

Intraday Scalping on the NSE after the 2025–26 Cost and Algorithmic-Trading Regime Changes: A Review of the Evidence

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Abstract

Intraday “scalping” of index derivatives is popular among Indian retail traders, yet the market regulator reports that most individual derivatives traders lose money. This paper reviews a small, purposively selected body of evidence on one question: under what conditions can a short-horizon strategy on Nifty derivatives earn a positive net return, and who is likely to earn it? We synthesise (i) a cost-aware study of simple intraday rules on S&P 500 futures, (ii) two working papers on high-frequency trader (HFT) behaviour on Indian exchanges, (iii) a recent article on intraday volatility on the National Stock Exchange (NSE), (iv) the Securities and Exchange Board of India’s (SEBI) FY2025–26 studies of individual derivatives traders, and (v) the 2025–26 changes to the retail algorithmic-trading framework and to securities transaction tax (STT). Three themes emerge. First, transaction costs, rather than signal quality, usually decide whether a scalping rule survives. Second, profits in Indian derivatives are concentrated among algorithmic participants, although the regulator’s definition of an “algo entity” is broad. Third, backtests of short-horizon strategies are fragile to fill assumptions, regime change and over-fitting. We add a simple breakeven calculation showing that the April 2026 STT increase more than doubled the all-in index-point hurdle for a Nifty futures round trip in an illustrative case, and we state five testable propositions. This is a narrative review and presents no new empirical results.

Keywords: scalping; intraday trading; algorithmic trading; high-frequency trading; transaction costs; backtest overfitting; Nifty; NSE; India

JEL classification: G12; G14; G18

1. Introduction

Scalping, in the sense used by traders, means opening and closing positions within seconds or minutes to capture small price moves, and repeating this many times a day. In India the practice is concentrated in index derivatives, where contracts on the Nifty 50 are among the most heavily traded instruments. Retail participation in equity derivatives grew for roughly a decade before falling in FY2026 (Business Standard, 2026), but the regulator’s studies consistently report that most individual derivatives traders lose money (SEBI, 2026a, 2026b). At the same time, retail access to automated trading has been formalised through a framework that became fully applicable on 1 April 2026.

Two features make the Indian market a useful setting. First, the NSE is an order-driven market without a designated market maker, and algorithmic orders are identified in exchange data, which has allowed researchers to study high-frequency traders without relying on proxies (Banerjee et al., 2022). Second,

2025–26 brought simultaneous changes to the regulation of retail algorithms and to the cost of trading derivatives, which together alter the economics of short-horizon strategies.

We ask four questions. (RQ1) How much of a short-horizon strategy’s gross edge is consumed by trading costs? (RQ2) Who earns the profits in Indian derivatives, and how do high-frequency traders behave around information shocks? (RQ3) Why do backtested scalping strategies often fail when traded live? (RQ4) What changed in 2025–26 that matters for answering the first three?

The paper makes four contributions. It brings together evidence that is usually scattered across market-microstructure, retail-finance and practitioner sources. It grades the sources by reliability and flags inconsistencies in them. It provides a transparent breakeven calculation that reflects the April 2026 STT change. And it proposes testable propositions and data requirements for future work. The paper does not test any trading strategy, and nothing in it should be read as a claim that any particular strategy is or is not profitable, or as investment advice.

2. Scope and method of the review

This is a narrative review. The core sources are four research papers: Donninger (2014), Banerjee et al. (2022), Bang and Thirumalai (n.d.) and Madhubabu (2025). These were supplemented with regulatory and exchange material and with recent reporting on SEBI’s FY2025–26 studies, located through web searches in September–October 2026. The selection is purposive rather than systematic, and the review does not claim to cover the wider literature on intraday trading. Table 1 summarises the sources and our assessment of their reliability.

Table 1. Core research sources and reliability notes

Source	Type	Market and period	Review status	Reliability notes
Donninger (2014)	Working paper (SSRN)	S&P 500 E-mini futures, 2010–2014, 1-minute data	Not peer reviewed	Explicit transaction costs; parameters tuned in-sample; author notes data-snooping risk; US market
Banerjee et al. (2022)	Preprint (SSRN)	NSE, 166 stocks, 2015, 1-minute data	Not peer reviewed	Exact HFT identifiers; associations are contemporaneous; text and tables disagree on some extreme-period coefficients
Bang & Thirumalai (n.d.)	Working paper	BSE 200 stocks, 2011	Not stated	Only two macroeconomic events; trader categories identified by the exchange
Madhubabu (2025)	Online journal article	NSE derivatives, “several months”	Journal states it is peer reviewed	Data not specified; chart and table disagree; error figures differ between text and chart
SEBI (2026a, 2026b)	Regulator studies	Individual F&O traders, FY2022–FY2026	Not applicable	Figures here come from secondary reports; primary documents should be consulted

Source: author’s assessment.

Two points deserve emphasis. First, three of the four research papers are working papers or preprints that have not been peer reviewed, or whose review status is not stated. Second, several SEBI statistics were obtained from secondary reports rather than from the SEBI documents themselves. Where reports differed, we used the figure supported by more than one source and note the discrepancy in Section 11.

3. Institutional background

3.1 Market structure and algorithmic participation

The NSE is a limit-order-driven market with price-time priority and no traditional market maker or specialist (Banerjee et al., 2022). Banerjee et al. report that in 2015 proprietary algorithmic traders, their proxy for HFTs, accounted for 76.37% of message traffic but only 13.18% of trades, a pattern typical of high order-to-trade ratios. More recently, NSE's Market Pulse report for December 2025, as summarised by QuantInsti, puts the algorithmic share of equity-futures turnover at about 69% in FY2026 to date, and of equity-options turnover at about 60%.

3.2 Contract-design changes, 2024–26

Following the regulatory measures announced in 2024, weekly index contracts have been available for only one benchmark index per exchange from 1 December 2024 (Nifty 50 on the NSE), index-option contract sizes were increased, an additional exposure margin of 2% applies to short option positions on expiry day, and calendar-spread margin benefits were removed on expiry day from 1 February 2025 (Zerodha, 2024). The Nifty lot size has since been reduced to 65 units. Despite these curbs, SEBI's FY2026 study reports that 59% of index-options turnover still occurred on expiry day and 75% within one day of expiry (Free Press Journal, 2026, reporting SEBI data).

3.3 The retail algorithmic-trading framework

SEBI issued a framework for safer retail participation in algorithmic trading in February 2025. Implementation was postponed several times; a circular of 30 September 2025 set milestones through January 2026 and made the full framework, including exchange standards, applicable to all stockbrokers from 1 April 2026 (SEBI, 2025). Under the NSE standards, retail API access requires a static IP address mapped to the client's credentials; the exchange sets a threshold of 10 orders per second per exchange segment; algorithms below the threshold need not be registered but their orders must carry an algorithm tag; algorithms above it must be registered and receive a unique identifier; third-party algorithm providers must be empanelled; and brokers are responsible for orders routed through their systems (NSE, 2025; Zerodha, 2025). Brokers have additionally reported daily two-factor authentication and the automatic conversion of market orders into market-price-protection orders (FYERS, 2026).

The regulatory climate also includes enforcement. In July 2025 SEBI barred Jane Street over alleged manipulative algorithmic trading practices (Sahi, 2026). We take no position on the merits of that matter; we note it only as evidence of heightened supervisory attention to algorithmic activity.

3.4 Securities transaction tax

The Union Budget for 2026–27 raised STT on equity derivatives with effect from 1 April 2026. On futures the rate rose from 0.02% to 0.05% of the traded value, and on options from 0.1% to 0.15% of the premium, in both cases levied on the sell side (Angel One, 2026). Section 8 quantifies the implications for short-horizon strategies.

4. Evidence from cost-aware tests of simple intraday rules

Donninger (2014) tests several published intraday rules on S&P 500 E-mini futures using 1-minute data from 24 August 2010 to 24 August 2014. The rules include an opening-range breakout (ORB; Holmberg et al., as cited in Donninger, 2014), gap-fade rules, a rebound rule and a downside-volatility rule. Portfolio size is normalised, with one E-mini contract per USD 30,000 of the index level, and a regime filter based on the ratio of one-month to three-month implied volatility indices (VIX/VXV) is applied in several variants.

The central result concerns costs. With zero costs, the ORB rule earns a cumulative 139.8% against 105.2% for buy-and-hold in the SPY, with Sharpe ratios of 1.012 and 1.025. When one tick (USD 12.5) is charged per trade per contract, which makes a round trip USD 25, the profit falls to 35.4% and the Sharpe ratio to 0.469. Tripling the leverage raises the profit to 82.8% but lowers the Sharpe ratio to 0.321. Restricting trading to a medium-volatility regime raises the cost-inclusive result to 43.5% with a Sharpe ratio of 0.812. Table 2 summarises the cost-inclusive results for each rule.

Table 2. Cumulative results reported by Donninger (2014), S&P 500 E-mini futures, 2010–2014

Rule (cost assumption)	Cumulative return	Sharpe ratio	Notes
ORB, no costs	139.8%	1.012	SPY buy-and-hold: 105.2%, Sharpe 1.025
ORB, USD 25 round trip	35.4%	0.469	Spread cost only; broker fees ignored
ORB, 3x leverage, with costs	82.8%	0.321	Volatility drag offsets part of leverage gain
ORB with VIX/VXV filter [0.93, 1.0], with costs	43.5%	0.812	Mostly out of the market
Gap-fade with VIX/VXV filter ≤ 0.94 , with costs	36.9%	0.861	No costs: 57.1%, Sharpe 1.032
“Sid” gap rule (stricter filters), with costs	30.7%	1.047	Smooth curve; long idle periods; over-fitting flagged
Rebound rule, with costs	27.1%	0.863	Few trading occasions
Downside-volatility rule, with costs	30.1%	0.786	Similar to rebound rule

Source: Donninger (2014). Returns are the cumulative “overall win” reported over the sample; all rules are long-only.

Four features of the study are relevant to this review. First, the author concludes that published claims for these rules are generally exaggerated or assume unrealistically low trading costs. Second, the short side did not work in the sample, and the author notes that the S&P 500 rose strongly over the period.

Third, the study criticises the original ORB paper for relying on daily data and continuity assumptions, since a daily high and low do not reveal their order, which is a general warning for any backtest built on aggregated bars. Fourth, the strongest rule relies on tightly specified filters whose thresholds (for example 0.93, 0.94 and 0.95) appear to have been selected on the same data, and the author acknowledges the danger of data-snooping.

The transferable lessons are methodological rather than numerical: charge explicit costs, test regime filters, and treat very smooth equity curves from heavily filtered rules with suspicion. The specific parameters were estimated on a US market in a rising period and should not be assumed to carry over to Nifty derivatives.

5. High-frequency traders on Indian exchanges

5.1 Order-flow direction and returns

Banerjee et al. (2022) use order and trade data for 166 NSE stocks over 246 trading days in 2015 to study how HFT order imbalance relates to one-minute returns. Order imbalance follows the construction of Chordia et al. (2002) and Chordia and Subrahmanyam (2004): buyer-initiated minus seller-initiated trades, scaled by total trades. They report four main findings. HFT order imbalance is positively associated with contemporaneous idiosyncratic returns for all 166 stocks, although the average explanatory power is low (an average R^2 of about 0.03). The sign of the imbalance matters far more than its size: the sign coefficient is positive and significant for 164 of 166 stocks, whereas the magnitude coefficient is significant for only 11. Decomposing HFT imbalance into stock-specific and market-wide components using a single-factor model, both components are positively related to returns, with the stock-specific coefficient about four times the market-wide coefficient on average. And the relative weight of the market-wide component rises during extreme price movements, though the text and tables of the paper report different average coefficients for the extreme-return model, so we rely only on the qualitative direction.

For scalping, the key limitation is that these are contemporaneous associations. The paper does not show that order imbalance in one minute predicts returns in the next, and the authors state that they do not disentangle whether HFTs respond to the market or move it. The findings are consistent with a view that fast participants read and act on direction in the order flow, but they cannot be treated as a trading signal.

5.2 Behaviour around information shocks

Bang and Thirumalai (n.d.) use exchange data for BSE 200 stocks in 2011 to compare normal traders, buy-side algorithms and HFTs around 153 earnings surprises and two Reserve Bank of India rate increases (3 May and 26 July 2011). Around earnings surprises HFTs did not change the number of orders they submitted but used more liquidity-demanding orders (51 more per day), consistent with trading on information, while buy-side algorithms increased activity. Around the macroeconomic shocks, HFTs submitted about one-third fewer orders, order size roughly halved, liquidity-supplying orders fell from 84 to 31 per day and liquidity-demanding orders from 109 to 62. Realised spreads suggested no information advantage on market-wide news, and the authors interpret the withdrawal as

avoidance of losses to informed traders. The evidence on macroeconomic shocks rests on only two events and a single year.

5.3 Related findings

The wider literature, as summarised by Banerjee et al. (2022), finds that HFTs improve price discovery and quote efficiency (Brogaard et al., 2014; Hendershott et al., 2011), that some HFTs can anticipate the order flow of other traders (Hirschey, 2021), and that HFT liquidity provision can retreat in stress, as in the 2010 US flash crash (Kirilenko et al., 2017). Together with Bang and Thirumalai (n.d.), this implies that liquidity that is visible in calm conditions may disappear around scheduled macroeconomic announcements, which raises slippage for any strategy that relies on being filled quickly at a quoted price.

6. Intraday volatility patterns on the NSE

Madhubabu (2025) reports an intraday U-shape in NSE volatility, with the highest average volatility at the open and close and the lowest around midday, and reports that a dilated convolutional neural network forecasts hourly volatility with lower error than GARCH(1,1) and a multivariate GARCH variant. Table 3 reproduces the reported hourly pattern.

Table 3. Hourly intraday volatility on the NSE as reported by Madhubabu (2025)

Interval (IST)	Average volatility (%)	Standard deviation (%)
9:15–10:00	1.8	0.25
10:00–11:00	1.2	0.18
11:00–12:00	0.9	0.12
12:00–13:00	0.95	0.13
13:00–14:00	1.1	0.15
14:00–15:00	1.6	0.21
15:00–15:30	2.0	0.29

Source: Madhubabu (2025), Table 1, reproduced as reported. Intervals have unequal length (45, 60 and 30 minutes).

We treat this evidence cautiously. The article does not specify the instruments, dates or training and test design; its chart appears to show volatility rising steadily through the day rather than a U-shape; the error figures in the text differ in scale from those in its bar chart; and no significance tests are reported for the claims of significant differences. A U-shaped intraday pattern is widely documented in other markets, so the qualitative claim is plausible, but we do not rely on the magnitudes or on the forecasting comparison.

The pattern, if it holds, has an implication for scalping that we state as a hypothesis rather than a finding. When the typical price range available in a period is small, as around midday, a fixed round-trip cost absorbs a larger share of each potential gain. Whether scalpers' net results differ by time of day is an empirical question that the reviewed sources do not answer.

7. Outcomes of individual derivatives traders

SEBI's studies of individual traders in equity derivatives for FY2025–FY2026 are the most comprehensive evidence on outcomes. They are the fourth in a series published since January 2023 (Outlook Money, 2026). Table 4 summarises the main reported figures.

Table 4. Selected findings from SEBI's FY2025–26 studies of individual derivatives traders

Finding	Reported value
Active individual traders, FY2025 → FY2026	98.1 lakh → 78.6 lakh (about –20%)
Share of individual traders with net losses, FY2026	87.7%
Aggregate net losses of individuals, FY2025 → FY2026	about ₹1.12 lakh crore → ₹91,685 crore
Implied average loss per active trader, FY2026	about ₹1.17 lakh (aggregate ÷ active traders)
Share of individuals' aggregate losses from options, FY2026	about 92%
Transaction costs paid by individuals, FY2026	about ₹25,000 crore
Share of profits of proprietary traders and FPIs earned by “algo entities”	99%
Gross profits of proprietary traders and FPIs, FY2026	₹58,379 crore (₹44,483 crore + ₹13,896 crore)
Traders active throughout FY2022–FY2026: profitable in all five years / loss-making in every year	0.5% / 65.6%
Share of index-options turnover on expiry day, FY2026	59%
Traders under 30: share of individual traders / share with losses, FY2026	43% / 89%
Cumulative individual losses over five years to FY2026	nearly ₹3.85 lakh crore

Sources: *Open Magazine* (2026); *TaxGuru* (2026); *Sahi* (2026a); *Outlook Money* (2026); *Free Press Journal* (2026), all reporting SEBI (2026a, 2026b). The average-loss figure is the author's division of two reported aggregates and is consistent with the figure of ₹1.17 lakh reported in a government reply (*Moneylife*, 2026).

Four cautions apply when reading these figures. First, SEBI defines an algo entity as any entity that placed at least one algorithmic order during the year (TaxGuru, 2026), so the 99% figure describes algorithm users broadly and is not a measure of the profits of ultra-fast firms. Second, the concentration of profits among algorithm users does not by itself show that algorithms cause retail losses; the groups differ in capital, costs, strategy and risk management. Third, individual traders are a heterogeneous population that includes hedgers and option sellers as well as scalpers, and the studies are not specific to scalping. Fourth, the average-loss figure is a mean and says little about the distribution. With those cautions, the picture is consistent across years: losses are persistent, concentrated in options, and not reduced by experience in the sample, since only 0.5% of traders active throughout five years were profitable in every year.

8. The cost regime and a breakeven calculation

Costs enter scalping in a simple way. Let L denote the index level, τ the STT rate on the sell side, c all other per-lot charges (brokerage, exchange fees, GST, stamp duty) expressed in index points, and s the expected slippage in index points over the round trip. The minimum favourable index move needed to break even on one futures round trip is then:

$$B = \tau L + c + s$$

A broker-published example for a Nifty futures lot of 65 units with the index near 22,845 (contract value about ₹14.85 lakh) puts total charges at about ₹392 before the April 2026 STT change and about ₹837 after it, of which STT is about ₹297 and ₹742 respectively (Angel One, 2026). Dividing by the lot size gives all-in breakevens of roughly 6 and 13 index points, so the hurdle more than doubled. The other charges in that example are about ₹95 per lot, or about 1.5 index points. Table 5 applies the formula to three hypothetical index levels, holding other charges at 1.5 points for simplicity and setting slippage to zero.

Table 5. Illustrative breakeven for one Nifty futures round trip (index points)

Index level (L)	STT only, 0.02% (before)	STT only, 0.05% (after)	All-in after, with $c \approx 1.5$ and $s = 0$
22,000	4.4	11.0	12.5
24,000	4.8	12.0	13.5
26,000	5.2	13.0	14.5

Source: author's calculation from the published STT rates; other charges taken from the example in Angel One (2026) and held constant. Slippage is excluded and would raise every figure. Some charge components scale with turnover, so the other-charges term is approximate.

Three implications follow. First, any rule whose average gross gain per trade was set with the old cost schedule in mind needs to be re-evaluated, because the same signals now face a hurdle about twice as large in points. Second, because B grows with the index level, the hurdle in points rises as the index rises even if rates are unchanged. Third, for options the STT component is smaller in rupee terms: at a premium of ₹100 and a lot of 65 units, sell-side STT is about ₹9.75 per lot. Spread and slippage are therefore likely to dominate for option scalps, but the reviewed sources provide no measurements of option spreads, so this remains an empirical question.

A note of caution on interpretation: STT is a statutory rate that applies to all participants equally. Differences in outcomes between participant types therefore arise from other costs, from spread capture and slippage, and from the gross edge itself, not from the tax.

9. Why backtested scalping strategies fail in live trading

Practitioners often report that a short-horizon strategy performs well in a backtest and for a period live, then deteriorates, and that stops are hit shortly before price moves in the intended direction. The reviewed sources do not study this phenomenon directly, but they point to several mechanisms that are not mutually exclusive. Table 6 organises them and links each to the available evidence and to a diagnostic test.

Table 6. Mechanisms behind backtest-to-live performance gaps

Mechanism	Description	Evidence in reviewed sources	Diagnostic
Intrabar ordering and fill assumptions	Bars show open, high, low and close but not the sequence; backtests may assume favourable fills	Donninger (2014) criticises continuity and ordering assumptions in daily-data tests	Replay on tick data; adopt a pessimistic rule when a bar touches both stop and target
Spread and slippage	Live fills occur at worse prices than signal prices	ORB result falls from 139.8% to 35.4% once a one-tick cost per trade is charged (Donninger, 2014)	Compare signal price with fill price for every trade
Cost misspecification	Backtest uses outdated or incomplete charges	STT rates changed on 1 April 2026 (Angel One, 2026)	Re-run with a date-specific cost schedule
Regime dependence	Edge exists only in certain volatility or liquidity states	Regime filter transforms results (Donninger, 2014); HFT liquidity withdraws around macro shocks (Bang & Thirumalai, n.d.)	Split results by volatility regime and by event days
Over-fitting and data-snooping	Parameters match sample-specific noise	Acknowledged in Donninger (2014); see Bailey et al. (2014), Bailey and López de Prado (2014), Harvey et al. (2016)	Out-of-sample and walk-forward tests; adjust for the number of trials
Look-ahead bias and repainting	Signals use information not available at the time	General methodological point; not tested in reviewed sources	Audit timestamps; test with delayed signals
Edge decay and crowding	Common patterns lose profitability as more traders use them	General point; not tested in reviewed sources	Track rolling expectancy net of costs

Source: author's synthesis.

The experience of being stopped out just before the market moves favourably has at least three non-exclusive explanations: a stop placed inside the normal intrabar noise of the current volatility regime, adverse fills at the stop, and the selection effect that a trader remembers favourable reversals more than continuations. None of the reviewed sources provides evidence on deliberate targeting of stop orders, and we make no claim about it.

10. Discussion: can algorithms beat human scalpers?

The question is often posed as a single contest, but the evidence supports distinguishing three comparisons. Institutional and high-frequency algorithms against retail traders: here the evidence is strong that algorithm users capture a very large share of derivatives profits (SEBI, 2026a, 2026b, as reported), with the caveat on the breadth of the definition. Institutional algorithms against retail algorithms: speed, co-location, cost structure and capital favour the former, and the retail framework adds constraints such as a static IP and a 10-orders-per-second threshold, although a scalping strategy rarely needs more than that rate. Retail algorithms against retail discretionary traders: we found no study that makes this comparison for Nifty scalping. An algorithm provides consistency, precise

execution of stops and testable rules, but it does not create a positive gross edge, and a rule without one will lose faster when automated.

A research opportunity follows from the new framework. Because all retail algorithmic orders must now carry an algorithm tag (NSE, 2025; Zerodha, 2025), exchange and regulator data could, in principle, separate retail algorithmic from discretionary order flow and allow a direct comparison of net outcomes. We state the following propositions as hypotheses for such work. They are not findings of this review.

P1. Holding the signal fixed, the share of gross edge absorbed by costs in Nifty futures scalping rose after 1 April 2026, mechanically, through the higher STT.

P2. Holding gross edge per trade constant, net returns of scalping strategies decrease with trade frequency.

P3. The backtest-to-live performance gap is larger for strategies whose average gross gain per trade is small relative to round-trip costs and for shorter bar intervals.

P4. Liquidity-taking scalps around scheduled macroeconomic announcements show larger slippage than the same strategies in non-event periods, because liquidity supply is withdrawn.

P5. Adopting algorithmic execution does not improve net outcomes for retail traders unless the underlying strategy has a positive expected return net of all costs.

Testing these propositions would need trade-level data with order timestamps, fill prices, charges and algorithm tags; tick-level market data for realistic fill simulation; walk-forward evaluation across the pre- and post-April 2026 cost regimes; and event-study designs around the STT change and around scheduled announcements.

11. Limitations

This review has several limitations. The source set is small and purposively chosen, and no systematic search of the literature was conducted. The evidence spans different markets and periods (US futures in 2010–2014, Indian equities in 2011 and 2015, and Indian derivatives in 2025–26), so the pieces are not directly comparable. Three of the research papers are not peer reviewed, one contains internal inconsistencies that limit its use, and another reports results from only two macroeconomic events. SEBI figures were drawn from secondary reports; one report gives the number of active retail traders in FY2026 as 87.5 lakh while most report 78.6 lakh, and we used the latter. Some cost and framework details come from broker publications and may differ from the regulatory documents. Finally, rules, tax rates and contract specifications are changing quickly, and details that hold at the time of writing may change.

12. Conclusion

The evidence reviewed here points in a consistent direction. Costs, not the elegance of the signal, decide whether short-horizon strategies survive; algorithmic participants capture most derivatives profits; liquidity is least reliable when information shocks are largest; and backtests are fragile to fill assumptions, regime change and over-fitting. The 2025–26 reforms raised the cost hurdle for futures

scalps by more than a factor of two in an illustrative case and formalised retail access to algorithms without changing the need for a positive net expected return. The direct comparison of retail algorithmic and discretionary scalpers on the NSE remains an open empirical question, one that newly tagged order data may make answerable.

Declarations

Data availability. No new data were generated. All figures are taken from the cited sources or calculated from them as described.

Disclaimer. This paper is for research and educational purposes only. It is not investment advice and makes no recommendation to trade any security or strategy.

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