolio benefits of financial inclusion, our study suggests that the effect of stimulating stock market participation on initiating trading habits, the persistence of these habits, and financial well-being are interesting research questions. Another open question is whether the negative wealth effects of speculative trading extend to health and other dimensions of well-being. We leave these issues to future research.

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

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Figure 1: Retail options market participation

This figure shows monthly retail participation in options trading. The four subplots show the numbers of active traders, and the aggregate contract, premium, and notional volumes, respectively.

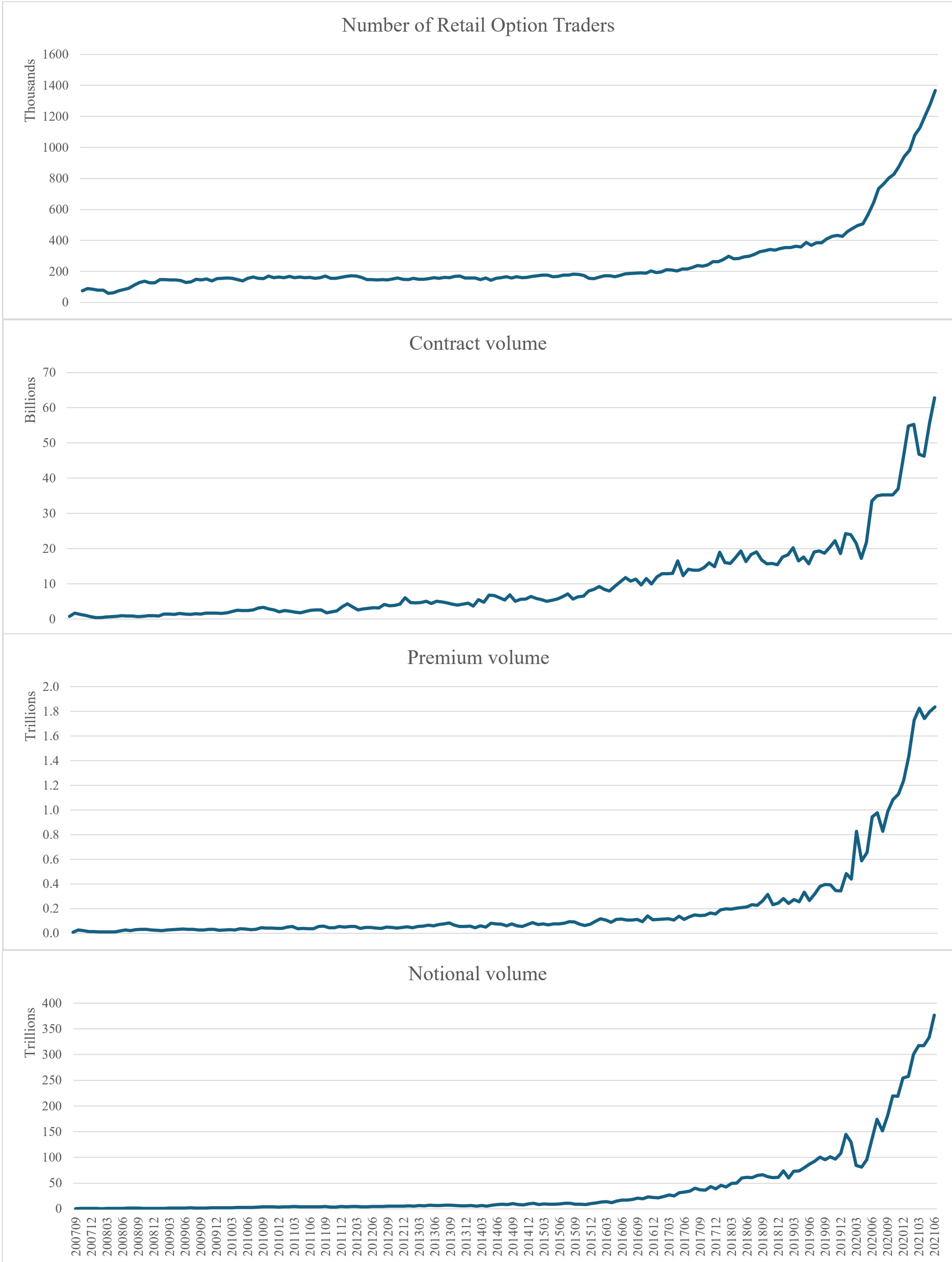
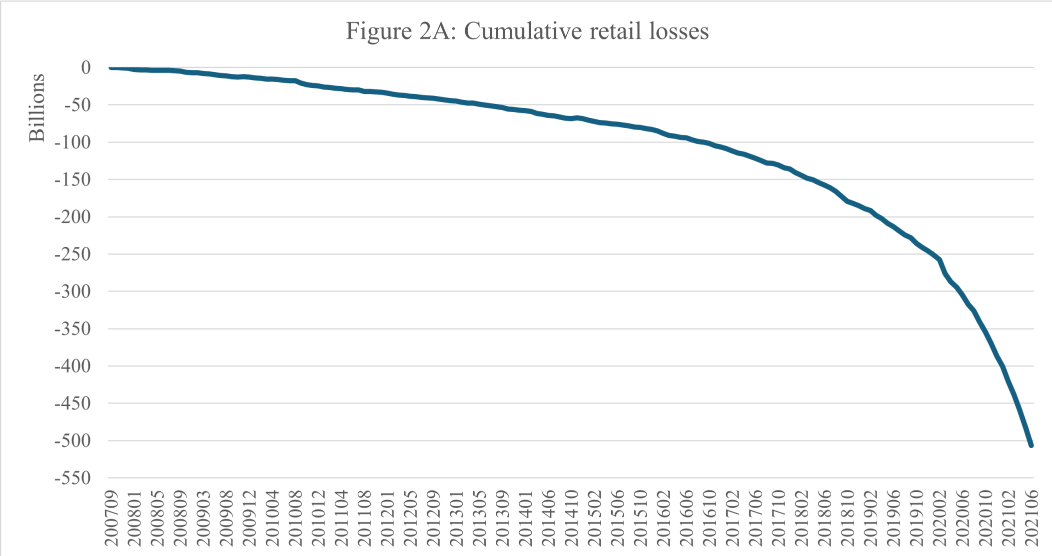


Figure 2: Trading P&L and wealth redistribution

Figure 2A shows the cumulative losses for retail option trades. The losses of all retail investors are aggregated from the start of the sample period to each corresponding month. In Figure 2B, traders are classified into profit makers and loss makers based on their P&L in each month. Within each month, the plot shows the total profits made by profit makers, and total loss by loss makers.



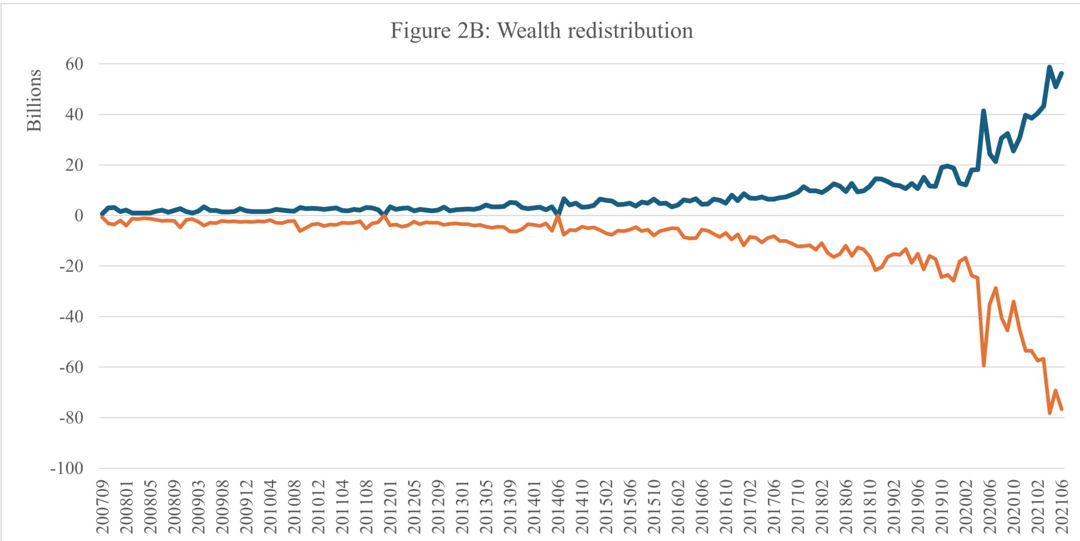
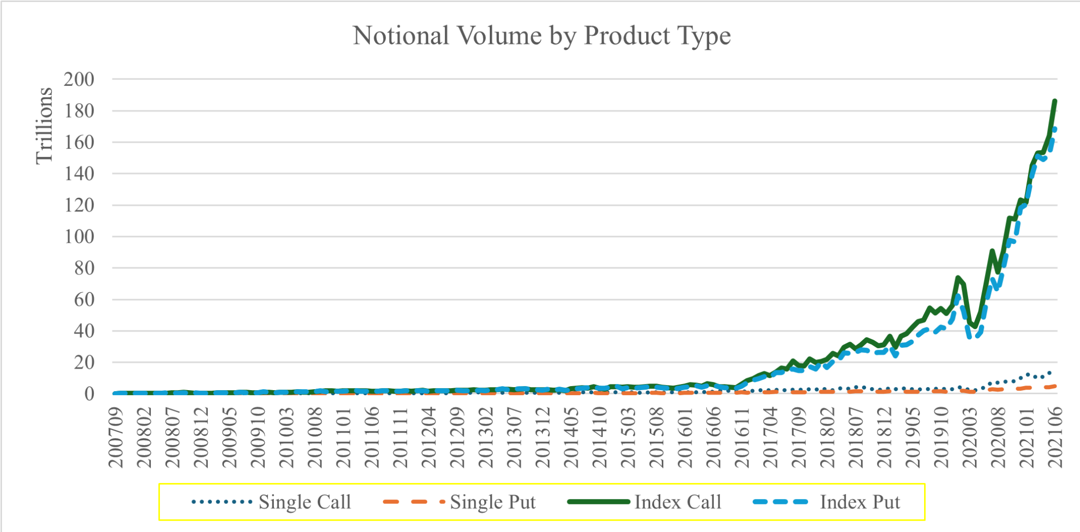


Figure 3: Trading volume on index and single stock options

Figure 3 shows the retail trading volume by each product category: index calls, index puts, single stock calls, and single stock puts. The first subplot shows the notional volume and the second subplot shows the premium volume in each month.



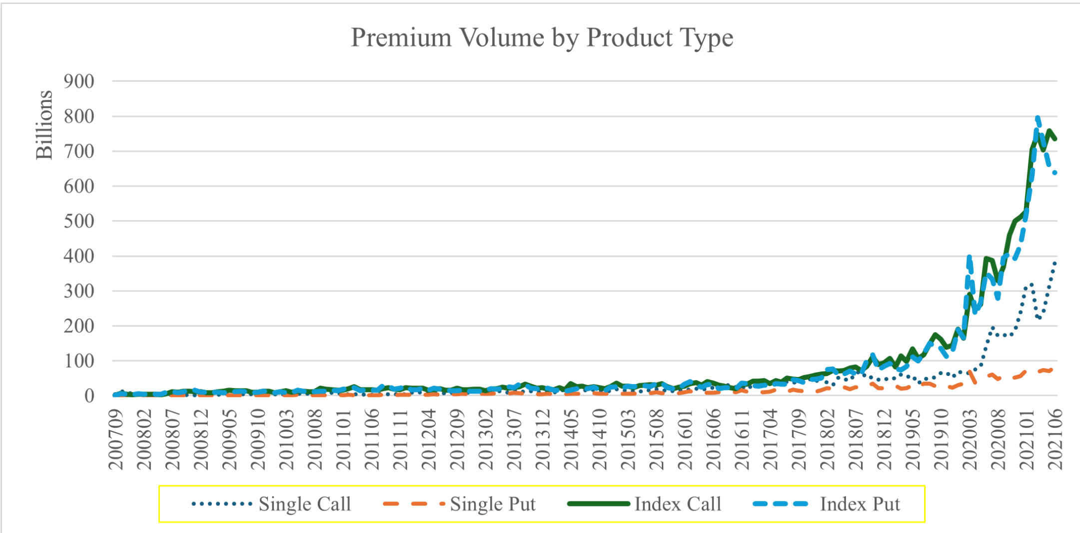
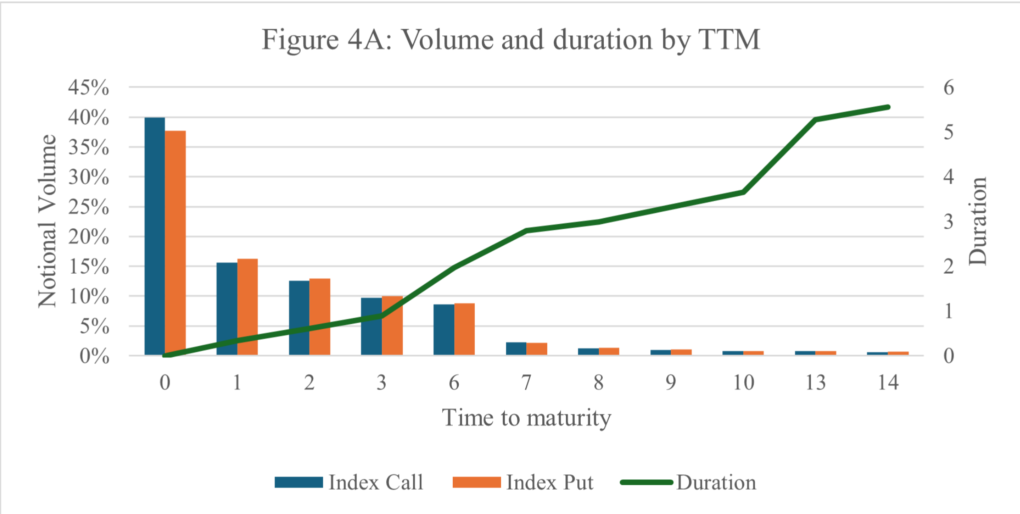


Figure 4: Time to maturity and trading behavior

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.



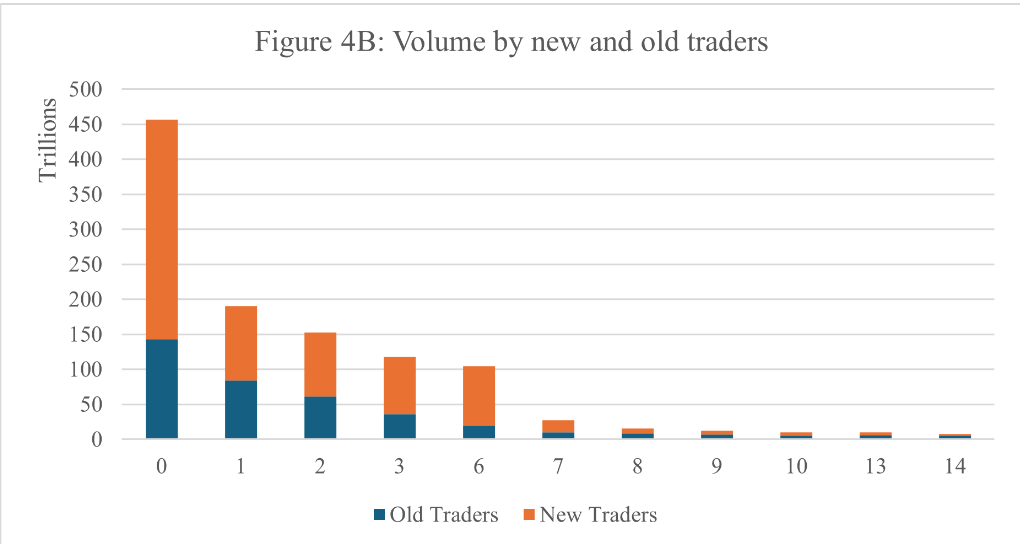
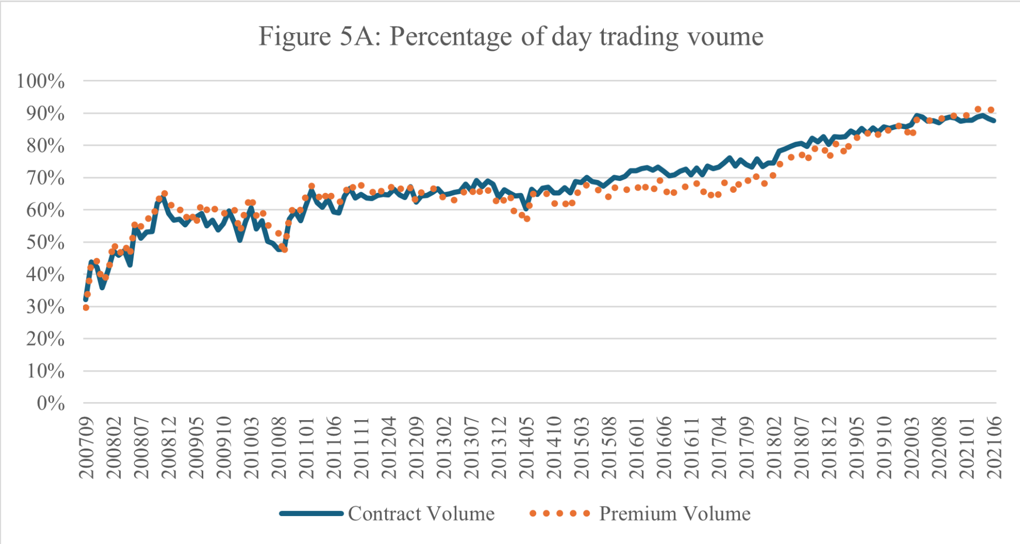


Figure 5: Day trading

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



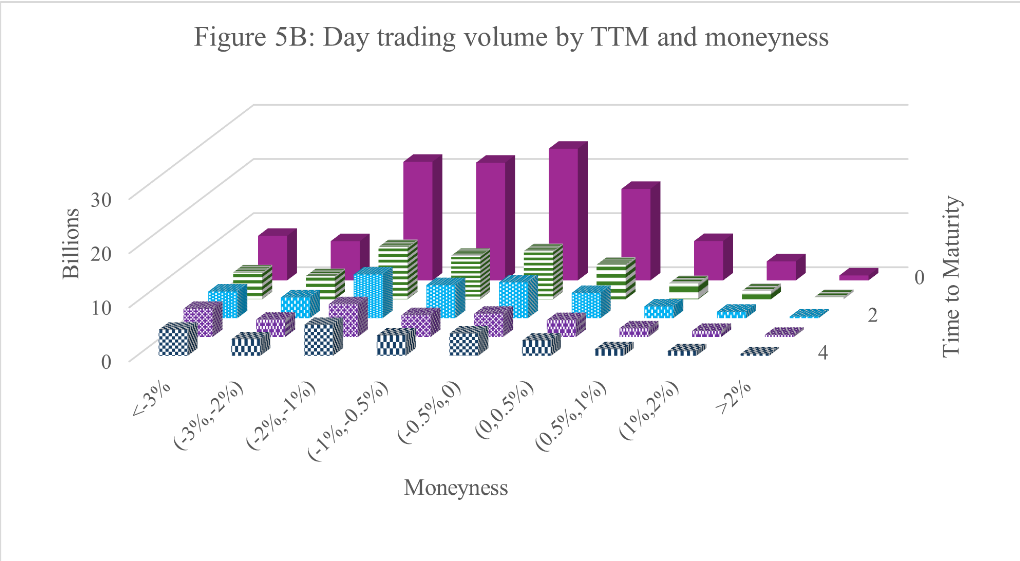
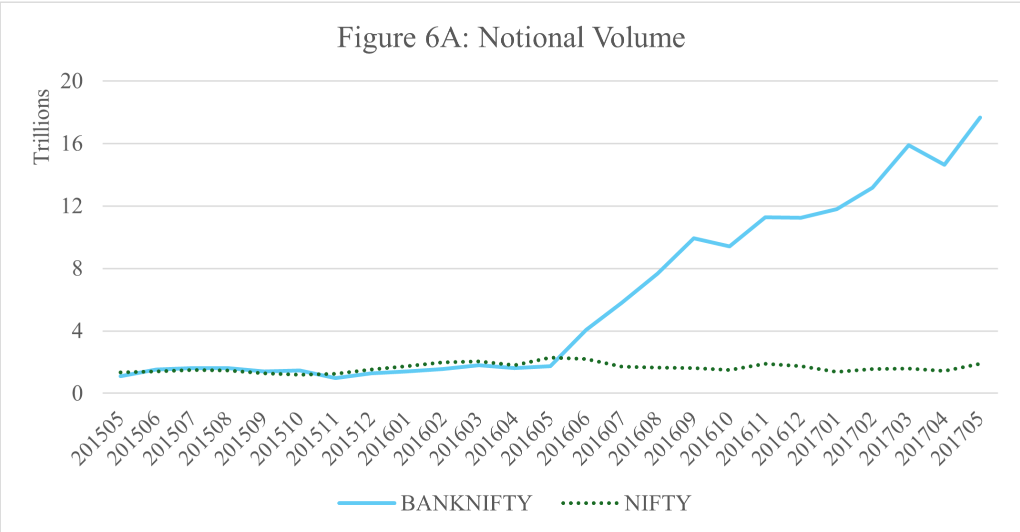


Figure 6: Introduction of weekly BANKNIFTY

Figure 6A shows the monthly retail notional volume volume around May 2016. The volume of NIFTY50 is scaled by 5. Figure 6B shows the number of traders where the number of NIFTY50 traders is scaled by 3. Figure 6C shows the numbers of old and new investors on BANKNIFTY and their monthly per capita volume. Old (new) investors are those who traded (did not trade) BANKNIFTY options in the pre-event period. Figure 6D displays the dynamic treatment effects of trading volume around the shock. For each investor, the treated volume is on BANKNIFTY options and control is on NIFTY50 options. Figure 6E shows the net stock investment around an investor's entry into BANKNIFTY options. For new investors who entered options trading within the two years after the shock, the net stock investment is measured as monthly net buys, scaled by the average of buys and sells. The figure plots the monthly dynamic treatment effects of net stock buys around the event month of entry into options, where the not-yet-treated investors are the controls. In figures 6D and 6E, the triangles and circles denote the pre- and post-event months, respectively; and the error bars denote the 95% confidence bands.



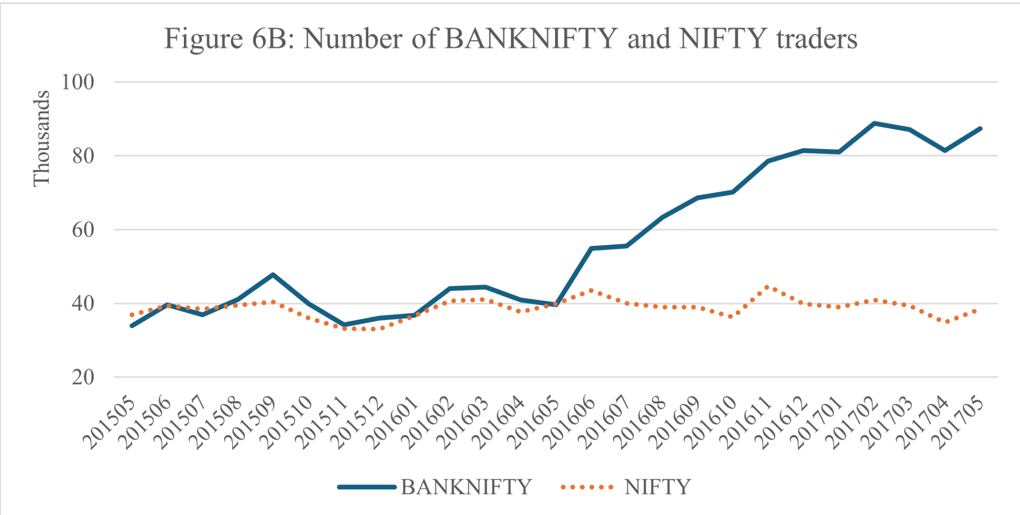


Figure 6C: Old and new traders on BANKNIFTY

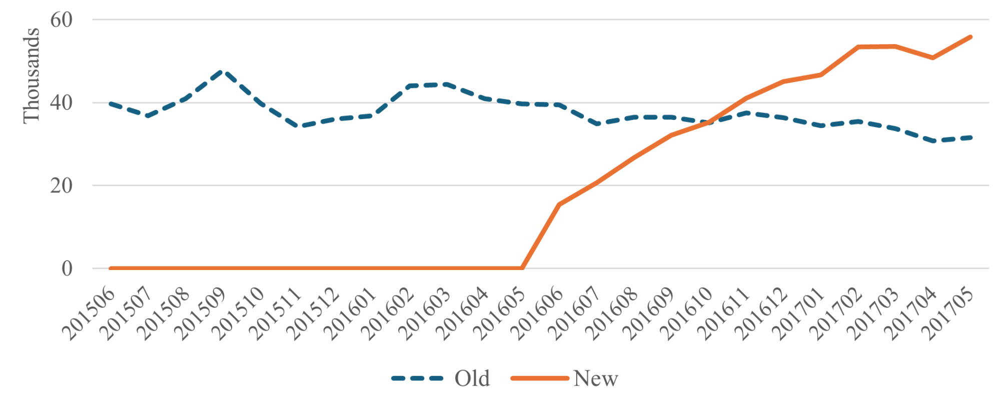


Figure 6D: Dynamic DiD estimates of trading volume

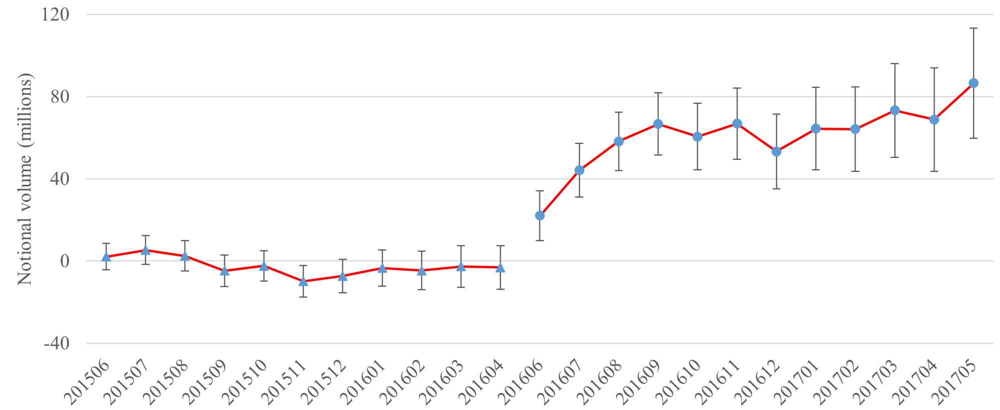


Figure 6E: Stock investment around BANKNIFTY options entry

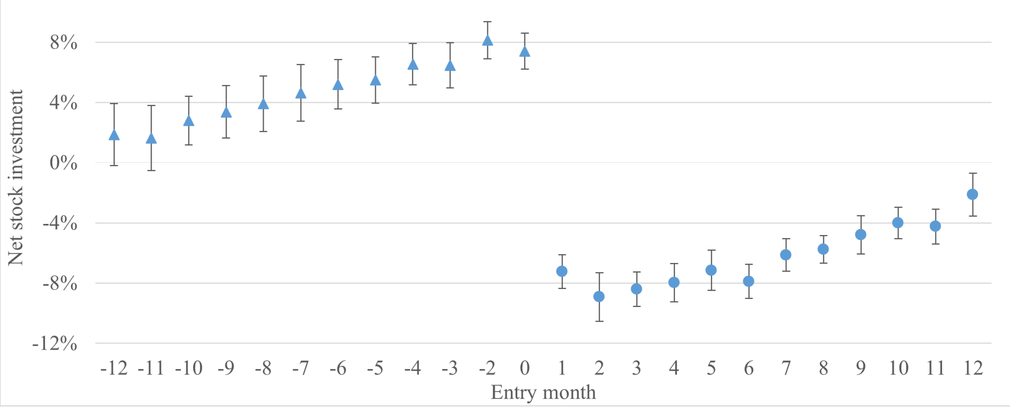
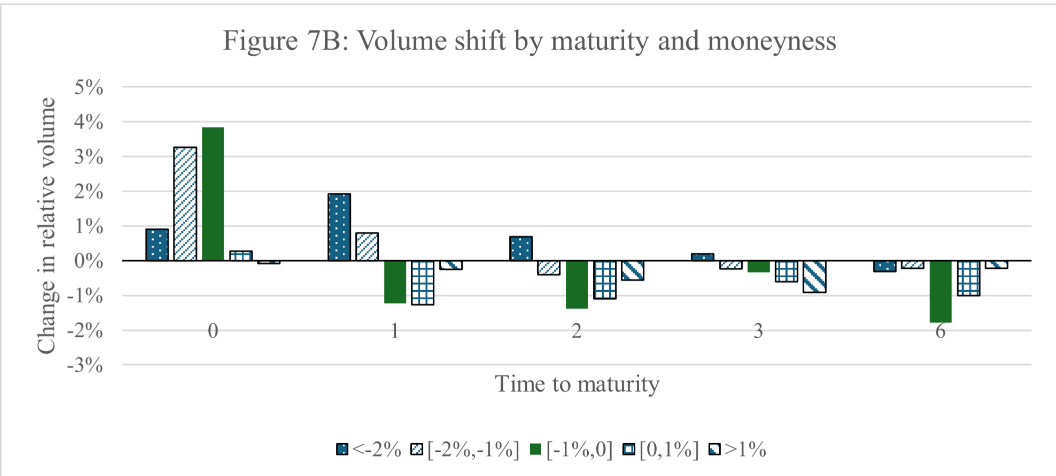


Figure 7: Lot size experiment

Figure 7A plots the average premium volume for each month on index options around the lot size experiment. Figure 7B 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 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 7C displays the monthly dynamic treatment effects of trading volume around the lot size experiment. Treated investors are those who always traded below the new lot sizes before the shock, and the control group consists of investors who traded between [75, 250] on NIFTY50, or [30, 90] on BANKNIFTY before the shock. The triangles denote the estimated treatment effects in pre-event months, and the circles denote the treatment effects in post-event months. The error bars denote the 95% confidence bands.



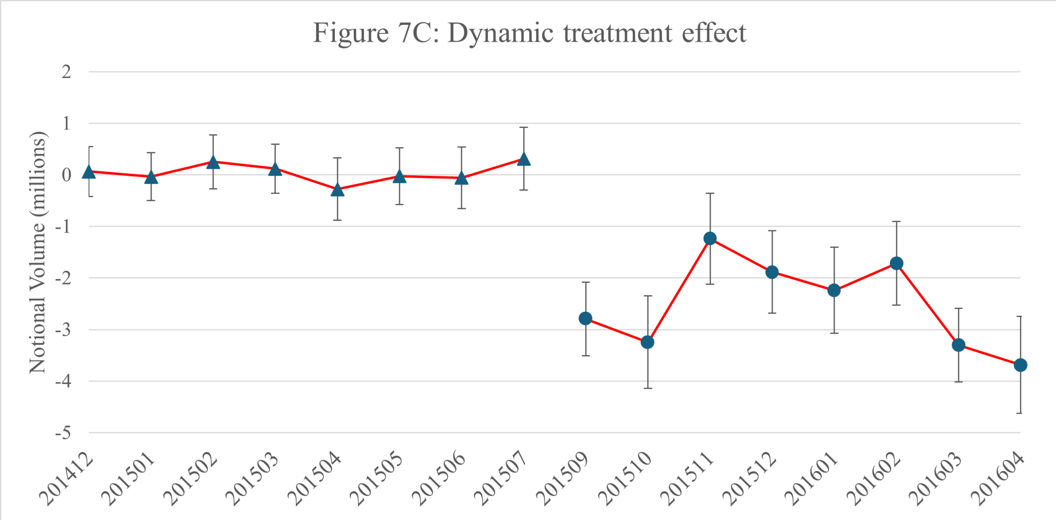


Figure 7C: Dynamic treatment effect
Notional Volume (millions)
2
1
0
-1
-2
-3
-4
-5
201412
201501
201502
201503
201504
201505
201506
201507
201509
201510
201511
201512
201601
201602
201603
201604

Figure 8: Dynamic DiD estimates of short maturity trading: physical settlement

This figure displays the dynamic treatment effects of the proportions of short maturity volume around the rule change. For each trader every month, the proportion of short maturity volume is the volume on options with less than a week to maturity, scaled by the total volume. Treated investors are those whose average time to maturity of stock option trades during the pre-event period is in the bottom quartile. The triangles denote the estimated treatment effects in pre-event months, and the circles denote the treatment effects in post-event months. The last month in the pre-event window is omitted and the error bars denote the 95% confidence bands.

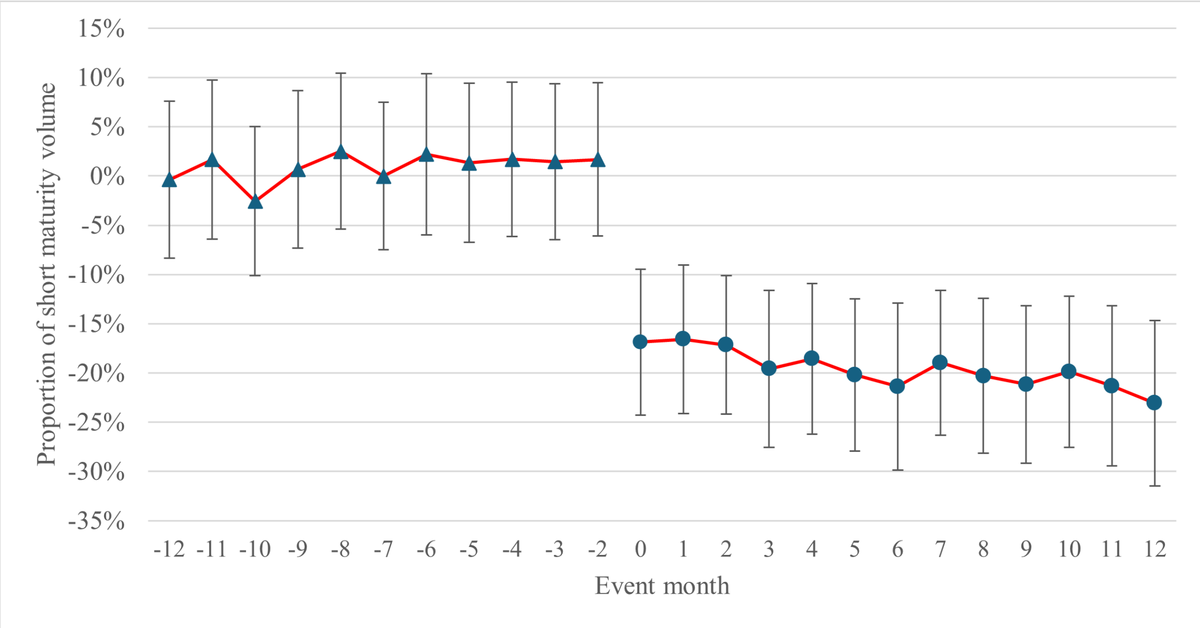
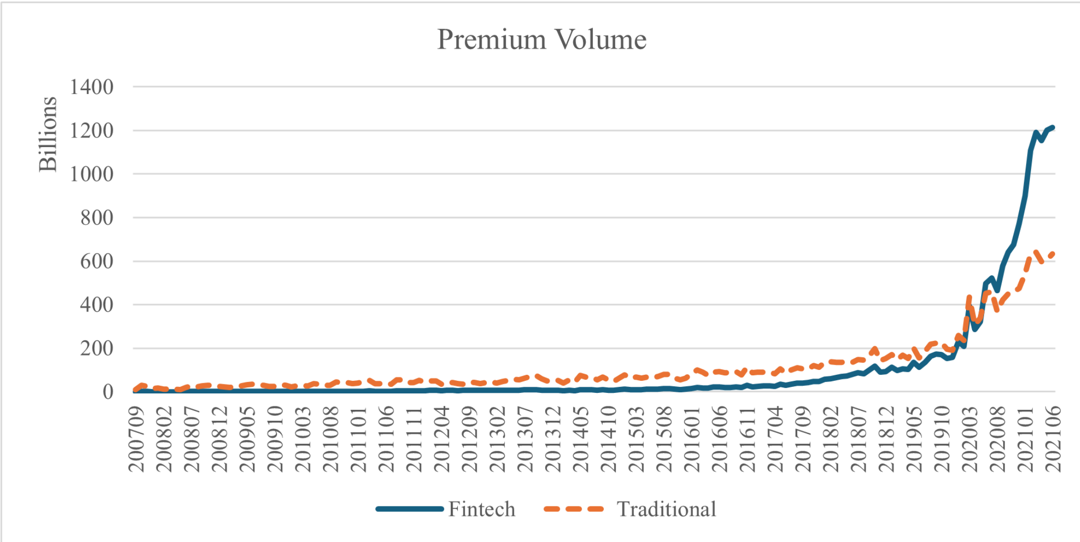


Figure 9: FinTech brokers

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



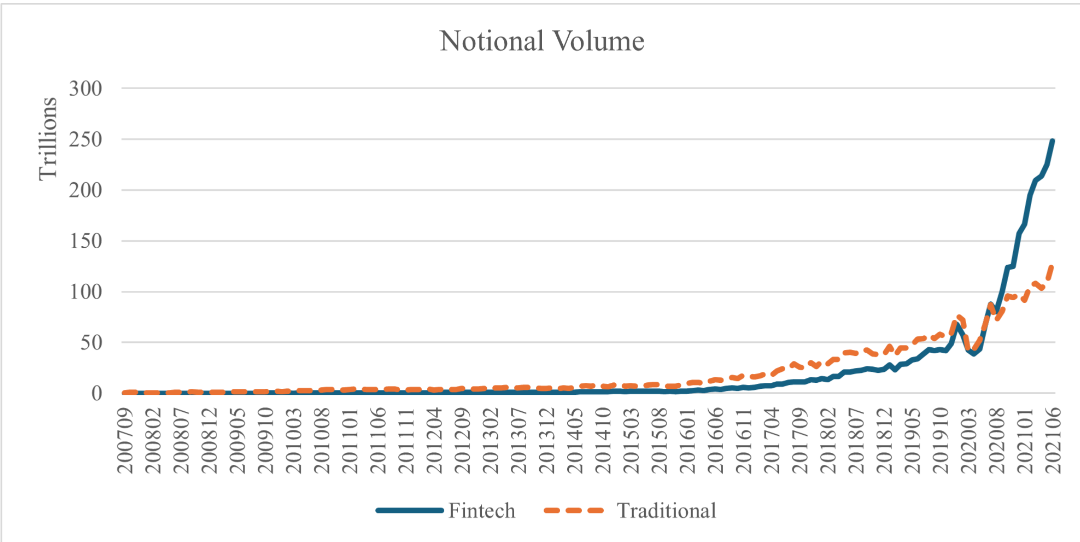


TABLE 1: Summary statistics

This table reports the descriptive statistics of retail options trading. Panel A shows the trading volume at the investor level. The sample includes 4 million traders in index options and 3 million traders in single stock options. The notional amounts are in millions and the premium and contract volume are in thousands. Panel B shows the statistics of individual level profits and losses (P&L), defined in Appendix A, in thousands. Panel C 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 before maturity, or if not closed out, till the contract expiration.

Panel A: Trading volume

			Mean	10th	25th	Median	75th	90th
Premium	Single	C	2,238	9	42	235	1,216	4,549
		P	1,067	6	27	120	551	2,008
	Index	C	3,443	8	42	261	1,449	6,206
		P	3,271	7	39	236	1,320	5,810
Contract	Single	C	350	1	6	35	170	621
		P	181	1	4	18	82	300
	Index	C	51	0	1	4	20	83
		P	47	0	1	4	18	77
Notional	Single	C	110	1	3	14	64	222
		P	60	1	2	8	33	112
	Index	C	821	2	9	56	312	1,336
		P	742	2	8	49	280	1,230

Panel B: Trader performance

		Mean	10th	25th	Median	75th	90th
Single	C	−50.5	−141.0	−41.9	−8.1	0.0	9.3
	P	−12.6	−60.3	−16.6	−2.6	1.0	12.4
Index	C	−42.9	−103.3	−28.6	−5.4	−0.1	6.1
	P	−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: Trade duration

		Mean	10th	25th	Median	75th	90th
Single	C	5.0	0	0	1	7	17
	P	4.9	0	0	1	6	17
Index	C	2.4	0	0	0	2	6
	P	2.3	0	0	0	2	6

TABLE 2: Trading strategies

This table reports the classification of retail options trading into various 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

Category	Type	Strategy	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 investor trading behavior. The pre-event period is from June 2015 to May 2016, and the post-event period is from June 2016 to May 2017. In Panel A, *treat* is equal to one for trading BANKNIFTY options, and zero for NIFTY50 options. *post* is an indicator for the post-event period. The notional volume is scaled by 1 million. Panel B relates trading behavior to investor demographics. The trading volumes are aggregated during the pre- and post-event periods respectively for each trader. All standard errors are double clustered at the trader and time levels.

Panel A: Introduction of weekly BANKNIFTY: DiD estimation

	(1) *premvol*	(2) *undervol*	(3) *contravol*	(4) *P&L*
$treat \times pre$	−24,442	−190	−6.36	362
	(−1.44)	(−1.06)	(−1.58)	(0.20)
$treat \times post$	91,020***	3,623***	65.56**	−2,352**
	(3.79)	(9.26)	(18.84)	(−2.70)
Time FEs	Y	Y	Y	Y
Trader FEs	Y	Y	Y	Y
Observations	4,186,425	4,186,425	4,186,425	4,186,425
Adjusted R^2	0.249	0.279	0.276	0.113

Panel B: Trader demographics and participation

	Without Fixed Effects				With Fixed Effects			
	(1) *premvol*	(2) *undervol*	(3) *contravol*	(4) *P&L*	(5) *premvol*	(6) *undervol*	(7) *contravol*	(8) *P&L*
$male \times post$	0.08***	59.74***	2,978***	−1,887**	0.20***	133.32***	6,708***	−4,635***
	(6.56)	(11.74)	(11.27)	(−2.32)	(7.69)	(11.00)	(10.97)	(−3.10)
$age18\_40 \times post$	0.02	39.75***	1,993***	−3,257***	0.21***	144.25***	7,296***	−7,402***
	(1.59)	(6.05)	(5.82)	(−3.20)	(6.71)	(10.15)	(10.18)	(−4.39)
$age41\_60 \times post$	0.02	20.21***	1,078***	−3,292***	0.09***	61.95***	3,222***	−3,107*
	(1.33)	(2.90)	(2.97)	(−3.00)	(3.00)	(4.33)	(4.47)	(−1.75)
$tier1 \times post$	0.04***	32.03***	1,493***	1,354*	0.09***	38.60***	1,883***	−1,265
	(4.01)	(6.64)	(5.98)	(1.86)	(3.92)	(3.38)	(3.26)	(−0.99)
male	−0.00	6.33**	370**	−1,806**	–	–	–	–
	(−0.21)	(2.57)	(2.56)	(−2.50)				
age18_40	−0.05***	−3.43	−169	2,375***	–	–	–	–
	(−4.61)	(−1.06)	(−0.89)	(2.64)				
age41_60	−0.02*	−6.50*	−376*	935	–	–	–	–
	(−1.66)	(−1.93)	(−1.91)	(0.96)				
tier1	0.08***	18.28***	1,085***	−5,158***	–	–	–	–
	(10.37)	(7.92)	(8.01)	(−7.94)				
post	0.30***	168.44***	7,933***	1,948*	0.49***	221.75***	10,537***	−5,729***
	(17.42)	(23.22)	(21.01)	(1.68)	(14.26)	(14.08)	(13.24)	(−2.87)
Trader FE	N	N	N	N	Y	Y	Y	Y
Observations	289,944	289,172	289,944	289,944	98,176	97,642	98,176	98,176
Adjusted R^2	0.012	0.021	0.018	0.001	0.662	0.623	0.637	0.615

TABLE 4: Change in lot size of index options

This table reports the estimation results of a difference-in-differences regression on trading behavior and performance around an increase in the lot size of index options in August 2015. *post* is equal to 1 during the post-event period from September 2015 to April 2016, and zero during the pre-event window from December 2014 to July 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) per day before the shock. 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 per day before the shock. *post* is an indicator for the post-event window, and *pre* is an indicator for the quarter before the event. Panel A shows the change in premium volume (*premvol*), contract volume (*contravol*), and notional volume (*undervol*, in millions) at the trader-contract level. Panel B shows the change in contract price (*ContraPrice*), percentage moneyness (*%Moneyness*), time to maturity (*TTM*), and dollar profit and loss (*P&L*) at the trader-contract level.

Panel A: Trading volume

	(1) *premvol*	(2) *contravol*	(3) *undervol*
$treat \times pre$	$1,507$	-4.89	-0.03
	(1.34)	(-0.42)	(-0.29)
$treat \times post$	$-3,213$**	-104.61***	-0.84***
	(-2.71)	(-6.81)	(-5.74)
Time FEs	Y	Y	Y
Trader FEs	Y	Y	Y
Observations	585,870	585,870	585,870
Adjusted R^2	0.414	0.476	0.459

Panel B: Unintended consequences

	(1) *ContraPrice*	(2) *%Moneyness*	(3) *TTM*	(4) *P&L*
$treat \times pre$	3.94	0.03	0.04	-29.04
	(1.40)	(0.57)	(0.25)	(-0.22)
$treat \times post$	-7.13**	-0.26***	-0.65***	-161.64
	(-2.30)	(-4.05)	(-3.05)	(-1.36)
Time FEs	Y	Y	Y	Y
Trader FEs	Y	Y	Y	Y
Observations	585,870	585,870	585,870	585,870
Adjusted R^2	0.466	0.336	0.202	0.118

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 changes in 2019. *post* is an indicator variable that is equal to one if a trader trades a stock option that is already subject to the physical delivery requirement. *treat* is an indicator variable for treated investors, defined as those whose average time to maturity of stock option trades during the pre-event period is ranked in the bottom quartile. For each trader in every event month, *ShortMat* is the notional volume of trading short maturity options with less than one week to maturity. *LongMat* is the notional volume of trading long maturity options with more than one week to maturity. *OTM* is the notional volume of trading OTM options with moneyness less than −5%. *ITM* is the notional volume of trading ITM and ATM options with moneyness greater than −5%. Panel A uses the whole sample and Panel B excludes the Covid period, contracts that expire in March 2020. The regressions control for trader and month fixed effects and the standard errors are double-clustered at the trader and month levels.

Panel A: Whole sample

	(1) *ShortMat*	(2) *LongMat*	(3) *ITM*	(4) *OTM*	(5) *P&L*
$treat \times pre$	14.52	−13.84	−5.11	6.02	109
	(1.62)	(−1.63)	(−0.35)	(0.40)	(0.50)
$treat \times post$	−79.03***	78.11***	−56.43***	58.87***	−777***
	(−9.78)	(9.98)	(−4.87)	(4.93)	(−3.24)
Time FEs	Y	Y	Y	Y	Y
Trader FEs	Y	Y	Y	Y	Y
Observations	5,482,019	5,482,019	5,482,019	5,482,019	5,482,019
R-squared	0.327	0.323	0.399	0.402	0.063

Panel B: Excluding Covid period

	(1) *ShortMat*	(2) *LongMat*	(3) *ITM*	(4) *OTM*	(5) *P&L*
$treat \times pre$	14.30	−13.61	−4.95	5.86	82.26
	(1.59)	(−1.59)	(−0.34)	(0.39)	(0.41)
$treat \times post$	−78.54***	77.61***	−55.81***	58.22***	−761.32***
	(−9.56)	(9.75)	(−4.76)	(4.82)	(−3.27)
Time FEs	Y	Y	Y	Y	Y
Trader FEs	Y	Y	Y	Y	Y
Observations	5,396,049	5,396,049	5,396,049	5,396,049	5,396,049
R-squared	0.329	0.325	0.402	0.405	0.071

TABLE 6: FinTech brokers

Panel A reports the summary statistics by FinTech and traditional brokers based on the sample of all traders at the trader-month level. Panel B presents the regression estimates based on a subset of traders who use both FinTech and traditional brokers. For each trader every month, the corresponding variables are aggregated for all trading activities via FinTech and traditional brokers, respectively. *finbroker* is an indicator variable for trades placed through FinTech brokers. The premium and notional volumes are in millions. The regressions have 34 million trader-month observations and the standard errors are double-clustered at the trader and month levels. Panel C reports the monthly per capita notional volume (in millions) for those who switch from traditional to FinTech and never switch back, who switch back and forth or use both types of brokers simultaneously, and who switch from FinTech to traditional and never switch back.

Panel A: Summary statistics by broker type

	Duration	*%DayTrade*	*premvol*	*undervol*	*P&L*
Traditional	3.7	50.6	0.47	99.3	−6,278
FinTech	1.8	74.0	0.81	194.2	−9,671

Panel B: Trading behavior and performance of switchers

	(1) *Duration*	(2) *%DayTrade*	(3) *premvol*	(4) *undervol*	(5) *P&L*
finbroker	−0.04***	7.42***	0.28***	62.43***	−2,791***
	(−3.97)	(30.75)	(15.20)	(17.49)	(−19.45)
Time FEs	Y	Y	Y	Y	Y
Trader FEs	Y	Y	Y	Y	Y
Adjusted R^2	0.331	0.468	0.359	0.395	0.082

Panel C: Subgroups of switchers

	Traditional to FinTech	Transitory	FinTech to Traditional
Volume via Traditional	60.7	136.3	130.2
Volume via FinTech	189.4	232.1	120.5

TABLE 7: Determinants of 0DTE trading

This table reports the determinants of 0DTE trading. The dependent variable is the fraction of 0DTE trading, defined as the notional volume of an investor's 0DTE trading scaled by their total volume in a given month. *experience* is the number of years since the trader's first option trading. *cum_profit* is the logarithm of cumulative profit over the last 12 months, and is set to zero if the investor made a loss. *cum_loss* is the logarithm of cumulative losses over the last 12 months, and is set to zero if the investor made a profit. *cum_vol* is the aggregate premium volume over the last 12 months.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
experience	2.13***	0.64***	2.15***				
	(16.36)	(13.48)	(3.27)				
cum_profit	0.24***	0.03**	0.30***	0.20***	0.03***	0.29***	−0.00
	(6.34)	(2.17)	(5.03)	(8.70)	(3.54)	(9.80)	(−0.04)
cum_loss	0.38***	0.08***	0.47***	0.33***	0.08***	0.45***	0.27***
	(8.29)	(5.99)	(6.52)	(13.13)	(9.06)	(15.32)	(7.35)
cum_vol	−0.67***	−0.30***	−0.95***	−0.51***	−0.35***	−0.67***	−0.40***
	(−3.09)	(−8.22)	(−3.62)	(−13.08)	(−15.87)	(−14.14)	(−9.65)
male							1.50***
							(11.54)
Age18-40							4.00***
							(12.46)
Age41-60							1.34***
							(9.17)
tier1							−0.51***
							(−7.76)
Trader FEs	Y	Y	Y	Y	Y	Y	N
Time FEs	N	N	N	Y	Y	Y	N
Observations	25,403,512	7,490,171	17,820,057	25,403,512	7,490,171	17,820,057	16,844,345
Adjusted R^2	0.420	0.266	0.389	0.446	0.268	0.418	0.149

TABLE 8: Trader entry and exit in the options market

Panel A reports the estimation results of a linear probability model of traders' entry into options trading. The data panel is based on a random 10% sample of stock traders. For each trader every month, *Performance* is the trader's stock trading performance during the past three months, calculated by volume-weighting market-adjusted stock returns. *Highperf* and *Lowperf* are indicator variables for the top and bottom deciles of *Performance* in a month. *Retvol* is the volume-weighted stock return volatility of stocks traded, *Maxret* is the volume-weighted maximum daily return of stocks traded, and *Stockvol* is the logarithm of stock trading volume, all measured over the past 3 months. *Experience* is the number of months since a trader started trading stocks. *Highretvol* is an indicator for *Retvol* above the 75^{th} but *Maxret* below 75^{th}; *Highmaxret* for *Maxret* above 75^{th} but *Retvol* below 75^{th}; and *Highretvol&max* if both *Retvol* and *Maxret* are above the 75^{th} percentiles. All stock activity measures are set to zero for non-trading. The dependent variable *entry* is equal to 1 for the month when a trader started options trading, and 0 for all months before entry, or if the trader never entered options trading. Observations after the entry month are excluded. 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 returns, probability of trading in the next month, and returns in the next month for each group.

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)
Highmaxret				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)
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

Table 8 – Continued from previous page

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 9: Participation in single stock options

This table reports the determinants of single stock options trading. 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, multiplied by 1,000 for expositional convenience. *highprice* is an indicator variable that is equal to one if the stock's price per share ranks above the 90th percentile during the previous day, and zero otherwise. *lagret* is the lagged daily stock return. *premium* is the average price per contract paid by the representative retail investor during the trading day. *ttm* is the time-to-maturity in days. *moneyness* is the percentage moneyness. *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

ONLINE APPENDIX

Appendix A. Variable Definitions

Variable	Definition
Options trading	
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	(Stock/index price − strike price)/stock/index price for calls, reversed for puts. Stock/index prices are measured at the market open to avoid look-ahead bias.
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.
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.
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 the first to the last day of trading a contract if the positions are closed before maturity, or to the maturity day if not fully closed.
%Return	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.
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.
Demographics	
male	Indicator for male investors.
age18_40	Indicator for investors aged 18–40 years.

Continued on next page

Variable	**Definition**
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	Stock trading performance during the past 3 months, calculated as the volume-weighted market-adjusted stock returns, measured from the day of trading until the end of the period.
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 of all stocks traded during the past three months.
Maxret	Volume-weighted maximum daily return of all 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.
Highmaxret	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.
entry	Indicator 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. For each day and option contract, O/S = notional amount of options trading volume ÷ 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 2024. 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. 0DTEs with only hours to expiration are omitted due to the lack of intraday data. For each of these time to maturity category, we further sort options into different moneyness buckets, as shown in Appendix Table B.1. Option moneyness is computed based on option strike prices and the closing index values 6, 3, 2, and 1 day(s) before the maturity, and we eliminate options that are more than 10% in the money and −10% out of the money.

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 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

Moneyness	TTM (call)				TTM (put)			
	1	2	3	6	1	2	3	6
(−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

Moneyness	TTM (call)				TTM (put)			
	1	2	3	6	1	2	3	6
(−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: Portfolios of single stock options

		Call			Put		
	TTM	7	18	48	7	18	48
Skewness	Low	0.07	−0.30	0.38	0.38	0.62	1.28
	2	0.57	0.16	0.76	0.77	1.20	1.86
	3	1.09	0.71	0.96	1.35	1.76	2.80
	4	1.82	1.37	1.17	2.09	2.70	3.94
	High	2.68	1.64	1.48	2.71	4.55	7.01

Appendix Table B.1 (Continued)

Panel D: Stock portfolios

	Holding period			
Decile	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 78 times the median notional volume of retail investors shown in Table 1 (₹56 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.

In untabulated results, we find that protail investors achieved profitability in 72 of the 169 months in our sample, a stark contrast to the broader retail population which recorded profits in only 4 of those months. Protail investors also have longer trade duration, and are net sellers of both index calls and puts. Their net selling absorbs only a small fraction of the aggregate positions of the broader retail population, i.e., institutions are the major counterparts to retail open positions. Overall, these 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

			Mean	10^{th}	25^{th}	Median	75^{th}	90^{th}
Premium	Single	C	41,042	54	266	1,657	10,221	49,569
		P	18,357	35	145	753	4,210	19,460
	Index	C	181,008	1,455	7,281	30,735	110,858	332,347
		P	168,497	1,304	6,597	28,277	104,015	314,951
Contract	Single	C	9,586	4	21	143	937	5,133
		P	2,957	2	11	62	387	2,104
	Index	C	2,332	16	72	287	1,057	3,431
		P	2,164	15	67	276	1,027	3,320
Notional	Single	C	1,993	2	11	68	408	1,906
		P	859	2	7	35	186	839
	Index	C	34,686	157	878	4,342	16,978	53,814
		P	31,692	145	826	4,163	16,208	52,108

Panel B: Trader performance

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

Appendix D: Pandemic Trading

In this appendix, we report investor trading around March 2020 as the COVID-19 pandemic unfolded. We classify all traders based on their overall positions over the 6 months before COVID (August 2019 to January 2020). For each trader, we compute daily end-of-the-day positions for each options contract, and then 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. About 5.9% of the traders are net sellers of both calls and puts, and 87.7% of the traders are net buyers of calls and puts. Some investors that traded after COVID had no trades in the pre-COVID period, and are classified as new traders.

The shaded area of Figure D.1 shows the daily India VIX and the solid lines show the aggregate open interests of different groups of investors. The sawtooth patterns are consistent weekly volume cycles when options turn into 0DTEs. The open interest of the long call-long put group had been persistently positive before March 2020, on both index calls and index puts. In contrast, the open interest of the short call-short put group had been persistently negative before March 2020, also on both calls and puts, indicating that the major division of the groups is into long-only and short-only strategies. Note that 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 open interests of the other groups are relatively small.

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 on March 26, 2020. The long call-long put group reduced their positions, particularly on long put positions, consistent with premature realizations of gains. The short call-short put group indeed reduced their short positions, especially the puts, although they did not fully close these positions that led to dramatic losses as we illustrate below.

The first part of Figure D.2 displays the profits or losses by investor groups on the

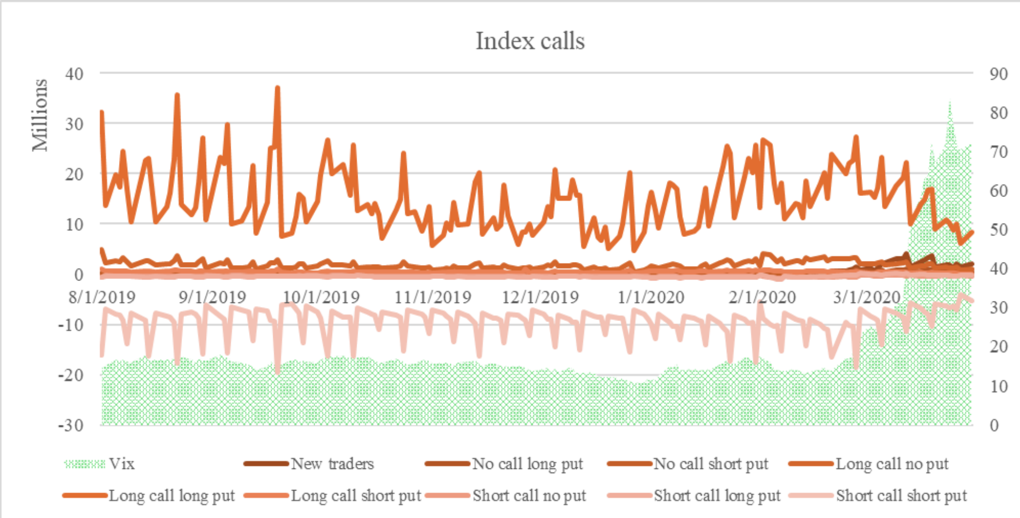
March 2020 expiry contract. The retail losses come almost exclusively from the short investors (mainly their short puts positions), especially those who sold both calls and puts in the pre-event period. The total loss by option sellers amount to ₹11 billion in March 2020. To put the number in perspective, the total retail gain from options selling during our entire sample period - including sellers during the COVID periods and all other period - was ₹3 billion. In the second part of Figure D.2, we find that short sellers profited from short volatility strategies during the pre-event period, although they capture only a small fraction of the losses by the long call-long put group. Thus, retail selling of volatility produces profits during normal times, reflecting a variance risk premium, but extreme losses during market downturns. In contrast, institutions not only profit from the VRP during normal times, but also during the crisis by switching to put buyers.

Next, we focus on the March 26, 2020 contract and the group of short call-short put investors, and classify them based on the last day the exited the contract in Figure D.3. The top subplot shows that most traders hold positions until expiration on March 26, 2020, and the day before. Trading losses are mostly attributable to these two groups of traders with sticky strategies that are consistent with the distaste of realizing losses due to the disposition effect.

Overall, these results suggest that option sellers sell volatility during normal times and profit from the variance risk premium. They indeed closed some of their short puts after adverse market movements, but did not fully close or turn into buyers of puts. The resulting stickiness combines with leverage embedded in options to generate large losses. The unlimited loss potential in short option positions, compounded by significant embedded leverage, makes option writing particularly hazardous for retail investors. The behavioral biases are exacerbated and the associated consequences are much 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 from August 1, 2019 to March 30, 2020.



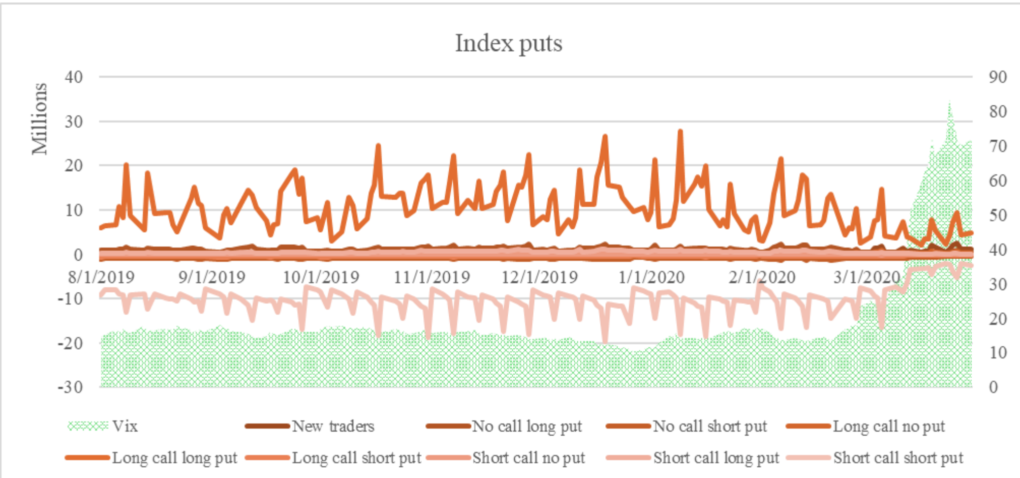
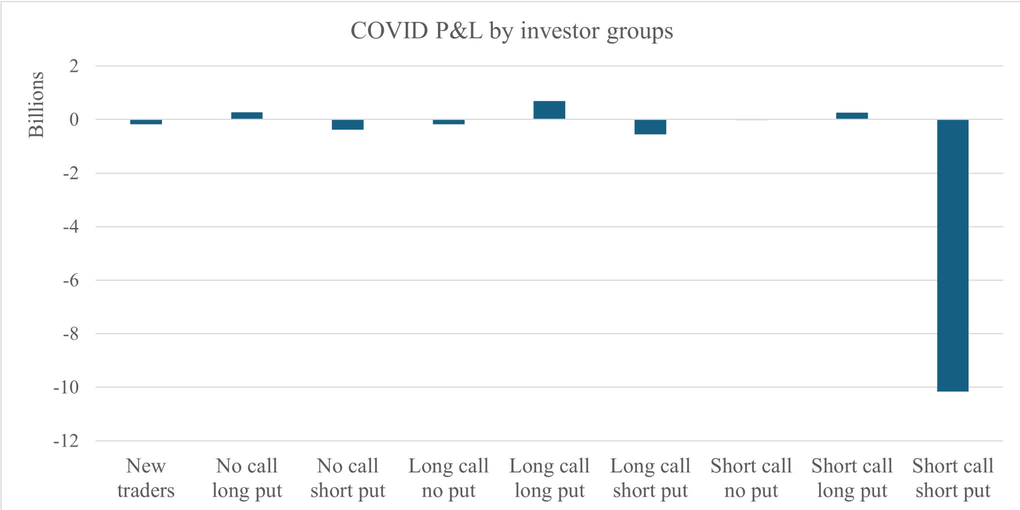


Figure D.2: P&L by investor groups around COVID-19

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.



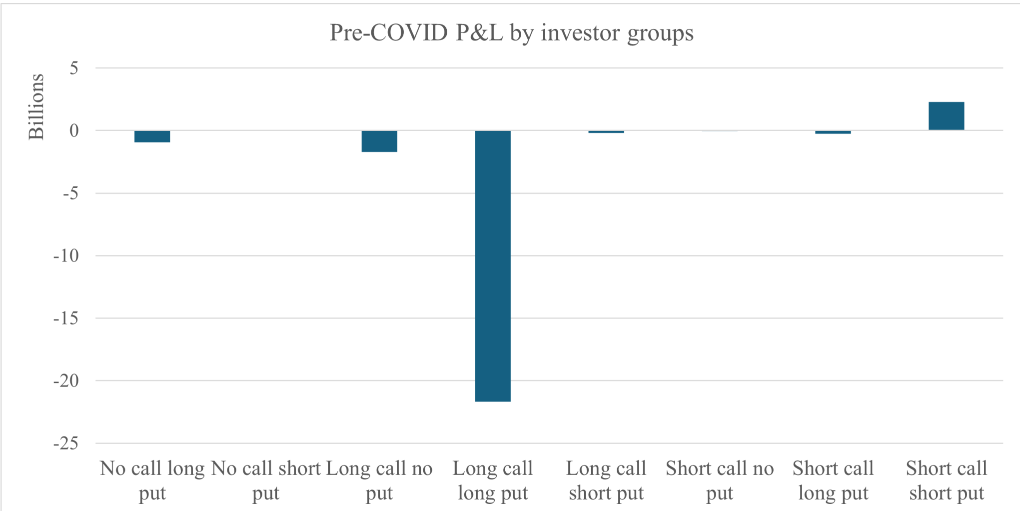


Figure D.3: Trader exit

Investors who were net sellers of both call and put options between August 1, 2019 and January 31, 2020 are classified into different groups 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.