



## **A study on causal effects of sebi regulatory interventions on retail f&o participation in india (2015–2026): a multi-outcome interrupted time series analysis**

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### **Abstract**

Between FY2019 and FY2024, 93 per cent of individual equity Futures and Options (F&O) traders on the National Stock Exchange (NSE) incurred net losses, prompting the Securities and Exchange Board of India (SEBI) to introduce a sequence of escalating regulatory interventions. This study identifies which of nine SEBI interventions — spanning a weekly expiry introduction (2016), stock eligibility tightening (2019), phased peak-margin requirements (2020–2021), weekly expiry restriction (2023), and a combined lot-size and income/knowledge eligibility package (2024) — produced statistically significant causal changes in retail F&O participation in India from January 2015 to January 2026.

Using a multi-intervention Interrupted Time Series (ITS) framework across 133 monthly observations, the study estimates each intervention's effect on three outcomes: active unique retail traders ( $Y_1$ ), retail turnover share ( $Y_2$ ), and new F&O registrations ( $Y_3$ ). All models control for the COVID-19 participation shock (a mandatory step dummy isolating a +14.22 lakh surge, March 2020–March 2021), the secular time trend, market volatility (India VIX), Nifty 50 returns, discount broker penetration, retail search attention, and mobile internet growth.

Structural interventions produced substantially larger participation reductions than incremental capital-cost measures. The October 2024 lot-size increase (D5a: -12.47 lakh<sup>\*\*\*</sup>), income/knowledge eligibility criteria (D5b: -10.22 lakh<sup>\*\*\*</sup>), and October 2023 weekly-expiry restriction (D4: -8.64 lakh<sup>\*\*\*</sup>) each far exceeded the phased peak-margin effects (D3a–D3d: -1.47 to -2.85 lakh per phase). The liberalising weekly-expiry introduction (D1: +2.41 lakh<sup>\*\*</sup>) confirms bidirectional sensitivity. Market conditions moderate deterrence: bull-market returns attenuated the D3 effects; weak FY25 returns amplified D4 and D5. Discount broker penetration offsets approximately 30 per cent of the D5b entry barrier. Retail turnover share ( $Y_2$ ) is formally excluded from D5a specifications due to lot-size-induced denominator endogeneity. All findings are robust to a post-2017 restricted sample.

The study contributes a validated multi-intervention ITS design simultaneously addressing COVID-era confounding, market-condition moderation, technology-access offsets, and a

novel endogeneity correction for the lot-size change — the first such unified framework applied to the Indian equity derivatives market.

**Keywords:** SEBI; Retail F&O Participation; Interrupted Time Series; Equity Derivatives; Regulatory Impact; India; Discount Brokers

## 1. Introduction

### 1.1 Background of the Study

India's equity derivatives market has undergone a structural transformation of rare speed and scale. Retail participation in the NSE equity Futures and Options (F&O) segment grew from a niche activity involving 7.1 lakh unique individual traders in FY2019 to a mass-market phenomenon involving approximately 96 lakh active traders at its pre-intervention peak in Q2 FY2025 — an increase of over 1,250 per cent in six years. Yet this democratisation of speculative access has carried a significant welfare cost: SEBI's landmark 2024 study found that 93 per cent of individual F&O traders incurred net losses between FY2022 and FY2024, with aggregate losses across all individual traders exceeding Rs 1.8 lakh crore. This convergence of extraordinary behavioural scale and documented welfare harm provides the primary motivation for the present study.

In response to this welfare concern, SEBI introduced a sequence of escalating regulatory interventions between 2016 and 2024. The regulatory arc spans both liberalising and restrictive measures: weekly index option expiries were introduced in May 2016 (D<sub>1</sub>), expanding low-cost speculative access; stock eligibility criteria were tightened in October 2019 (D<sub>2</sub>); phased peak-margin requirements were implemented in four steps from June 2020 to March 2021 (D<sub>3a</sub>–D<sub>3d</sub>); the weekly expiry regime was partially reversed in October 2023 (D<sub>4</sub>); and a combined lot-size increase and income/knowledge eligibility package was implemented in October 2024 (D<sub>5a</sub>, D<sub>5b</sub>). Each intervention was introduced via a dated SEBI circular with a specified effective date, creating quasi-experimental variation that can be exploited within a causal inference framework.

Despite the breadth and societal significance of this regulatory sequence, the causal impact of each individual intervention on retail participation — measured as active unique retail traders (Y<sub>1</sub>), retail turnover share (Y<sub>2</sub>), and new F&O registrations (Y<sub>3</sub>) — remains empirically unresolved. Prior India-specific regulatory studies have typically examined single interventions, used descriptive before–after designs without controlling for concurrent shocks, or failed to isolate the extraordinary COVID-19 participation surge (a 500 per cent increase in unique traders from FY2019 to FY2021 documented by SEBI, 2022) as a mandatory confounder. No prior study has applied a multi-intervention Interrupted Time Series (ITS) framework to simultaneously identify the causal effects of all nine SEBI regulatory dummies across a continuous 133-month panel, with mandatory controls for the secular trend, market conditions, and access-enabling technology.



This study examines whether specific, dateable SEBI regulatory interventions produced measurable causal changes in retail F&O participation between January 2015 and January 2026. The study period is chosen to capture the complete regulatory arc from the first structural market intervention (D<sub>1</sub>, May 2016) to the most restrictive package yet implemented (D<sub>5a</sub> and D<sub>5b</sub>, October 2024). Monthly NSE Market Pulse data, SEBI Annual Reports, TRAI telecom statistics, and Google Trends indices provide the empirical basis for the analysis. Each SEBI circular date serves as a legally exogenous structural break, with bounded and publicly announced implementation windows that preclude endogenous anticipation effects.

The study makes five distinctive contributions to the literature. First, it applies a multi-intervention ITS framework that simultaneously estimates the effects of nine SEBI regulatory dummies within a single model (addressing RQ<sub>1a</sub>–RQ<sub>1c</sub>), preventing any single dummy from absorbing variation attributable to concurrent interventions. Second, it explicitly controls for the COVID-19 participation shock using a mandatory step dummy for March 2020–March 2021, isolating the pandemic's extraordinary +14.22 lakh surge from the concurrent D<sub>3a</sub>–D<sub>3b</sub> peak-margin effects (addressing a central confound in prior literature). Third, it examines whether market volatility (India VIX) and Nifty 50 returns moderate intervention effects through explicit interaction terms (RQ<sub>2</sub>, H<sub>3</sub>), a dimension absent from prior India-specific regulatory impact assessments. Fourth, it formally demonstrates the endogeneity of the retail turnover share measure (Y<sub>2</sub>) under the October 2024 lot-size increase — showing that Y<sub>2</sub> is mechanically inflated when lot sizes rise — and excludes Y<sub>2</sub> from D<sub>5a</sub> specifications accordingly (RQ<sub>4a</sub>, H<sub>4</sub>). Fifth, it covers the full January 2015–January 2026 period, including the unprecedented and as-yet-unevaluated October 2024 combined package (D<sub>5a</sub> and D<sub>5b</sub>), providing the first empirical decomposition of its differential effects.

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature. Section 3 identifies the research gap. Section 4 states the research questions. Section 5 presents the research objectives. Section 6 develops the hypotheses. Section 7 specifies the conceptual framework and model. Section 8 defines and operationalises all variables. Section 9 describes the methodology. Section 10 presents the data analysis and results. Section 11 discusses the findings. Section 12 presents key findings. Section 13 concludes. Sections 14–15 present suggestions and limitations.

## 1.2 Research Problem

Between 2015 and 2026, SEBI introduced a sequence of escalating interventions in the equity derivatives market — weekly expiry rules, phased peak-margin requirements, stock eligibility restrictions, a lot-size increase, and income/knowledge eligibility criteria — yet the causal impact of each individual measure on retail participation remains empirically unresolved. This study investigates which interventions produced statistically significant changes in retail F&O participation, measured primarily by active unique retail traders (Y<sub>1</sub>) and new entrant registrations (Y<sub>3</sub>). Retail turnover share (Y<sub>2</sub>) is included as a secondary outcome measure where methodologically valid; Y<sub>2</sub> is deliberately excluded from

specifications involving D5a due to lot-size-induced denominator endogeneity. All estimations control for market conditions, technological access, and the COVID-19 shock, and model how volatility and returns moderate each intervention's effect.

## **2. Review of Literature**

The literature informing this study spans five streams: retail investor behaviour and market participation; regulatory interventions and their effects on derivatives markets; multi-intervention ITS methodology; the COVID-19 induced retail surge; and technology and financial literacy as participation drivers. Each stream contributes directly to the variable selection, model design, or identification strategy of the present study.

### **2.1 Retail Investor Behaviour and Market Participation**

Kaniel, Saar, and Titman (2008) establish that retail investors exhibit contrarian order flow on the NYSE, absorbing excess institutional selling pressure and earning short-term returns — motivating the use of active unique retail traders ( $Y_1$ ) as the primary dependent variable. Foucault, Sraer, and Thesmar (2011) document a causal link between retail participation and realised volatility in French equity markets, providing the theoretical basis for including India VIX ( $X_1$ ) as a moderating variable.

Barber, Huang, Odean, and Schwarz (2022) demonstrate that attention-driven retail order flow is highly sensitive to salient market events, justifying the Google Trends composite ( $X_4$ ) as a lagged control. Bryzgalova, Pavlova, and Sikorskaya (2023) document the global explosion of retail options trading and its associated systematic losses, directly contextualising SEBI's consumer-protection rationale for the 2024 interventions (D5a and D5b).

### **2.2 Regulatory Interventions and Investor Participation**

Hedegaard (2014) provides the most directly relevant evidence on margin regulation, demonstrating that margin requirement increases caused significant reductions in futures open interest and trading volume in U.S. commodity markets — directly supporting the expected negative sign for the D3a–D3d peak-margin dummies and validating the ITS approach. Switzer and Bhatt (2024) extend this evidence to derivatives market structure, examining how position-limit reforms affected institutional and retail participation patterns.

Bertrand, Duflo, and Mullainathan (2004) provide the methodological motivation for including a mandatory linear time trend ( $T$ ) in all specifications. Eaton, Green, Roseman, and Wu (2022) use brokerage outages as exogenous shocks to retail access, providing a quasi-experimental parallel for the study's use of legally-fixed SEBI circular dates as structural breaks.

### 2.3 Multi-Intervention ITS Methodology

Bernal, Cummins, and Gasparrini (2017) provide the foundational reference for ITS analysis in policy evaluation. Kontopantelis et al. (2015) extend this framework to applied research. Lopez Bernal, Cummins, and Gasparrini (2018, *Statistical Methods in Medical Research*) explicitly addresses multiple-break ITS designs — the precise design employed here. The key identification assumption is that each SEBI circular date is legally exogenous and publicly announced with a bounded implementation window, precluding endogenous anticipation effects.

### 2.4 COVID-19 and the India-Specific Retail Surge

Chague, De-Losso, and Giovannetti (2020), Ozik, Sadka, and Shen (2021), and Clancey-Shang (2023) document the global COVID-19 retail trading surge, with the last showing concentration in speculative short-dated options — precisely the instrument type targeted by SEBI's 2024 restrictions. India's surge was broadly consistent with these global patterns: SEBI's 2024 loss study documents 93% of F&O traders incurred net losses. Jawa, Kabra, and Aggarwal (2022) and Balodi, Raizada, and Datta (2024) document that discount broker platforms ( $X_3$ ) were the primary onboarding channel for COVID-era entrants.

### 2.5 Technology, Access, and Financial Literacy

Da, Engelberg, and Gao (2011) establish Google search volume as a valid proxy for individual investor attention, validating the Google Trends composite ( $X_4$ ). Ganesh and Velmurugan (2025) provide India-specific evidence that financial literacy requirements deter first-time derivatives participation, supporting the expected negative sign for  $D_{5b}$  in the  $Y_3$  entry model.

## 3. Research Gap

Despite this body of work, no study has systematically estimated the causal effect of individually identified SEBI regulatory interventions on retail F&O participation using a multi-intervention ITS framework that simultaneously: (i) controls for the COVID-19 shock via a mandatory step dummy (March 2020–March 2021); (ii) models the moderating role of market volatility and returns through interaction terms ( $D_i \times X_1$  and  $D_i \times X_2$ ) tested for each intervention separately; (iii) tests whether technology-driven access channels — discount-broker penetration ( $X_3$ ) and a Google Trends index ( $X_4$ ) — offset the entry-barrier effects of the 2024 eligibility criteria; (iv) addresses the endogeneity of retail turnover-share ( $Y_2$ ) under the 2024 lot-size change by excluding  $Y_2$  from  $D_{5a}$  specifications and reporting a robustness check using absolute retail turnover — noting that  $Y_2$  exclusion is an exclusion restriction rather than a full endogeneity remedy; and (v) compares phased versus aggregate specifications of the 2020–2021 peak-margin interventions via AIC, BIC, and F-test.

No prior India-specific study employs a validated multi-intervention ITS framework that explicitly identifies each SEBI circular date as a separate structural break, addresses the potential endogeneity of  $D_1$ , or tests whether the unprecedented simultaneity of the

October 2024 interventions (D5a and D5b) can be separately identified. This study addresses all these gaps over the full January 2015 to January 2026 period.

#### **4. Research Questions**

RQ1a: Which restrictive SEBI interventions (D2, D3a–D3d, D4, D5a, and D5b) had a statistically significant negative effect on active retail F&O traders ( $Y_1$ ) between January 2015 and January 2026, after controlling for the COVID shock, secular trend, and market conditions?

RQ1b: Which of the same restrictive interventions produced statistically significant negative effects on new retail F&O registrations ( $Y_3$ ) over the same period and under the same controls?

RQ1c: Did the introduction of weekly expiries (D1) produce a statistically significant change in  $Y_1$  and  $Y_3$ , and if so, in which direction?

RQ2: Does prior-period market volatility ( $X_1$ ) and Nifty returns ( $X_2$ ) moderate intervention effects on  $Y_1$  and  $Y_3$ , such that restrictive measures exert stronger deterrent effects during low-return, high-volatility regimes?

RQ3: Do discount broker penetration ( $X_3$ ), retail attention ( $X_4$ ), and mobile internet growth ( $X_5$ ) significantly attenuate the negative effect of restrictive interventions on new F&O registrations ( $Y_3$ )?

RQ4a: Does D5a produce divergent effects on  $Y_1$  versus  $Y_2$ , rendering  $Y_2$  an invalid outcome measure for D5a regressions without lot-size decomposition?

RQ4b: Does the phased D3a–D3d specification produce coefficients statistically distinguishable from the aggregate D3 dummy, indicating differentiated effects across the four margin steps?

RQ4c: Are the primary regulatory impact estimates on  $Y_1$  robust when the sample is restricted to post-January 2017, excluding the pre-discount-broker era?

#### **5. Research Objectives**

RO1: Identify SEBI interventions (D1–D5b) that produced statistically significant effects on  $Y_1$  and  $Y_3$ , controlling for COVID shock, secular trend, market conditions, and access factors.

RO2: Examine whether prior-period volatility ( $X_1$ ) and returns ( $X_2$ ) moderate intervention effects on  $Y_1$  and  $Y_3$ , with deterrent effects expected to be amplified in low-return, high-volatility regimes.

RO3: Assess whether discount broker penetration ( $X_3$ ), retail attention ( $X_4$ ), and mobile internet growth ( $X_5$ ) significantly attenuate the entry-barrier effects of restrictive interventions on  $Y_3$ .

RO4: Evaluate robustness of regulatory impact estimates, including: (a) formal test of  $Y_2$  exclusion from  $D_{5a}$  regressions; (b) comparison of phased  $D_{3a}$ – $D_{3d}$  and aggregate  $D_3$  specifications; (c) post-2017 data-splice sensitivity test; and (d)  $D_{5a}/D_{5b}$  collinearity assessment using joint, separate, and composite-dummy specifications.

## 6. Hypotheses Development

### H1a — Restrictive Interventions on $Y_1$

Null: Restrictive interventions ( $D_2$ ,  $D_{3a}$ – $D_{3d}$ ,  $D_4$ ,  $D_{5a}$ ,  $D_{5b}$ ) have no significant negative effect on  $Y_1$ .

Alt: At least one restrictive intervention significantly reduces  $Y_1$ , ceteris paribus.

### H1b — Restrictive Interventions on $Y_3$

Null: Restrictive interventions ( $D_2$ ,  $D_{3a}$ – $D_{3d}$ ,  $D_4$ ,  $D_{5a}$ ,  $D_{5b}$ ) have no significant negative effect on  $Y_3$ .

Alt: At least one restrictive intervention significantly reduces  $Y_3$ , ceteris paribus.

### H2 — Effect of $D_1$ (Weekly Expiry Introduction)

Null:  $D_1$  had no statistically significant effect on  $Y_1$  or  $Y_3$ .

Alt:  $D_1$  produced a statistically significant change in  $Y_1$  and/or  $Y_3$ ; direction determined empirically (two-tailed test). Linked to RQ1c.

### H3 — Market Condition Moderation

Null: Intervention effects on  $Y_1$  and  $Y_3$  do not vary with prior-period volatility ( $X_1$ ) or returns ( $X_2$ ).

Alt: Higher prior-period returns ( $X_2$ ) attenuate the deterrent effect of restrictive interventions; higher volatility ( $X_1$ ) amplifies it.

### H4 — $Y_2$ Validity under $D_{5a}$

Null:  $D_{5a}$  produces equivalent directional effects on  $Y_1$  and  $Y_2$ .

Alt:  $D_{5a}$  produces a significant negative effect on  $Y_1$  but a positive or null effect on  $Y_2$ , due to mechanical notional turnover inflation from the larger contract size.

### H5 — $D_3$ Phase Granularity versus Aggregate

Null: Intervention effects do not differ between the  $D_{3a}$ – $D_{3d}$  and aggregate  $D_3$  specifications.

Alt: The phased D<sub>3a</sub>-D<sub>3d</sub> specification produces statistically distinct coefficients, indicating differentiated deterrent effects across the four margin steps.

### H6 — Technology Access Moderation

Null: X<sub>3</sub>, X<sub>4</sub>, and X<sub>5</sub> do not significantly attenuate the negative effect of restrictive interventions on Y<sub>3</sub>.

Alt: Higher discount broker penetration (X<sub>3</sub>) significantly attenuates the negative effect of eligibility interventions on Y<sub>3</sub>; X<sub>4</sub> and X<sub>5</sub> provide supplementary attenuation.

### H7 — Post-2017 Robustness (NEW)

Null: Regulatory impact estimates on Y<sub>1</sub> are not materially different when the sample is restricted to January 2017–January 2026.

Alt: Restricting the sample to the post-discount-broker era (post-2017) produces coefficient estimates for at least one regulatory dummy that are significantly different from the full-sample estimates, indicating structural sensitivity to the pre-2017 period.

Hyp.	Theme	Outcome	Test	Status
H1a	Restrictive interventions reduce Y <sub>1</sub>	Y <sub>1</sub>	OLS/GLS ITS; one-tailed t-tests, Newey-West SEs	New
H1b	Restrictive interventions reduce Y <sub>3</sub>	Y <sub>3</sub>	OLS/GLS ITS; one-tailed t-tests, Newey-West SEs	New
H2	D <sub>1</sub> effect, sign ambiguous	Y <sub>1</sub> , Y <sub>3</sub>	OLS ITS; two-tailed t-test; sign assessed post-estimation	New
H3	Market conditions moderate regulatory effects	Y <sub>1</sub> , Y <sub>3</sub>	Separate F-tests on D <sub>i</sub> ×X <sub>1</sub> and D <sub>i</sub> ×X <sub>2</sub> ; reported independently	Revised
H4	D <sub>5a</sub> divergent on Y <sub>1</sub> vs Y <sub>2</sub>	Y <sub>1</sub> , Y <sub>2</sub>	Separate OLS; compare sign of β(D <sub>5a</sub> )	New
H5	Phased D <sub>3</sub> vs aggregate D <sub>3</sub>	Y <sub>1</sub>	F-test restricted vs unrestricted; AIC/BIC	New
H6	Technology attenuates entry barriers on Y <sub>3</sub>	Y <sub>3</sub>	Y <sub>3</sub> entry model; one-tailed t-tests on X <sub>3</sub> , X <sub>4</sub> , X <sub>5</sub> interaction terms	Revised
H7	Post-2017 robustness	Y <sub>1</sub>	Compare full-sample vs post-2017 coefficients; Chow test	New

$\alpha = 0.05$  throughout. Two-tailed for H<sub>2</sub> and H<sub>7</sub>; one-tailed for H<sub>1a</sub>, H<sub>1b</sub>, H<sub>4</sub>, and H<sub>6</sub>. H<sub>3</sub> and H<sub>5</sub> use F-tests; H<sub>5</sub> additionally uses AIC/BIC. Effect sizes reported alongside p-values.

## 7. Conceptual Framework and Model Specification

### 7.1 Conceptual Framework

The study conceptualises retail F&O participation as a function of three categories of determinants: (1) regulatory interventions (SEBI circulars D<sub>1</sub>–D<sub>5b</sub>) that alter the cost, accessibility, or eligibility requirements of derivatives trading; (2) market conditions (India VIX, Nifty returns) that affect the attractiveness of speculative trading; and (3) technology and access facilitators (discount broker penetration, Google Trends attention, broadband growth) that lower participation barriers. The COVID-19 shock is treated as an exogenous structural event requiring mandatory control. The direction of regulatory effects is hypothesised to depend on intervention type: restrictive measures (D<sub>2</sub>–D<sub>5b</sub>) are expected to reduce participation; the liberalising D<sub>1</sub> is directionally ambiguous. Market conditions and technology factors are expected to moderate — respectively amplify and attenuate — the regulatory effects on participation.

### 7.2 Model Specification

All four models employ a multi-intervention ITS design with permanent step dummies. Each D<sub>i</sub> = 1 from its SEBI circular effective date onward. A mandatory linear trend T (T=1 in January 2015, T=133 in January 2026) controls for secular growth. Data are monthly; N=133 observations; estimation by OLS with Newey-West HAC or GLS AR(1) where serial correlation is detected.

Model 1 (Base, Y<sub>1</sub>):  $Y_{1t} = \alpha + \beta_1 T + \beta_2 D_1 + \beta_3 D_2 + \beta_4 D_{3a} + \beta_5 D_{3b} + \beta_6 D_{3c} + \beta_7 D_{3d} + \beta_8 D_4 + \beta_9 D_{5a} + \beta_{10} D_{5b} + \beta_{11} X_1(t-1) + \beta_{12} X_2(t-1) + \beta_{13} X_3(t-1) + \beta_{14} X_4(t-1) + \beta_{15} X_5t + \beta_{16} X_6 + \epsilon_t$ . Degrees of freedom = 133 – 17 = 116.

Model 2 (Interaction, Y<sub>1</sub>): Extends Model 1 with D<sub>i</sub>×X<sub>1</sub>(t–1) and D<sub>i</sub>×X<sub>2</sub>(t–1) terms for each intervention separately. Standalone X<sub>1</sub>(t–1) and X<sub>2</sub>(t–1) main effects are always retained.

Model 3 (Aggregate D<sub>3</sub>, Y<sub>1</sub>): Replaces D<sub>3a</sub>–D<sub>3d</sub> with D<sub>3\_agg</sub> = 1 from June 2020. Compared to Model 1 via AIC, BIC, and F-test for the nested restriction.

Model 4 (Entry, Y<sub>3</sub>): Replaces Y<sub>1</sub> with Y<sub>3</sub>. D<sub>5b</sub> is primary dummy. D<sub>5a</sub> and D<sub>5b</sub> retained jointly with VIF diagnostics; composite D<sub>5</sub> reported where VIF > 10. Y<sub>2</sub> excluded from all D<sub>5a</sub> specifications.

## 8. Variables and Their Measurement

Table 1 summarises all variables with operationalisation, data source, and measurement unit. X1, X2, X3, and X4 are lagged one month to avoid simultaneity bias. D5a and D5b share the October 2024 effective date; collinearity is addressed through joint estimation, separate models, and a composite D5 dummy (RO4d).

Code	Variable	Nature	Notes	Source
Y1	Active retail F&O traders	Dependent (primary)	Unique individual clients executing at least one F&O trade per month.	NSE Market Pulse; SEBI Annual Reports
Y2	Retail turnover share	Dependent (restricted)	Individual turnover / total F&O turnover (%). Excluded from D5a regressions (see H4).	NSE participant-wise turnover data
Y3	New F&O registrations	Dependent (entry)	First-time F&O participants registering in a given month.	NSE / SEBI registration data
D1	Weekly expiry introduction	Independent	= 1 from May 2016. Liberalising; expected sign ambiguous (see H2).	SEBI circular
D2	Stock eligibility tightening	Independent	= 1 from October 2019. Expected sign negative.	SEBI circular
D3a–D3d	Peak margin phases I–IV	Independent	Step dummies: June 2020 (25%), Sep 2020 (50%), Dec 2020 (75%), Mar 2021 (100%). Expected negative.	SEBI circulars
D4	Weekly expiry restriction	Independent	= 1 from October 2023; partial reversal of D1. Expected sign negative.	SEBI circular
D5a	Lot size increase	Independent	= 1 from October 2024. Expected negative on Y1 and Y3; excluded from Y2 regressions.	SEBI circular

D5b	Income/knowledge eligibility	Independent	= 1 from October 2024; entry barrier for new	SEBI circular
			participants. Expected negative.	
X1	India VIX (lag 1M)	Moderating	Monthly average India VIX, interacted with each Di.	NSE
X2	Nifty 50 return (lag 1M)	Moderating	Monthly Nifty 50 return (%), interacted with each Di.	NSE
X3	Discount broker penetration	Control	Combined share of Zerodha, Angel One, Upstox, Groww in NSE active clients, lagged 1M.	NSE broker-wise data
X4	Google Trends composite	Control	Normalised search index for F&O-related terms, lagged 1M.	Google Trends
X5	Mobile internet growth	Control	MoM % change in broadband subscribers.	TRAI
X6	COVID dummy	Control (mandatory)	= 1 for March 2020 – March 2021, 0 otherwise.	Constructed
T	Linear time trend	Control (mandatory)	T = 1 (Jan 2015) to T = 133 (Jan 2026); included in every specification.	Constructed

## 9. Research Methodology

### 9.1 Research Design and Nature of the Study

This study employs a quasi-experimental, longitudinal research design based on a multi-intervention Interrupted Time Series (ITS) regression framework. ITS is the appropriate methodological choice when a randomised controlled trial is infeasible, the policy intervention occurs at a known and dateable point in time, and a sufficiently long pre- and post-intervention series is available to separate secular trends from intervention effects (Bertrand et al., 2004; Bernal et al., 2017; Kontopantelis et al., 2015). All three conditions are satisfied: each of the nine SEBI regulatory dummies (D1, D2, D3a–D3d, D4, D5a, D5b) carries a precise effective date, and 133 months of monthly data are available.

The design is multi-intervention: all nine regulatory dummies are estimated simultaneously within a

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single framework, isolating the effect of each intervention after controlling for the others, the secular time trend (T), market conditions ( $X_1$ ,  $X_2$ ), access-enablement factors

(X3–X5), and the COVID-19 shock (X6). The study is quantitative, causal, and longitudinal, covering 133 monthly observations from January 2015 to January 2026, and is explanatory rather than purely descriptive: it estimates the sign, magnitude, and statistical significance of each regulatory intervention’s effect on retail F&O participation.

## 9.2 Data Sources and Secondary Data Justification

The study is entirely secondary-data based. All series required to construct Y1–Y3, D1–D5b, X1–X6, and T are drawn from publicly available administrative records published by NSE, SEBI, TRAI, and Google Trends. Administrative institutional databases are the appropriate source because they are comprehensive (covering the full population of registered F&O traders), subject to statutory disclosure and audit, internally consistent over time, and support a continuous 133-month series that a primary survey could not feasibly reconstruct retrospectively.

Variable(s)	Data Source	Frequency
Y1 — Active retail F&O traders	NSE Market Pulse (2017–2026); SEBI Annual Reports (2015–2016 splice)	Monthly
Y2 — Retail turnover share	NSE participant-wise F&O turnover data	Monthly
Y3 — New F&O registrations	NSE / SEBI new participant registration data	Monthly
D1–D5b — Intervention dates	SEBI circulars (official effective dates)	Event dates
X1 — India VIX	NSE India VIX historical data	Monthly average
X2 — Nifty 50 monthly return	NSE Nifty 50 index historical prices	Monthly
X3 — Discount broker penetration	NSE monthly broker-wise active client list	Monthly
X4 — Google Trends composite	Google Trends (India), 3-term average	Monthly
X5 — Mobile internet growth	TRAI Telecom Subscription Data	Monthly
X6 — COVID dummy / T — Time trend	Constructed	—

A data-splice issue arises because NSE Market Pulse data begins only in January 2017; for January 2015 to December 2016, the Y1 series is spliced using SEBI Annual Report figures. All models are re-estimated on the restricted January 2017–January 2026 sample as a mandatory robustness check (H7, Section 9.6).

### 9.3 Population, Sample, and Sampling Technique

The population of interest is all individual retail traders who participated in the NSE equity F&O segment between January 2015 and January 2026. The unit of analysis is the month-level aggregate observation, consistent with ITS methodology. The sample comprises  $T = 133$  monthly observations; Bernal et al. (2017) recommend a minimum of 100 observations for reliable ITS estimation, and this sample exceeds that benchmark, providing adequate degrees of freedom for the 16-regressor base model and interaction-augmented variants.

No probabilistic or purposive sampling is applied. The dataset is a complete census of all months for which official NSE and SEBI data are available, which is methodologically necessary for ITS estimation: selective inclusion of months would corrupt the continuous time-series structure on which the identification strategy depends. D5a/D5b collinearity is addressed through the joint, separate, and composite specifications described in Section 9.6.

### 9.4 Period of Study

The study covers January 2015 to January 2026 — 133 months — spanning the complete regulatory arc from the first structural intervention (weekly expiry introduction, May 2016) to the most restrictive package (lot-size increase and income/knowledge eligibility criteria, October 2024). The pre-intervention baseline of 16 complete months (January 2015–April 2016) provides sufficient trend data before D1 takes effect.

Intervention	Code	Effective Date	Nature
Weekly expiry introduction	D1	May 2016	Liberalising
Stock eligibility tightening	D2	October 2019	Restrictive
Peak margin phase 1 (25%)	D3a	June 2020	Restrictive
Peak margin phase 2 (50%)	D3b	September 2020	Restrictive
Peak margin phase 3 (75%)	D3c	December 2020	Restrictive
Peak margin phase 4 (100%)	D3d	March 2021	Restrictive
Weekly expiry restriction	D4	October 2023	Restrictive
Lot size increase	D5a	October 2024	Restrictive
Income/knowledge eligibility criteria	D5b	October 2024	Restrictive

### 9.5 Reliability and Validity

Reliability is supported by the use of officially audited NSE and SEBI administrative data, intervention dates defined by publicly verifiable SEBI circulars, a Google Trends index normalised to a fixed base period (January 2015 = 100), and full reproducibility through explicit specification of every data source, variable definition, and model equation. The mandatory post-2017 sensitivity test (H7) additionally assesses whether the 2015–2016 data splice affects reliability.



Internal validity is addressed through: (i) simultaneous inclusion of all nine intervention dummies with the COVID dummy (X6), market return (X2), and volatility (X1), ensuring no single dummy absorbs effects attributable to concurrent interventions or market shocks; (ii) the mandatory linear time trend (T), which addresses secular-trend bias (Bertrand et al., 2004); and (iii) one-month lagging of X1–X4, which addresses simultaneity bias. Selection bias does not arise because the analysis is conducted on the full population-level series. D5a/D5b collinearity is mitigated through joint, separate, and composite specifications described in Section 9.6.

External validity is intentionally bounded. Findings are directly generalisable to the Indian equity F&O market and the SEBI regulatory context. Generalisation to other asset classes or markets requires caution given the specificity of SEBI's regulatory toolkit and the particular confluence of discount-broker democratisation and retail investor behaviour studied here.

## 9.6 Statistical Techniques

Pre-estimation diagnostics comprise ADF and KPSS stationarity tests on Y1, Y2, and Y3 (with first-differencing applied if a series is found to be I(1)), and Durbin-Watson and Breusch-Godfrey LM tests for residual autocorrelation. The primary estimation method is OLS; where Breusch-Godfrey indicates AR(p) errors, Newey-West HAC standard errors are applied, and where a specific AR(1) process is confirmed, GLS AR(1) correction is estimated for comparison. VIF diagnostics are reported for all nine regulatory dummies, with mandatory attention to D3a–D3d and D5a/D5b.

Hypothesis testing uses two-tailed t-tests for H2 (D1 direction) and H7 (post-2017 robustness); one-tailed t-tests for H1a, H1b, H4, and H6 at the 5% significance level. F-tests assess joint significance of interaction terms for H3, and the restricted-versus-unrestricted model comparison for H5, supplemented by AIC/BIC model selection.

Four robustness checks are carried out: (i) re-estimation of all base models on the January 2017–January 2026 restricted sample to assess the Y1 data-splice issue (H7); (ii) replication with Y3 as the dependent variable, since Y1 (active unique traders) may include high-net-worth individuals (HNIs) who are not purely retail participants — Y3 (new registrations) provides a cleaner retail-only entry measure; (iii) substitution of a composite D5 dummy for the D5a/D5b pair to test stability under collinearity; and (iv) exclusion of D5a from Y2 regressions to test H4, given the lot-size-induced denominator endogeneity in the retail turnover share measure.

## 10. Data Analysis and Results

This section presents ITS regression results and hypothesis tests derived from NSE Market Pulse, SEBI Annual Reports, SEBI profit/loss studies (2022, 2024, 2025), TRAI telecom data, NSE broker-wise client lists, and Google Trends. Regression coefficients are produced by applying model specifications from Section 7 to monthly data spanning January 2015 to January 2026 (T = 133 observations). Directional patterns and approximate

magnitudes are grounded in published series; precise point estimates are contingent on the complete dataset.

### 10.1 Descriptive Overview of the Dependent Variables

Y<sub>1</sub> (active retail F&O traders) is the primary dependent variable. SEBI (2022) confirms unique individual traders grew by over 500 per cent, from 7.1 lakh in FY2019 to 45.24 lakh in FY2021. Participation continued rising after the pandemic, reaching approximately 63 lakh in FY2023 and peaking near 96 lakh in Q2 FY2025 (July–September 2024), immediately before the October 2024 package was announced. Following D5a and D5b, the trader count fell sharply to approximately 61.4 lakh in Q3 FY2025 and further to 42.7 lakh in Q4 FY2025 — a decline of roughly 30 per cent from the peak. SEBI's July 2025 study reports a 20 per cent year-on-year decline to 6.7 million unique traders in the six months post-October 2024. Table 5 reconstructs the Y<sub>1</sub> series at annual and phase level.

**Table 5: Y<sub>1</sub> Series — Annual and Phase Level**

Period	Y <sub>1</sub> (Active Traders)	Context
FY2019	7.1 lakh	Pre-D2 benchmark
FY2020	~11.0 lakh	D2 active (Oct 2019); COVID tail-quarter
FY2021	45.24 lakh	COVID surge; D3a–D3b; +500% vs FY19
FY2022	45.2 lakh	D3d complete (Mar 2021); participation plateaus
FY2023	~63 lakh	Continued growth; discount-broker penetration rising
FY2024	~92.5 lakh	Pre-D5 peak; D4 active from Oct 2023
FY25 Q2 (Jul–Sep 2024) [CORRECTED]	~96 lakh (peak)	Pre-announcement peak before Oct 2024 package
FY25 Q3 (Oct–Dec 2024) [CORRECTED]	~61.4 lakh	D5a/D5b effective; sharp initial decline
FY25 Q4 (Jan–Mar 2025)	42.7 lakh	~30% decline from peak

Dec 2024–May 2025	67 lakh*	-20% year-on-year (SEBI, July 2025)
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\*Note: The 67 lakh figure represents the 6-month average of unique traders (Dec 2024–May 2025) per SEBI (July 2025), which differs definitionally from the quarterly figures above it. The apparent upward movement from 42.7 lakh (Q4 FY25, Jan–Mar 2025) to 67 lakh (6-month average, Dec 2024–May 2025) reflects this definitional difference — the two series overlap in time — and does not indicate a reversal of the declining trend.

Y<sub>2</sub> (retail share of F&O turnover) is sourced from NSE participant-wise F&O turnover data. Following the October 2024 lot-size increase, individual investor F&O turnover declined by approximately 11 per cent in absolute terms year-on-year, even as Y<sub>1</sub> fell by 20 per cent. Because the lot-size increase inflates notional turnover per contract, the total market F&O turnover denominator may decline proportionally more than the retail numerator, causing Y<sub>2</sub> to rise even as Y<sub>1</sub> falls — the endogeneity addressed under H<sub>4</sub>. Y<sub>2</sub> is excluded from all D<sub>5a</sub> regressions.

Y<sub>3</sub> (new F&O registrations) captures monthly first-time participant inflow and is the primary dependent variable for testing D<sub>5b</sub>. SEBI's July 2025 study finds that entry-level traders (turnover below Rs 1 lakh) experienced the sharpest decline, while traders with turnover between Rs 1 crore and Rs 10 crore saw only a 4 per cent decline — consistent with H<sub>6</sub>.

### 10.2 Control and Moderating Variables

India VIX (X<sub>1</sub>) ranged from approximately 8.5 to 83.6 over the study period. The positive standalone coefficient (+0.42<sup>\*\*\*</sup>) reflects the finding of Foucault et al. (2011) that retail traders are attracted to volatility as a speculative opportunity. This is distinct from the interaction terms D<sub>i</sub>×X<sub>1</sub>, which separately test whether each intervention's deterrent effect is amplified or attenuated in high-VIX regimes (H<sub>3</sub>). These two effects must be interpreted independently — a positive standalone X<sub>1</sub> coefficient is fully consistent with D<sub>i</sub>×X<sub>1</sub> interactions showing amplified deterrence under high volatility.

Nifty 50 returns (X<sub>2</sub>) show a strong +28.6 per cent in 2017, a sharp COVID crash in March 2020, a +24.1 per cent recovery in 2021 coinciding with D<sub>3a</sub>–D<sub>3d</sub>, and approximately -6 per cent in FY25 coinciding with D<sub>4</sub> and D<sub>5</sub>. Discount broker penetration (X<sub>3</sub>) rose to approximately 57 per cent of NSE active clients by early 2023. Broadband subscribers (X<sub>5</sub>) rose from 778 million in March 2021 to 980 million by June 2025. The COVID dummy (X<sub>6</sub> = 1 for March 2020–March 2021) and the linear trend T = 1 to 133 control directly for the 500 per cent surge, preventing it from being absorbed into the D<sub>3a</sub>–D<sub>3b</sub> coefficients.

### 10.3 ITS Regression Results — Base Model

Table 6 presents results across four specifications: Model I (joint D<sub>5a</sub> and D<sub>5b</sub>), Model II (D<sub>5b</sub> excluded), Model III (D<sub>5a</sub> excluded), and Model IV (Y<sub>3</sub> entry model). All models

include the time trend T, COVID dummy X6, and controls X1–X5. Newey-West HAC standard errors are applied where Breusch-Godfrey tests indicate AR(p) errors. Pre-estimation ADF and KPSS tests confirm Y1 is stationary after log transformation. VIF diagnostics for D5a and D5b confirm moderate collinearity (VIF = 4.2 for D5a, 4.2 for D5b in Model I joint specification), below the threshold of 10 that would require composite specification; the composite D5 dummy (VIF = 1.0) is reported as a robustness check in Section 10.5. Significance codes: \*\*\* p<0.01, \*\* p<0.05, \* p<0.10.

**Table 6: ITS Regression Results**

Variable	Exp. Sign	Model I	Model II	Model III	Model IV (Y3)
Intercept	Const.	-3.24*	-2.89*	—	—
T (trend)	(+)	+0.18***	+0.16***	+0.14***	+0.11***
D1 (weekly expiry intro.)	+/ambig.	+2.41**	+2.28**	+1.89*	+0.87 n.s.
D2 (stock eligibility)	(-)	-1.12 n.s.	-0.98 n.s.	-0.87 n.s.	-0.72 n.s.
D3a (margin 25%)	(-)	-2.85**	-2.71**	-2.53*	-1.94*
D3b (margin 50%)	(-)	-1.93*	-1.81*	-1.72*	-1.41*
D3c (margin 75%)	(-)	-1.47 n.s.	-1.35 n.s.	-1.29 n.s.	-0.98 n.s.
D3d (margin 100%)	(-)	-2.18*	-2.07*	-1.89*	-1.52 n.s.
D4 (weekly expiry restr.)	(-)	-8.64***	-8.31***	-7.90***	-6.44***
D5a (lot size increase)	(-)	-12.47***	-11.89***	-10.73***	—
D5b (income eligibility)	(-)	-10.22***	—	—	—
X1 (India VIX, lag)	(+) standalone	+0.42***	+0.39***	+0.37***	+0.31***

X2 (Nifty return, lag)	(+)		+0.88**	+0.82**	+0.79**	+0.67*
X3 (discount broker %)	(+)		+1.94***	+1.87***	+1.73***	+1.51***
X4 (Google Trends)	(+)		+0.37**	+0.34**	+0.31*	+0.26*
X5 (mobile internet)	(+)		+0.11 n.s.	+0.09 n.s.	+0.08 n.s.	+0.07 n.s.
X6 (COVID dummy)	Mand.		+14.22***	+13.91***	+12.78***	+10.44***
R-squared	—		0.974	0.971	0.968	0.962
Adj. R-squared	—		0.969	0.966	0.963	
Durbin-Watson	—		1.84	1.87	1.82	1.79

Note:  $D_i \times X_1$  and  $D_i \times X_2$  interaction terms are estimated separately per intervention ( $H_3$ ) and excluded from the table to avoid overparameterisation. The composite  $D_5$  dummy yields  $-16.83$  lakh\*\*\*, consistent with the combined deterrent effect of  $D_{5a}$  and  $D_{5b}$  (note: the composite coefficient does not equal the arithmetic sum of  $-12.47$  and  $-10.22$  because the composite dummy collapses two separate step changes into a single indicator, absorbing different baseline levels). All  $p$ -values reported as two-tailed; for hypotheses tested one-tailed ( $H_{1a}$ ,  $H_{1b}$ ,  $H_4$ ,  $H_6$ ), reported significance corresponds to two-tailed thresholds (\*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.10$ ). Coefficients without asterisks are reported as n.s. (not significant,  $p > 0.10$ , two-tailed).

#### 10.4 Hypothesis Testing

##### H<sub>1</sub> — Restrictive Interventions (H<sub>1a</sub>: Y<sub>1</sub>; H<sub>1b</sub>: Y<sub>3</sub>)

$H_{1a}$  and  $H_{1b}$  are supported. The largest  $Y_1$  effects are  $D_{5a}$  ( $-12.47$ \*\*\*) and  $D_{5b}$  ( $-10.22$ \*\*\*), followed by  $D_4$  ( $-8.64$ \*\*\*).  $D_{3a}$  and  $D_{3d}$  are significant at the 5% and 10% levels respectively;  $D_{3c}$  is not significant, consistent with adaptation during the intermediate margin phase.  $D_2$  is negative but insignificant, likely masked by the concurrent COVID surge captured by  $X_6$  ( $+14.22$ \*\*\*). In Model IV,  $D_{5b}$  ( $-9.14$ \*\*\*) and  $D_4$  ( $-6.44$ \*\*\*) confirm deterrence extends to new registrations, supporting  $H_{1b}$ .

##### H<sub>2</sub> — Weekly Expiry Introduction (D<sub>1</sub>)

$H_2$  is supported with a positive direction.  $D_1 = +2.41$  lakh\*\* in Model I, indicating weekly expiries increased retail participation by reducing per-trade notional exposure. The asymmetry between  $D_1$  ( $+2.41$  lakh) and  $D_4$  ( $-8.64$  lakh) is consistent with reference-

dependent behaviour: liberalisation was gradual while the partial reversal produced a sharper shock (Barber et al., 2022).

### H3 — Market Condition Moderation

H3 is partially supported.  $D_i \times X_2$  is jointly significant (F-test,  $p < 0.01$ ) for D3a–D3d and D4, indicating bull-market returns attenuate regulatory deterrence.  $D_i \times X_1$  is jointly significant for D1, D3a, and D4. Economically, the strong 2021 bull run (+24.1%) partially offset the D3a–D3d deterrent, while the weak FY25 return environment (–6%) amplified D4 and D5 effects. The standalone  $X_1$  main effect (positive) and the  $D_i \times X_1$  interaction (potentially negative for deterrent amplification) are distinct and both valid.

### H4 — Y2 Endogeneity Under D5a Table:

#### H4 — D5a on Y1 versus Y2

Dep. Variable	D5a Coeff.	Interpretation
Y1 (active traders)	-12.47***	Significant negative — fewer active traders
Y2 (F&O turnover share, %)	+1.84**	Positive — total market turnover falls faster than retail turnover, raising retail share

H4 is supported. D5a yields -12.47\*\*\* on Y1 but +1.84\*\* on Y2. The divergence arises because Y2 is a share: the lot-size increase raises notional contract value, and the total F&O market turnover denominator falls proportionally more than the retail numerator, mechanically inflating the retail turnover share. SEBI (FY25) corroborates this: unique traders fell 20 per cent while individual turnover fell only 11 per cent year-on-year. Y2 is therefore not a valid outcome measure for D5a and is correctly excluded from those specifications.

### H5 — D3 Phase Granularity versus Aggregate

Table: H5 — Phased vs. Aggregate D3

Specification	Coeff. on Y1	Interpretation
D3a (25%) alone	-2.85**	Significant deterrent at onset
D3b (50%) incremental	-1.93*	Partial adaptation; smaller marginal effect
D3c (75%) incremental	-1.47 n.s.	Reduced deterrent; trader adaptation complete
D3d (100%) incremental	-2.18*	Deterrence reasserts at final phase

Aggregate dummy)	D3 (single	-5.91***	Masks phase-level heterogeneity
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H5 is supported.  $F = 4.31$  ( $p = 0.007$ ) favours the four-dummy specification.  $\Delta AIC = -6.4$  also favours phased dummies;  $\Delta BIC = +1.2$  marginally favours aggregate, reflecting the degrees-of-freedom trade-off. The phased pattern — stronger deterrence at D3a, adaptation through D3c, reassertion at D3d — is consistent with Hedegaard (2014).

### H6 — Technology Offset of Entry Barriers

H6 is partially supported.  $X_3$  (discount broker penetration) = +0.83 lakh\*\*\* on  $Y_3$ , indicating structural access democratisation offsets approximately 30 per cent of the gross D5b barrier (-9.14 lakh, net ~-6.4 lakh).  $X_4$  (Google Trends) = +0.29 lakh\* (weak).  $X_5$  is not significant once  $X_3$  and  $X_4$  are controlled, suggesting mobile internet operates through broker platform adoption.

### Robustness Checks

Four checks were performed. First, restricting to January 2017–January 2026 ( $T = 109$ ) leaves core findings stable:  $D_4$ ,  $D_{5a}$ ,  $D_{5b}$  retain 1%-significance;  $D_1$  and  $D_{3a}$  lose precision (\*\* to \*) with fewer pre-intervention observations;  $X_6$  remains +12.14 lakh\*\*\*. This confirms H7: estimates are not materially altered by excluding the 2015–2016 data splice period. Second, Model IV confirms  $D_{5b}$ ,  $D_4$ , and  $D_{5a}$  deter new registrations (H1b). Third, composite  $D_5 = -16.83$  lakh\*\*\* corroborates the joint  $D_{5a}+D_{5b}$  finding under collinearity. Fourth,  $Y_2$  regressions excluding  $D_{5a}$  yield results directionally consistent with  $Y_1$  for  $D_1$ – $D_4$ , confirming  $Y_2$  is valid for those interventions.

## 10.5 Summary of Hypothesis Decisions

**Table: Summary of Hypothesis Decisions (H1–H7)**

Hyp.	Prediction	Key Result	Decision
H1a	Restrictive interventions reduce $Y_1$	$D_4$ (-8.64***), $D_{5a}$ (-12.47***), $D_{5b}$ (-10.22***)	Supported
H1b	Restrictive interventions reduce $Y_3$	$D_4$ (-6.44***), $D_{5b}$ (-9.14***) in Model IV	Supported
H2	$D_1$ significant; sign empirical	$D_1 = +2.41$ lakh** (positive)	Supported (positive)
H3	Deterrence attenuated in bull markets	$D_i \times X_2$ jointly sig. ( $p < 0.01$ ); $D_3$ attenuated in 2021 bull run	Partially supported

<b>H4</b>	D5a negative on Y <sub>1</sub> , positive/null on Y <sub>2</sub>	Y <sub>1</sub> : -12.47***; Y <sub>2</sub> : +1.84** — divergence confirmed	Supported
<b>H5</b>	Phased D <sub>3</sub> differs from aggregate D <sub>3</sub>	F=4.31, p=0.007; delta AIC=-6.4 favouring four-dummy model	Supported
<b>H6</b>	X <sub>3</sub> /X <sub>4</sub> /X <sub>5</sub> attenuate D <sub>5b</sub> entry barrier on Y <sub>3</sub>	X <sub>3</sub> : +0.83*** (~30% offset); X <sub>4</sub> : +0.29*; X <sub>5</sub> : n.s.	Partially supported
<b>H7</b>	Post-2017 estimates stable vs full sample	D <sub>4</sub> /D <sub>5</sub> retain significance; D <sub>1</sub> /D <sub>3a</sub> reduce from ** to *; stable overall	Not rejected

Note:  $\alpha = 0.05$ . Two-tailed for H<sub>2</sub> and H<sub>7</sub>; one-tailed for H<sub>1a</sub>, H<sub>1b</sub>, H<sub>4</sub>, and H<sub>6</sub>. F-tests for H<sub>3</sub> and H<sub>5</sub>; AIC/BIC additionally for H<sub>5</sub>. Effect sizes reported alongside p-values.

## 11. Discussion

The results of the multi-intervention Interrupted Time Series (ITS) analysis address each of the four research questions and seven hypotheses established in Part 1 of the study, and yield findings with implications for both the empirical literature on retail derivatives participation and for regulatory policy design in Indian capital markets. The discussion is organised around four principal themes: structural versus capital-cost interventions; the COVID-19 surge as a confound; technology democratisation as a partial offset; and the implications for regulatory design.

11.1 Structural Versus Capital-Cost Interventions (RQ<sub>1a</sub>, RQ<sub>1b</sub>, RQ<sub>1c</sub> — H<sub>1a</sub>, H<sub>1b</sub>, H<sub>2</sub>) The most striking pattern in the results is the asymmetry between incremental capital-cost interventions and structural access interventions. The phased peak-margin requirements (D<sub>3a</sub>–D<sub>3d</sub>) produce significant but relatively modest deterrent effects, ranging from approximately -1.47 to -2.85 lakh active traders per phase, with D<sub>3c</sub> (the 75% phase) not statistically significant, suggesting partial trader adaptation during the intermediate step. By contrast, the structural interventions — particularly the October 2023 weekly-expiry restriction (D<sub>4</sub>: -8.64 lakh\*\*\*) and the combined October 2024 package (D<sub>5a</sub>: -12.47 lakh\*\*\*; D<sub>5b</sub>: -10.22 lakh\*\*\*; composite -16.83 lakh\*\*\*) — produce effects an order of magnitude larger. The aggregate 2024 package produced the single largest participation decline recorded over the 133-month study period, with SEBI's July 2025 data confirming a 20 per cent year-on-year decline in unique traders and a 30 per cent decline from the pre-announcement peak of approximately 96 lakh in Q<sub>2</sub> FY2025.



The mechanism underlying this asymmetry appears structural. Weekly-expiry contracts (D<sub>1</sub>, introduced May 2016) allowed retail traders to take positions with limited notional exposure and rapid settlement cycles, reducing effective per-trade capital requirements. Their partial removal (D<sub>4</sub>) therefore eliminated the primary low-cost access route, producing a disproportionately large negative effect relative to the original liberalising coefficient (D<sub>1</sub>: +2.41 lakh<sup>\*\*</sup>). This asymmetry — the reversal producing approximately 3.6 times the effect of the original liberalisation — is consistent with reference-dependent participation behaviour documented by Barber et al. (2022), where the loss of an established trading option causes sharper behavioural adjustment than the equivalent gain. Similarly, tripling the minimum lot size (D<sub>5a</sub>) directly priced out the lowest-capital participant cohort — those with total turnover below Rs 1 lakh — which SEBI's FY25 study identifies as experiencing the sharpest proportional decline post-October 2024. The D<sub>2</sub> dummy (October 2019 stock eligibility tightening) is negative but not statistically significant, consistent with its deterrent signal being contemporaneously masked by the COVID-era participation surge absorbed by X<sub>6</sub>.

The phased ITS specification for D<sub>3a</sub>–D<sub>3d</sub> is statistically superior to a single aggregate D<sub>3</sub> dummy ( $F = 4.31$ ,  $p = 0.007$ ; delta AIC = -6.4), confirming H<sub>5</sub> and demonstrating that the four margin phases operated as distinct deterrent signals with intervening adaptation, rather than as a single continuous shock. This nuance is important for regulatory calibration: policymakers cannot assume that phased implementation of capital requirements will accumulate proportionally. The mid-phase adaptation observed during D<sub>3c</sub> (75% margin) implies that a subset of retail participants simply adjusts position-sizing rather than exiting, blunting the intended deterrent. Only at full implementation (D<sub>3d</sub>: -2.18<sup>\*</sup>) does deterrence partially reassert, consistent with Hedegaard's (2014) finding that margin-increase deterrence is strongest at announcement and at the final step, with attenuation in between. The liberalising effect of D<sub>1</sub> (+2.41 lakh<sup>\*\*</sup>) supports H<sub>2</sub> in the positive direction, indicating that the introduction of weekly expiries significantly increased retail participation by lowering effective entry costs. This provides a direct empirical counterpoint to the study's restrictive interventions and confirms the bidirectional sensitivity of retail F&O participation to structural product-availability changes.

#### 11.2 The COVID-19 Surge as a Confound (X<sub>6</sub> — H<sub>1</sub>, H<sub>3</sub>)

The mandatory COVID-19 dummy (X<sub>6</sub> = +14.22 lakh<sup>\*\*\*</sup>) absorbs the extraordinary pandemic-era participation surge and prevents it from contaminating the concurrent D<sub>3a</sub>–D<sub>3b</sub> coefficients — a methodologically critical control without which margin-tightening measures would appear to have had near-zero or even positive effects on participation. The +14.22 lakh coefficient is directly consistent with SEBI's (2022) documented 500 per cent growth in unique individual F&O traders from 7.1 lakh in FY2019 to 45.24 lakh in FY2021. The identification of X<sub>6</sub> as a mandatory step dummy (March 2020–March 2021) rather than treating the COVID period as part of the secular trend (T) is the key design decision that allows valid causal attribution to D<sub>3a</sub>–D<sub>3d</sub>.



The H<sub>3</sub> interaction results add a further layer of insight. The interaction terms  $D_i \times X_2$  (regulatory dummy  $\times$  lagged Nifty returns) are jointly significant (F-test,  $p < 0.01$ ) for D<sub>3a</sub>–D<sub>3d</sub> and D<sub>4</sub>, confirming that deterrent effects are systematically attenuated when prior-period returns are high. In practical terms, SEBI's 2020–2021 margin-tightening measures were partially undermined by the very bull-market conditions they were intended to moderate: the concurrent +24.1% Nifty return in 2021 offset a meaningful portion of the D<sub>3a</sub>–D<sub>3d</sub> deterrent effect. Conversely, the 2024 restrictions (D<sub>4</sub>, D<sub>5a</sub>, D<sub>5b</sub>) coincided with an approximately –6% FY25 return environment, which amplified rather than attenuated their participation-reducing impact. These results partially support H<sub>3</sub> — market conditions moderate regulatory deterrence, though the effect is heterogeneous across interventions and market regimes — and carry a significant implication for regulatory timing discussed in Section 11.4.

### 11.3 Technology Democratisation as a Partial Offset (RQ<sub>3</sub> — H<sub>6</sub>)

The technology-offset results confirm that discount broker penetration ( $X_3$ : +0.83 lakh\*\*\* on  $Y_3$ ) is the strongest positive predictor of new F&O registrations, and that it offsets approximately 30 per cent of the gross entry-barrier effect of D<sub>5b</sub> (gross: –9.14 lakh; net after offset: approximately –6.4 lakh). This finding is consistent with Jawa et al. (2022) and Balodi et al. (2024), who document the structurally transformative role of low-cost digital broker platforms in Indian retail market access, and with Clancey-Shang's (2023) evidence that platform access sustains participation even under adverse regulatory conditions. Google Trends-based attention ( $X_4$ : +0.29 lakh\*) provides a weaker supplementary positive signal, consistent with Da, Engelberg, and Gao's (2011) attention-driven trading mechanism. Mobile internet growth ( $X_5$ ) does not add incremental explanatory power once  $X_3$  and  $X_4$  are controlled, suggesting that broadband penetration's participation effect operates primarily through the adoption of discount-broker trading platforms rather than independently. The practical implication is that regulatory access barriers are partially porous: as long as low-cost digital platforms remain accessible and compliant, a meaningful share of deterred entrants will re-enter or delay exit through platform switching or deferred registration. This does not undermine the welfare motivation for SEBI's 2024 interventions — the 93 per cent loss rate among individual F&O traders documented by SEBI (2024) provides a strong consumer-protection rationale — but it does imply that eligibility criteria (D<sub>5b</sub>) may not be durably self-enforcing without complementary platform-level compliance verification. H<sub>6</sub> is therefore partially supported:  $X_3$  provides a statistically robust offset;  $X_4$  provides a weaker supplementary one;  $X_5$  is not independently significant.

### 11.4 Implications for Regulatory Design and Robustness (RQ<sub>2</sub>, RQ<sub>4</sub> — H<sub>4</sub>, H<sub>7</sub>)

Taken together, the results suggest that SEBI's most effective participation-management tools over the January 2015–January 2026 period were those that altered the structural availability of products (D<sub>1</sub>, D<sub>4</sub>) and minimum capital entry thresholds (D<sub>5a</sub>), rather than those that incrementally raised margin rates on existing products (D<sub>3</sub>). For a regulator



whose welfare objective is to reduce participation in systematically loss-making speculative strategies, structural product-availability and capital-threshold interventions therefore appear more effective per unit of regulatory effort than incremental capital-cost adjustments. The H<sub>4</sub> confirmation that Y<sub>2</sub> (retail turnover share) is endogenously inflated by lot-size changes underscores an important measurement caution for SEBI's post-October 2024 analytical work: unique-trader-count metrics (Y<sub>1</sub>, Y<sub>3</sub>) are the appropriate welfare indicators in this regime, not notional turnover share. The post-2017 robustness check (H<sub>7</sub>) confirms that the core regulatory impact estimates are not materially sensitive to the 2015–2016 Y<sub>1</sub> data-splice — D<sub>4</sub>, D<sub>5a</sub>, and D<sub>5b</sub> retain 1%-level significance in the restricted sample — providing confidence in the stability of the identification strategy across data vintages.

## 12. Key Findings

The following findings emerge from the ITS regression analysis presented in Section 10. Each is mapped to its corresponding hypothesis and supported by reported coefficient estimates.

**Finding 1: Structural Interventions Dominate Capital-Cost Interventions (H<sub>1a</sub>, H<sub>1b</sub>, H<sub>5</sub>)** The three largest participation reductions over the study period were produced by the October 2024 lot-size increase (D<sub>5a</sub>: -12.47 lakh<sup>\*\*\*</sup>), the October 2024 income/knowledge eligibility criteria (D<sub>5b</sub>: -10.22 lakh<sup>\*\*\*</sup>), and the October 2023 weekly-expiry restriction (D<sub>4</sub>: -8.64 lakh<sup>\*\*\*</sup>). These structural interventions far exceeded the phased peak-margin effects (D<sub>3a</sub>: -2.85<sup>\*\*</sup>; D<sub>3b</sub>: -1.93<sup>\*</sup>; D<sub>3c</sub>: -1.47 n.s.; D<sub>3d</sub>: -2.18<sup>\*</sup>), confirming H<sub>1a</sub> and H<sub>1b</sub>. The phased ITS specification for D<sub>3</sub> is superior to the aggregate dummy ( $F = 4.31$ ,  $p = 0.007$ ; delta AIC = -6.4), confirming H<sub>5</sub> and demonstrating phase-level heterogeneity with partial mid-phase adaptation.

**Finding 2: COVID-19 Surge Is the Largest Single Driver of Participation (X<sub>6</sub>)**

The COVID-19 control dummy (X<sub>6</sub> = +14.22 lakh<sup>\*\*\*</sup>) carries the largest coefficient in the base model, capturing the 500 per cent growth in unique individual traders from 7.1 lakh (FY<sub>2019</sub>) to 45.24 lakh (FY<sub>2021</sub>) documented by SEBI (2022). Its inclusion as a mandatory control is critical to valid identification of D<sub>3a</sub>–D<sub>3b</sub>, which were concurrent with the surge.

**Finding 3: Weekly Expiry Introduction Increased Retail Participation Asymmetrically (H<sub>2</sub>)**

D<sub>1</sub> (May 2016) produced a significant positive effect of +2.41 lakh<sup>\*\*</sup> on active retail traders, confirming H<sub>2</sub> in the positive direction. The reversal (D<sub>4</sub>) produced a decline of -8.64 lakh — approximately 3.6 times larger — confirming a reference-dependent asymmetry consistent with Barber et al. (2022).

**Finding 4: Market Conditions Moderate Regulatory Deterrence (H<sub>3</sub>)**

Interaction terms D<sub>i</sub>×X<sub>2</sub> are jointly significant ( $p < 0.01$ ) for D<sub>3a</sub>–D<sub>3d</sub> and D<sub>4</sub>, confirming that bull-market returns attenuate deterrent effects. D<sub>i</sub>×X<sub>1</sub> is jointly significant for D<sub>1</sub>,

D3a, and D4. H3 is partially supported: moderation is heterogeneous across interventions and market regimes.

**Finding 5: Y2 Is an Invalid Outcome Measure Under D5a (H4)**

D5a yields  $-12.47^{***}$  on Y1 but  $+1.84^{**}$  on Y2. This directional divergence confirms H4: Y2 (retail F&O turnover share) is mechanically inflated because the total market F&O turnover denominator falls proportionally faster than the retail numerator following the lot-size increase, causing the share to rise even as the absolute trader count falls. This is directly corroborated by SEBI's FY25 data showing a 20 per cent decline in unique traders alongside only an 11 per cent decline in individual turnover. Y2 is correctly excluded from all D5a regressions.

**Finding 6: Technology Access Offsets Approximately 30% of Entry Barriers (H6)** Discount broker penetration (X3:  $+0.83$  lakh<sup>\*\*\*</sup>, Y3 model) offsets approximately 30 per cent of the gross D5b entry-barrier effect (gross:  $-9.14$  lakh; net:  $\sim -6.4$  lakh), partially supporting H6. Google Trends attention (X4:  $+0.29^*$ ) provides a supplementary offset; mobile internet growth (X5) is not independently significant. Eligibility-based entry barriers are partially circumventable through low-cost digital platforms.

**Finding 7: Post-2017 Robustness Confirms Estimate Stability (H7)**

Restricting the sample to January 2017–January 2026 (T = 109) leaves D4, D5a, and D5b significant at the 1% level. D1 and D3a lose some precision (\*\* to \*). The COVID dummy remains  $+12.14$  lakh<sup>\*\*\*</sup>. H7 is not rejected: regulatory impact estimates are not materially sensitive to the 2015–2016 data splice, confirming the robustness of the identification strategy.

### 13. Conclusion

This study set out to identify which of nine SEBI regulatory interventions between January 2015 and January 2026 produced statistically significant changes in retail F&O participation in India's NSE equity derivatives segment, and to determine how these effects were moderated by market conditions and partially offset by technology-driven access channels. Employing a multi-intervention Interrupted Time Series framework across 133 monthly observations, with mandatory controls for the secular time trend, the COVID-19 shock, market conditions, and access-enablement factors, the study addresses a gap in the India-specific regulatory literature: no prior study had simultaneously handled multi-intervention identification, COVID-era confounding, market-condition moderation, technology-offset effects, and the specific endogeneity problem created by the 2024 lot-size change within a single unified ITS design.

The evidence supports H1a, H1b, H2, H4, and H5 in full, and provides partial support for H3 and H6. H7 is not rejected, confirming the stability of core estimates across the full sample and the post-2017 restricted sample. The two most consequential interventions were the October 2023 weekly-expiry restriction (D4:  $-8.64$  lakh<sup>\*\*\*</sup>) and the combined October 2024 package (D5a:  $-12.47$  lakh<sup>\*\*\*</sup>; D5b:  $-10.22$  lakh<sup>\*\*\*</sup>), both of which produced large, highly significant reductions in active trader counts (Y1) and new registrations (Y3). In absolute terms, the October 2024 package reduced the active retail trader population from its pre-announcement peak of approximately 96 lakh (Q2 FY2025)



to approximately 42.7 lakh by Q4 FY2025 — a decline of approximately 55 lakh unique traders, equivalent to a 57 per cent contraction — with SEBI's July 2025 study confirming a sustained 20 per cent year-on-year decline.

By contrast, the phased 2020–2021 peak-margin requirements (D3a–D3d) produced smaller, phase-heterogeneous effects ranging from  $-1.47$  to  $-2.85$  lakh per step, with the 75% phase (D3c) not statistically significant, consistent with partial trader adaptation. The superiority of the phased over the aggregate D3 specification ( $F = 4.31$ ,  $p = 0.007$ ) confirms that incremental capital-cost measures induce adaptive responses that are masked by a single aggregate dummy. The liberalising D1 intervention ( $+2.41$  lakh\*\*) confirms that structural product-availability changes work symmetrically in both directions, although the reversal (D4) produced a disproportionately larger negative shock, consistent with reference-dependent loss aversion.

Market conditions were found to meaningfully moderate regulatory deterrence (H3): bull-market returns attenuated the deterrent effects of D3a–D3d during the 2021 recovery, while the weaker FY25 return environment amplified the impact of D4 and D5. This timing interaction is an important practical finding — regulatory interventions calibrated to reduce speculative participation are most potent when market-return incentives are weakest. Discount broker penetration (X3) partially offset entry barriers, accounting for approximately 30 per cent of the gross D5b deterrent on new registrations, underscoring that platform-accessible eligibility barriers require complementary enforcement mechanisms to achieve durable participation reduction.

For policymakers, the central implication is that structural interventions affecting product availability and minimum capital thresholds produce substantially larger participation effects than incremental margin adjustments, and that the timing of restrictive measures relative to the market cycle materially influences their impact. SEBI's post-October 2024 welfare assessment should rely on unique-trader-count metrics (Y1, Y3) rather than turnover-share metrics (Y2), which are mechanically distorted by the lot-size change. For the literature, the study contributes a validated multi-intervention ITS framework for the Indian F&O market — directly replicable for future SEBI circulars — and provides the first empirical decomposition of the differential deterrent effects of nine individually identified regulatory interventions across a complete regulatory cycle spanning 2015 to 2026.

## 14. Suggestions

### 14.1 Suggestions for Regulatory Policy

Align intervention timing with market cycles. H3 results confirm that deterrence is amplified in flat or declining markets and attenuated during bull runs. SEBI should consider scheduling capital-access restrictions to coincide with market corrections to maximise participation-reduction effect, and should build in provision for enhanced enforcement during strongly rising markets when the deterrent signal is weakest.

Strengthen eligibility enforcement at platform level. H6 finds that discount broker penetration offsets approximately 30 per cent of the D5b entry-barrier effect, implying that criteria enforced through broker self-reporting are partially circumventable through

platform switching. SEBI should complement income and knowledge eligibility requirements with mandatory platform-level verification audits to improve durability.

Favour unique-trader-count metrics for post-2024 welfare assessment. H4 confirms that Y2 (retail turnover share) is mechanically inflated following lot-size increases. SEBI's analytical units should treat Y2 with caution in post-October 2024 studies and prioritise Y1 and Y3 as primary welfare indicators.

Consider graduated lot-size schedules. D5a's sharp single-step increase produced the largest trader-count decline in the study period. A phased schedule, analogous to D3a–D3d, may achieve welfare objectives more gradually while reducing abrupt market disruption and allowing market-maker liquidity provision to adjust.

## 14.2 Suggestions for Future Research

Trader-level panel analysis using NSE registration and trading-record data would allow estimation of heterogeneous treatment effects across income levels, age cohorts, and geographic regions.

Replication on BSE derivatives data would assess whether regulatory effects are exchange-specific or pan-market. A post-2026 follow-up with 18–24 additional months of data will assess whether the October 2024 trader-count decline is sustained or reverses as market conditions recover. A complementary welfare study quantifying net profit/loss trajectories of exiting versus retained traders post-D5a/D5b would directly test whether the interventions achieved SEBI's underlying consumer-protection objective.

## 15. Limitations

### 15.1 Methodological Limitations

The ITS framework operates on month-level aggregate series; heterogeneous treatment effects across trader subgroups (income, age, geography) cannot be estimated. The absence of a comparator market or difference-in-differences design means unobserved time-varying confounders beyond X1–X6 cannot be fully excluded. All intervention dummies assume instantaneous permanent adjustment; gradual or reversible effects would require slope-change ITS terms. Despite Newey-West HAC correction, complex seasonal autocorrelation patterns inherent in F&O monthly series (e.g., expiry-cycle effects) may not be fully captured by the Breusch-Godfrey test, and a SARIMA pre-whitening approach would provide additional robustness.

### 15.2 Data and Validity Limitations

The Y1 splice between SEBI Annual Reports (2015–2016) and NSE Market Pulse (2017–2026) may introduce a classification discontinuity, partially addressed by the H7 robustness check. NSE's 'individual' trader category conflates retail and HNI traders, meaning Y1 slightly overstates the purely retail count and may respond differently to eligibility interventions. The Google Trends composite (X4) may contain search-seasonality unrelated to trading intent, and the X3 discount-broker proxy — constructed from four named brokers — understates total structural access post-FY2023. External validity is bounded to the Indian NSE F&O segment; generalisation to other asset classes or regulatory environments requires caution. The study demonstrates that interventions reduced participation but does not directly evaluate whether this improved trader welfare or redirected



deterred traders to alternative instruments.



## 16. References

- Balodi, K. C., Raizada, A., & Datta, S. (2024). Trading war: Evolving landscape of discount brokerage in India. *Journal of Information Technology Teaching Cases*, 22(2), 457–493.
- Barber, B. M., Huang, X., Odean, T., & Schwarz, C. (2022). Attention-induced trading and returns: Evidence from Robinhood users. *The Journal of Finance*, 77(6), 3141–3190.
- Bernal, J. L., Cummins, S., & Gasparrini, A. (2017). Interrupted time series regression for the evaluation of public health interventions: A tutorial. *International Journal of Epidemiology*, 46(1), 348–355.
- Bertrand, M., Duflo, E., & Mullainathan, S. (2004). How much should we trust differences-in-differences estimates? *The Quarterly Journal of Economics*, 119(1), 249–275.
- Bryzgalova, S., Pavlova, A., & Sikorskaya, T. (2023). Retail trading in options and the rise of the big three wholesalers. *The Journal of Finance*, 78(6), 3465–3514.
- Chague, F., De-Losso, R., & Giovannetti, B. (2020). We are all aware of the Covid-19: How individual investors reacted to the pandemic. *Finance Research Letters*, 36, 101702.
- Clancey-Shang, D. (2023). COVID lockdown, Robinhood traders, and liquidity in stock and option markets. *International Review of Financial Analysis*, 90, 102837.
- Da, Z., Engelberg, J., & Gao, P. (2011). In search of attention. *The Journal of Finance*, 66(5), 1461–1499.
- Eaton, G. W., Green, T. C., Roseman, B. S., & Wu, Y. (2022). Retail trader sophistication and stock market quality: Evidence from brokerage outages. *Journal of Financial Economics*, 146(2), 502–528.
- Foucault, T., Sraer, D., & Thesmar, D. (2011). Individual investors and volatility. *The Journal of Finance*, 66(4), 1369–1406.
- Ganesh, B., & Velmurugan, V. (2025). Growing trends in equity derivative markets in India: Special reference to futures and options in NSE. *South Eastern European Journal of Public Health*, 4440–4451.
- Google Trends. (2015–2026). Search interest for 'options trading', 'Nifty options', 'F&O trading' — India region, monthly data.
- Hedegaard, E. (2014). Causes and consequences of margin levels in futures markets. *Review of Financial Studies*, 27(9), 2783–2818.
- Jawa, R., Kabra, R., & Aggarwal, R. (2022). Investment tech: The rise of discount brokers in India. *International Journal of Research — Granthaalayah*, 10(3), 176–193.
- Kaniel, R., Saar, G., & Titman, S. (2008). Individual investor trading and stock returns. *The Journal of Finance*, 63(1), 273–310.
- Kontopantelis, E., Doran, T., Springate, D. A., Buchan, I., & Reeves, D. (2015). Regression based quasi-experimental approach when randomisation is not an option: Interrupted time series analysis. *BMJ*, 350, h2750.
- Lopez Bernal, J. A., Cummins, S., & Gasparrini, A. (2018). Interrupted time series regression for the evaluation of public health interventions: A tutorial. *Statistical Methods in Medical Research*, 27(4), 1023–1043.
- National Stock Exchange of India (NSE). (2015–2026). Market Pulse monthly reports.



- National Stock Exchange of India (NSE). (2015–2026). India VIX historical data.
- National Stock Exchange of India (NSE). (2015–2026). Nifty 50 index historical prices.
- National Stock Exchange of India (NSE). (2015–2026). Monthly broker-wise active client list.
- National Stock Exchange of India (NSE). (2017–2026). Participant-wise F&O turnover data.
- Ozik, G., Sadka, R., & Shen, S. (2021). Flattening the illiquidity curve: Retail trading during the COVID-19 lockdown. *Journal of Financial and Quantitative Analysis*, 56(7), 2356–2388.
- Securities and Exchange Board of India (SEBI). (2022). Study on profit and loss of individual traders dealing in equity F&O segment (FY19–FY22). SEBI Press Release, January 25, 2023.
- Securities and Exchange Board of India (SEBI). (2024). Updated SEBI study: 93% of individual traders incurred losses in equity F&O between FY22 and FY24; aggregate losses exceed Rs 1.8 lakh crore. SEBI Press Release, September 23, 2024.
- Securities and Exchange Board of India (SEBI). (2025). Study on profit and loss of individual traders dealing in equity F&O segment — FY2024–25.
- Securities and Exchange Board of India (SEBI). (Various). Circulars on F&O market regulation.
- Switzer, L. N., & Bhatt, K. (2024). The impact of position limits on options trading. *International Review of Financial Analysis*, 91, 103009.
- Telecom Regulatory Authority of India (TRAI). (2015–2026). Indian Telecom Services — Yearly and Quarterly Performance Indicator Reports.