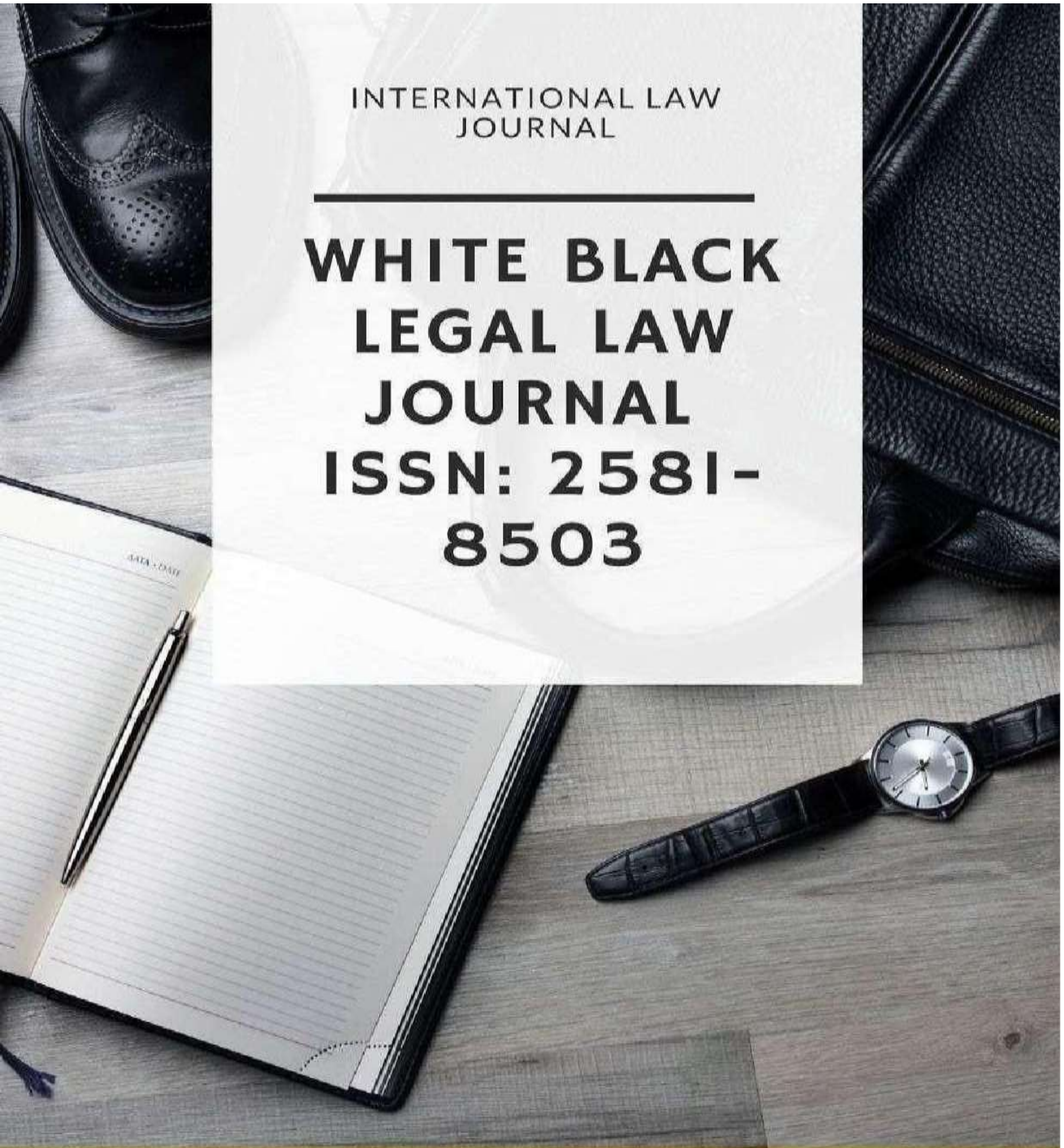

INTERNATIONAL LAW JOURNAL

# WHITE BLACK LEGAL LAW JOURNAL

ISSN: 2581-8503

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# ARTIFICIAL INTELLIGENCE IN CAPITAL MARKETS: AN ECONOMIC ASSESSMENT -THE POSITIVE AND THE NEGATIVES

AUTHORED BY - ARCHISHAA RANDHAWA

## Abstract

The increased deployment of artificial intelligence and algorithmic trading systems in capital markets has started to transform trading, market microstructure and investor engagement. Techniques of high-frequency trading, API-based trading strategies and AI-driven trading advice now engage in trading at a pace and complexity beyond human capabilities. These innovations have enhanced market efficiency and accessibility, but they also present concerns about transparency, market manipulation, systemic risk and investor protection. India's securities laws, such as the Securities and Exchange Board of India Act, 1992 and SEBI (Prohibition of Fraudulent and Unfair Trade Practices) Regulations, 2003, are based on human agents and may need to align with the complexities of self-learning and pattern-based trading algorithms.

This research conducts a doctrinal and comparative review of the Indian regulatory responses to algorithmic and AI-based trading, and review global developments such as the EU Artificial Intelligence Act, MiFID II and responses in the United Kingdom and the United States. It considers both the benefits of efficiency in using AI and the potential risks from algorithmic predictability, system interaction and technological concentration. This paper aims to critically evaluate the adequacy of the law and regulation to respond to these trends. It highlights the shortcomings of the current framework, especially with respect to accountability, enforcement and regulation of system-driven market impact. By highlighting these limitations, the study seeks to inform the understanding of regulatory issues associated with AI in capital markets.

## Literature Review:

The empirical justification for algorithmic trading is based on market microstructure evidence that automation narrows spreads and speeds up price discovery. Hendershott, Jones and Menkveld (2011) show that algorithmic trading is causally linked to lower bid-ask spreads, while Carrion (2013) finds high-frequency trading to be linked to faster price discovery and reduced bid-ask spreads.

Another line of research concerns the "predictability problem", where machine learning models trained on the same data sets produce correlated trading leading to exploitable market regularities. Brunnermeier and Pedersen (2009) and Lopez de Prado (2018) point to strategy crowding and algorithmic herding as potential sources of systemic risk, while empirical evidence from the NSE Digital Transformation Study shows an increase in observable mean-reverting patterns in line with algorithmically driven market regularities.

This evidence shows that efficiency gains are inequitably distributed in favour of technologically advanced traders. Overall, the literature shows that while algorithmic trading provides demonstrable efficiency gains, these gains are conditional, distributional, and come with systemic vulnerabilities and structural problems that are partially tackled by existing regulation.

## 1. The Efficiency Dividend: What Algorithmic Trading Actually Delivers

### 1.1 Transaction Costs and Bid-Ask Spreads

The most widely observed positive economic effect of algorithmic trading is the narrowing of the bid-offer spread and the reduction of transaction costs. The reason is simple: market-making algorithms supply tighter bid-ask quotes because they are faster in information processing, are continuously active, and adjust quotes to new information in milliseconds. The difference between the price at which a buyer can buy and a seller can sell, is the most easily observed measure of transaction costs and it has declined considerably in markets with high algorithmic activity.[1]

This is supported by evidence from the Indian markets. A 2024 study of NSE microstructure data covering the years 2020 to 2024 showed a 23.4% decline in the bid-ask spread over the years, with an 18.1% improvement in the market depth.[2] Studies using MCX energy futures data found that the intensity of algo trading positively predicted market tightness at a very high level of statistical significance ($p < 0.0001$) and with 63.69% variance explained in this measure.[3] The EEL study using NSE high-frequency order-book data also made a more specific observation: that retail algorithmic traders directly decreased the Nifty 50 spreads by 0.42 basis

[1] Terrence Hendershott, Charles M Jones and Albert J Menkveld, 'Does Algorithmic Trading Improve Liquidity?' (2011) 66(1) Journal of Finance 1.

[2] NSE, 'Digital Transformation of Indian Capital Markets: A Microstructure Analysis 2020–2024' (NSE Research Report, December 2024) https://www.nseindia.com accessed 23 April 2026.

[3] Kamran Rizvi, Owais Ahmad Wani, Shakeel Akther, Nargis Akhter Wani and Vidyasagar Singaram, 'Algorithmic Trading in India's Retail-Dominated Markets: Liquidity, Volatility, and Regulatory Challenges' (2025) 15(2) European Economic Letters 2360, https://doi.org/10.52783/eel.v15i2.3071 accessed on 15 April, 2026

points. This study also found that the price adjustment half-life (the time required for the new price to fully reflect the available information - which is dynamic) was reduced by 50% during the period of observation, suggesting that algorithmic markets are much quicker to price new information into the asset price.

### 1.2 Price Discovery and the Democratisation Argument

Price Discovery is the process by which information gets incorporated into prices, it's the primary economic role of capital markets. Algorithmic trading systems play a role in improving the informational efficiency of markets in that they process new information in a timely manner, much faster than human traders could, and they do so around the clock. This is confirmed by order imbalance and price delay regressions on the NSE. The API economy on one hand has enabled the democratisation of algorithmic trading software that has been previously inaccessible to retail investors, services such as Zerodha's Kite Connect, Upstox's API and AngelOne's SmartAPI have become accessible to retail investors to implement algorithmic strategies at low costs. Theoretically speaking, a retail investor with a sound algorithm at hand, has the efficiency of execution and the discipline of emotional control unavailable to manual trading and human judgement. The algorithm is not panicky; it is cool-headed; it does not lose money chasing losses; it does not trade excessively for lack of something to do. It is also, as Section 5 will demonstrate, a case which is almost completely theoretical for the vast majority of retail participants who have tried to implement it.

| Metric | Observation | Market/Period | Source |
|---|---|---|---|
| Bid-ask spread (Nifty 50) | 0.42 bps tightening by retail algos | NSE 2020-24 | EEL (2025) |
| Bid-ask spread (overall) | 23.4% decline over period | NSE 2020-24 | NSE Digital Study (2024) |
| Market depth | 18.1% increase | NSE 2020-24 | NSE Digital Study (2024) |
| Price adjustment half-life | 50% reduction (faster | NSE 2020-24 | NSE Digital Study (2024) |

| | | | |
|---|---|---|---|
| | price discovery)[4] | | |
| Algo participation - Stock Futures | 39% (FY15) to 73% (FY26) | NSE | NSE Market Pulse (Dec 2025)[5] |

***Table 1.1**: Documented Efficiency Gains from Algorithmic Trading on Indian Markets; NSE Market Pulse, December 2025.*

## 2 The Efficiency Illusion: When the Benefits Reverse

### 2.1 Phantom Liquidity and Market Stress

The liquidity these systems do provide during times of regular trading is not unconditional. Andrew Haldane's captured this problem with the term he coined the "*phantom liquidity*": the size of the market typically overestimates the liquidity in times when it is most needed. Algorithmic market-makers, due to their ultra-precise responsiveness to data signals, move away from their quotations very rapidly when the signals turn negative, which is when the other market participants would most like to have liquidity.

This is tempered by evidence from the NSE. The Nawn and Banerjee (2019) study showed that while the NSE's proprietary algorithmic traders don't completely withdraw quotations in volatile episodes, they do modify their quotation strategies in ways that can amplify price moves. The EEL 2025 Study found that while retail algorithmic traders narrowed spreads on the Nifty 50 index by 0.42 basis points, they also made small-cap volatility 14.7% higher during the same period, which highlights the segment-specific nature of the efficiency gain. This remains most apparent in the United States Flash Crash of 2010, where the Dow Jones lost almost 1,000 points in a matter of minutes through algorithmic feedback loops. India has witnessed similar events in 2011 and 2012.[6]

### 2.2 The SEBI Regulatory Trilemma

The EEL 2025 study makes a new finding that's relevant for regulatory policy: the clustering of retail algo systems, which react to the same signals in the same way, has the effect of

[4] NSE, 'Digital Transformation of Indian Capital Markets: A Microstructure Analysis 2020–2024' (NSE Research Report, December 2024) https://www.nseindia.com accessed 3 April 2026.
[5] NSE, 'Market Pulse' (NSE Monthly Report, December 2025) https://www.nseindia.com accessed 3 April 2026.
[6] Samarpan Nawn and Abhinava Tripathi, 'Do Proprietary Algorithmic Traders Withdraw Liquidity During Market Stress?' (2019) DOI:10.1111/fima.12238

increasing the volatility of small-cap stocks, with this retail algo herding hitting 2.7 orders per second in rising prices. So, the 2022 Sebi move to restrict order-to-trade ratio from 100:1 to 50:1 was successful in lowering the number of cancellations by 32%, but also raised the small-cap spreads by 0.15 basis points. This can be called as the SEBI Regulatory Trilemma: market stability, market liquidity, and regulatory innovation cannot be maximised together. Regulatory measures to enhance one will come at the cost of the other. There is no free lunch. There will be a trade-off, as there no such thing as a free lunch in algorithmic regulation and, hence, market regulation should only proceed if this is recognised

## 3. The Predictability Problem: When Order Becomes Exploitable

The literature on algorithmic trading in economics equates predictability with efficiency: the more predictable the market the more efficient it is. This is not necessarily wrong, but it is not the whole story. It's missing a big piece, particularly in terms of the overall effect of predictability that plays a significant role in markets where the players with the biggest computing power aren't price-takers but price-makers.

### 3.1 How AI Creates Patterns

Machine learning algorithms are pattern recognisers. They are fed historical data to find the statistical regularities in this data, they then respond to these perceived regularities. If a large enough percentage of market participants use algorithms that are trained on similar data sets and optimised for similar goals then the patterns identified become a self-fulfilling prophecy: the algorithm notices that other algorithms buy when indicator X exceeds threshold Y, so it buys just before the indicator reaches the threshold to capture the price movement following, thus causing the indicator to reach the threshold earlier, thus reinforcing the pattern when the algorithm is retrained. This becomes an ever tighter feedback loop over time.

The NSE Digital Transformation Study has empirical evidence, that confirms that this is not a hypothetical. It reveals that between 2022-2024, the NSE equity markets have become more mean reverting, and that there is statistical evidence that prices are moving in ways that are consistent with past observations. This is not allocatively-efficient markets; it is algorithmically-efficient markets. Prices aren't moving more quickly towards their fundamental values because superior information is being accounted for; they are oscillating in patterns that algorithms have learned, and in learning have made more likely.[7]

[7] Frank Zhang, 'High-Frequency Trading, Stock Volatility, and Price Discovery' (Yale School of Management Working Paper, December 2010) https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1691679

### 3.2 When Patterns Become Vulnerabilities

A market that's patterned is a market that's exploitable by anyone with the computing power to perceive the pattern before most other traders. This is the nature of the problem that is enabling the most complex forms of algorithmic front-running, not the brute force information-based front-running that knows of specific orders in the market (which is clearly prohibited by the PFUTP Regulations), but the more subtle pattern-based front-running that works with public market information to infer where the systems of other market participants are likely to be positioned.

### 3.3 The Predictability-Accountability Gap

The predictability problem creates what might be termed a predictability-accountability gap: a gap in which value is extracted from less technologically-advanced market participants through conduct that isn't fraudulent and manipulative in a traditional sense, but which is enabled by algorithmic patterns that effective market regulation should take into account.

**Real-World Illustration :** ***NSE Co-location, Advantage as Economic Harm***

The NSE co-location scandal exemplifies the predictability problem. The "fast" access to tick-by-tick data feeds that some market participants received was not just a regulatory no-no, it was a economic advantage that compounds. The three top HFT firms that captured 80% of HFT profits on NSE in 2010-2015 were trading in a market where co-location meant they got data milliseconds ahead of other market participants. To a high-frequency algorithm, milliseconds matter. In a market with price movements that algorithms forecast and exploit, being first to see the data means being first to see the pattern, and hence first to position for the pattern, and hence first to exploit the pattern.

The co-location advantage was a super-sized version of the exploitability of predictability: a major aspect of market design that translated informational timing into profits at the expense of those who had an equivalent access to the same underlying data, but with a slight delay in the receipt of the information. The cumulative financial loss totalling over INR 1,000 crore in litigation. The economic, the aggregate value of the value shift from the disadvantaged members to the co-location members over five years of differential access, was not computed for disgorgement or compensation.

## 4. The Distribution Diagnosis: Who Benefits and Who Pays

### 4.1 The SEBI F&O Study 2024: The Stark Numbers

There's no way around the distributional punchline of the September 2024 SEBI F&O Study in any assessment of the economic consequences of AI trading in India. The figures are worth spelling out, because they are the best economic case for stamping out the problem, and the best case against the unconditional democratisation story.

Proprietary traders have earned INR 33,000 crore in gross trading profits in the equity F&O market in financial year 2024. Foreign Portfolio Investors earned INR 28,000 crore. That's 97% of profits for FPIs and 96% for proprietary traders that is related to algorithmic trading either directly or indirectly. But 93% of 1.13 crore individual traders who traded in the F&O segment in the period FY2022 - FY2024 have lost money, with total losses in the last three years amounting to over INR 1.8 lakh crore. The retail algorithmic trading data are even more telling, only about 13% of individual traders availed algorithmic trading in FY2024. Yet, even these individual traders who used algorithmic trading, who took advantage of the democratised API economy, have also incurred losses of INR 27,700 crore. Algorithmic trading didn't democratise the markets, it enabled retail traders to lose money faster to better-trained, better-resourced institutional algorithms that enjoy advantages that retail algorithms can never overcome.[8]

These figures have an economic meaning in the predictability analysis. If institutional AI algorithms are exploiting the predictability of retail investors, placing themselves in front of the retail flows and siphoning value from the patterns that retail trading creates, then the distributional effect that SEBI reported is not just the result of retail investors taking on these enormous risks, the result of a market structure that has adapted to extract value from retail predictability at a scale and speed that human intuition cannot perceive or defend.

**4.2 The Generational Dimension**

The SEBI F&O Study also reveals another distributional issue: the proportion of young traders (below 30 years of age) in F&O has increased from 31% in FY2022-23 to 43% in FY2023-24. These traders are often financially naïve and are attracted by gamified trading and the social capital of trading. They are also more likely among those losing money in algorithmically intensive markets. The social cost of these losses extends beyond the immediate financial damage: young investors who sustain major losses early in their investment lives may exit the capital market entirely, thus reducing long-term retail participation and the democratic

[8] SEBI, 'Study on Analysis of Profit and Loss of Individual Traders dealing in Equity Futures and Options (F&O) Segment' (SEBI Research Report, September 2024) https://www.sebi.gov.in/reports-and-statistics/research/sep-2024/study-on-analysis-of-profit-and-loss-of-individual-traders-dealing-in-equity-futures-and-options-f-o-segment_86786.html

ownership of productive capital that healthy equity markets should promote. [9]

| Trader Category | Profit/Loss (FY24) | Algo-Attribution | Aggregate (FY22-24) |
|---|---|---|---|
| Foreign Portfolio Investors | + INR 28,000 cr (gross) | 97% via algo | Not disclosed separately |
| Proprietary Traders | + INR 33,000 cr (gross) | 96% via algo | Not disclosed separately |
| Individual Traders (algo-using) | – INR 27,700 cr | Algo use did not help | Subset of INR 1.8 lakh cr |
| Individual Traders (all) | – INR 61,000 cr | 93% incurred losses | – INR 1.8 lakh crore |

**Table 2:** SEBI F&O Study 2024 — Algorithmic vs Non-Algorithmic Trading Outcomes (FY2024). Source: SEBI, 'Study on Analysis of Profit and Loss of Individual Traders in the Equity F&O Segment' (September 2024).

## 5. The Market Concentration Problem and the CCI

### 5.1 The Structure of the AI Value Chain

The Competition Commission of India's (CCI) seminal Market Study on Artificial Intelligence and Competition released on 6 October 2025 is the first such regulatory examination of the impact of AI on market structures and competition in India. The Study highlights a key feature of the AI value chain: it's concentrated across the value chain. Foundation models are created by a few tech giants. The computing power is dominated by an even fewer number of cloud services providers. The data used to train the most advanced AI systems are proprietary and held by entities that have decades' worth of data that are difficult to replicate. In the context of the capital markets, this concentration issue plays out directly: the most advanced algorithmic trading systems, such as those that produced 97% of FPI profits in FY2024, are run by entities with access to proprietary data, more powerful computing resources and teams of quantitative

[9] Palak Shah, 'SEBI Study: 9 out of 10 F&O Traders Lose Money; Average Loss INR 1.1 Lakh' *The Hindu BusinessLine* (Mumbai, 25 September 2024) https://www.thehindubusinessline.com

analysts than retail participants and smaller institutions.[10]

### 5.2 When Does Algorithmic Concentration Trigger the CCI?

The Competition Act 2002 outlaws anti-competitive agreements (Section 3) and abuse of dominance (Section 4). There are three scenarios to consider in algorithmic trading. First, algorithmic collusion: the CCI AI Market Study 2025 expressly lists pricing algorithms as a risk of potentially creating unintentional coordination in pricing practices that may constitute a Section 3 violation. Algorithms can independently learn to coordinate their actions by responding to each other's signals, rather than interacting via humans. The Supreme Court's ruling in *Samir Agrawal v CCI* highlights the current challenges of applying Section 3 to this situation.

Second, dominance via data monopolisation: a company using superior market data to build AI systems that perform better than those of others may be using market power that feeds to the Section 4 dominance. Third, platform self-preferencing: Large brokerage platforms that operate both proprietary algorithmic trading systems and provide retail API access face a clear conflict of interest, their proprietary algorithms may be designed to take advantage of the order flow generated by the retail API users (in effect, training their algorithms using the data of their clients).[11]

## 6. The IndiaAI Mission and the Innovation Counterargument

A rigorous economic analysis needs to take into account the innovation counterargument. The IndiaAI Mission, India's own government funded mission with INR 10,300 crore and for the years 2024-29, is a commitment to build India as an AI superpower. The CCI AI Market Study 2025, by a "light-touch" approach, advocates for self-audits and increased transparency with a focus on competition rather than specific interventions. This is a real regulatory conundrum; firstly, a heavy-handed approach to address distributional and competition issues may impede innovation that leads to efficiency outcomes. And second, there is a direct policy implication in the SEBI Regulatory conundrum: interventions that benefit retail investors may harm market efficiency; interventions that improve market efficiency may harm retail investors. The answer is the principle of proportionality, tailoring regulatory requirements according to risk, imposing the highest governance standards on the AI applications which have the most potential for

[10] Competition Commission of India, 'Market Study on Artificial Intelligence and Competition in India' (CCI Market Study, October 2025)
[11] Ministry of Corporate Affairs, 'Report of the Committee on Digital Competition Law' (Government of India, March 2024)

harm, and leaving room for the AI applications that have been shown to have the least risk.[12]
The economic implications of AI-driven trading in Indian capital markets is, both, complex and worrying. Intricate, because there have been real gains in the financial structure of India: revealing to us in real-time, narrower spreads with deeper markets; quicker price discovery; and greater market participation. It is true, that there are efficiency gains. At the same time, it is also worrying because the distributional impact is significant and growing at an ever increasing pace (INR 1.8 lakh crore in retail losses in three years; institutional profits of approximately, 97% are directly/indirectly driven by algorithms; with the immediate and more morbid implication being that the young and financially naive retail population will keep losing to machines that they cannot compete with on level footing).

The predictability analysis adds to the normal efficiency-vs-distribution analysis; that the efficiency benefits and the distributional consequences are not simply the by-products of the same technology. They are related, it is a you-know-as-you-go-fact that, AI makes markets more efficient by making them more patterned. Exploitable markets by those with the big data capacity to exploit patterns. And the exploitation is easier against those who display 'predictable' behaviours. The more emotional and less diversified (strategically) behaviours become, the more predictable they become, and therefore structurally the most predictable, and the most exploitable in terms of economic forces that AI efficiency gives rise to. The CCI AI Market Study 2025 describes the competition law aspect in terms of concentration and algorithmic collusion. Efficiency, distribution and systemic risk and the exploitation of the pattern predictability combine to form this economic justification for regulatory intervention that extends beyond the conduct-specific market abuse prohibitions.

**Conclusion:**

This chapter has examined the economic consequences of AI and algorithmic trading in Indian capital markets across four analytical dimensions: gains, limits and reversals, the problem of predictability, and the distributional diagnosis of who ultimately benefits and who bears the costs. The efficiency dividend is not in dispute, the halving of the price adjustment half-life, and the growth in algorithmic participation in stock futures from 39% to 73% over a decade, these are material improvements in the quality of India’s capital markets as mechanisms for price discovery and capital allocation. They are improvements that benefit all market

[12] Ministry of Electronics and Information Technology, 'IndiaAI Mission' (Government of India, 2024) https://indiaai.gov.in

participants, including those who do not themselves use algorithms.

The efficiency case cannot be allowed to stand on its own. The predictability analysis adds a dimension to the efficiency–distribution trade-off that the existing literature has not fully integrated. Indian equity markets have become measurably more mean-reverting and patterned since 2022.

The conclusion that emerges is that the economic evidence for regulatory intervention in AI-driven Indian capital markets is strong, and multi-dimensional, it cannot be reduced to a simple efficiency-versus-risk framing.  None of these arguments is, by itself, decisive. Together, they constitute a case for regulatory reform that the following chapters develop in legal and institutional terms.