ALGORITHMIC PRICING AND COMPETITION LAW IN INDIA: CAN ARTIFICIAL INTELLIGENCE FACILITATE TACIT COLLUSION IN DIGITAL MARKETS?

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ABSTRACT

Firms across digital markets increasingly delegate pricing decisions to artificial intelligence ("AI") systems that observe rivals' prices and adjust in real time. Experimental economics literature and, more recently, findings by the Competition Commission of India ("CCI") itself, suggest that such systems can independently converge on supracompetitive prices without any human agreement, communication, or shared intent to restrain trade.

This paper examines whether Section 3 of the Competition Act, 2002, as amended in 2023, is doctrinally equipped to address this phenomenon. It distinguishes four categories of algorithm-facilitated coordination algorithm-as-implementation of an existing human agreement, hub-and-spoke coordination through a shared third-party algorithm, signalling through parallel but independently deployed algorithms, and fully autonomous tacit collusion between self-learning pricing agents and tests each against the statutory requirement of an "agreement" and the evidentiary standard the Supreme Court has developed in *Rajasthan Cylinders and Containers Ltd. v. Union of India* and the cement cartel litigation. It argues that while the 2023 amendment's hub-and-spoke proviso captures the second category, and ordinary agreement doctrine captures the first, the third and fourth categories the ones AI most distinctively enables sit outside the current framework's conceptual reach, which still anchors liability to a demonstrable meeting of minds.

Drawing on the CCI's October 2025 *Market Study on Artificial Intelligence and Competition*, the Ninth and Third Circuits' divergent rulings in *Gibson v. Cendyn Group* and *Cornish-Adebiyi v. Caesars Entertainment*, the United States Department of Justice's 2025 settlement with RealPage, and California's Assembly Bill 325, the paper situates the Indian position within

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a rapidly developing comparative landscape. It concludes that India need not, and should not, legislate a blanket presumption that algorithmic parallelism is collusive; instead it proposes a calibrated response combining a rebuttable evidentiary presumption keyed to specific technological "plus factors," mandatory algorithmic disclosure obligations modelled on the CCI's own self-audit guidance, and enhanced regulatory capacity within the Commission to interrogate pricing models directly.

Keywords: algorithmic collusion, tacit coordination, Competition Act 2002, hub-and-spoke cartels, Section 3, artificial intelligence, dynamic pricing, comparative antitrust

I. INTRODUCTION

Consider two competitors in a digital market, neither of whom ever communicates with the other, each of whom deploys a self-learning pricing algorithm to set prices for an identical product. Over thousands of iterations, each algorithm discovers without being told, and without any human at either firm intending it that undercutting the rival's price triggers retaliation, and that restraint is repaid with restraint. Prices settle at a level neither firm could have sustained unilaterally, and both algorithms simply continue doing what has proved profitable. No meeting occurred. No email was sent. No spreadsheet changed hands. Yet consumers pay more than they would in a competitive market, and the outcome is functionally indistinguishable from a cartel.

This scenario is no longer speculative. The Organisation for Economic Co-operation and Development ("OECD") flagged the theoretical possibility as early as 2017,[4] and a decade of experimental work using reinforcement-learning agents has since demonstrated that pricing algorithms can converge on collusive outcomes purely through repeated market interaction, with no line of code instructing them to collude.[5] The Competition Commission of India ("CCI"), in its October 2025 *Market Study on Artificial Intelligence and Competition*, has now formally recognised the same risk within Indian markets, describing it as the "novel risk of algorithmic collusion" and observing that self-learning algorithms may "independently adopt

[4]OECD, Algorithms and Collusion: Competition Policy in the Digital Age, OECD Roundtables on Competition Policy Papers No. 206 (2017).

[5]See Emilio Calvano et al., Artificial Intelligence, Algorithmic Pricing, and Collusion, 110 Am. Econ. Rev. 3267 (2020); Stephanie Assad et al., Algorithmic Pricing and Competition: Empirical Evidence from the German Retail Gasoline Market, 132 J. Pol. Econ. 723 (2024) (finding algorithmic adoption in the German fuel retail market associated with an approximately 15% increase in margins).

cooperative pricing strategies that maximise profits" without any human involvement.[6]

Indian competition law, however, was built for a different problem. Section 3 of the Competition Act, 2002 ("the Act") prohibits "agreements" that cause an appreciable adverse effect on competition, and Indian courts and tribunals following a long line of authority beginning with the cement cartel litigation and culminating in the Supreme Court's decision in *Rajasthan Cylinders and Containers Ltd. v. Union of India* have consistently insisted that mere parallel pricing, however suspicious, is not enough; some "plus factor" evidencing a meeting of minds is required.[7] The Competition (Amendment) Act, 2023 extended Section 3(3) to capture "hub-and-spoke" arrangements where competitors coordinate indirectly through a common, non-competing intermediary but even this amendment presumes that some party, somewhere, "participates or intends to participate in the furtherance" of an agreement.[8] The doctrinal architecture of Section 3, in other words, still assumes a human somewhere who intends to coordinate. Autonomous algorithmic collusion of the kind described above dispenses with exactly that assumption.

This creates a genuine gap, not merely a rhetorical one. If two firms independently decide, for entirely unilateral reasons, to adopt self-learning pricing software, and that software then converges on a coordinated outcome through pure market feedback, there is no agreement in the conventional sense, no communication, and frequently no way even for the firms themselves to explain why the algorithm settled on the price it did a consequence of what computer scientists call the "black box" problem inherent in deep reinforcement learning.[9] The question this paper asks is not whether AI *causes* collusion a claim far too broad to be analytically useful but rather: under what conditions can AI-powered pricing algorithms facilitate tacit coordination, and is the existing Indian competition law framework, even as amended in 2023, equipped to address the resulting harm?

A. Research Questions and Hypotheses

This paper is organised around four research questions.

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[6]Competition Commission of India, Market Study on Artificial Intelligence and Competition 49 (Oct. 6, 2025) [hereinafter CCI AI Study].
[7]Rajasthan Cylinders & Containers Ltd. v. Union of India, (2018) 16 SCC 413 (India); Builders Ass'n of India v. Cement Manufacturers' Ass'n, Case No. 29 of 2010 (CCI Aug. 31, 2016) (India).
[8]Competition (Amendment) Act, 2023, No. 9 of 2023, § 3(a), inserting a second proviso to § 3(3) of the Competition Act, 2002 (India).
[9]CCI AI Study, supra note 3, at 51 (noting that self-learning algorithms "often operate as black-boxes making it difficult to detect or address anti-competitive practices arising therefrom").

RQ1: What distinct forms does algorithmic pricing coordination take in digital markets?

RQ2: To what extent can AI-powered pricing algorithms facilitate tacit collusion among competing firms?

RQ3: Are the existing provisions of Section 3 of the Competition Act, 2002, including the 2023 amendment, adequate to address autonomous algorithmic coordination?

RQ4: What regulatory and enforcement mechanisms could India adopt to address algorithmic collusion while preserving the efficiency benefits of algorithmic pricing?

Correspondingly, the paper tests two hypotheses. **H1**: the increasing use of AI-powered pricing algorithms can facilitate stable tacit coordination by increasing market transparency, predictability, and the speed of competitive response, thereby creating enforcement challenges for traditional competition law doctrine. **H2**: the existing framework of Indian competition law faces evidentiary and conceptual difficulties in addressing autonomous algorithmic coordination where no demonstrable human agreement exists. Neither hypothesis assumes that AI adoption automatically produces collusive outcomes; both are tested against the specific market and technological conditions under which coordination becomes more, or less, likely.

Part II develops a typology of algorithmic pricing coordination. Part III examines the doctrinal foundations of Section 3 and the 2023 amendment against that typology. Part IV undertakes a doctrinal stress-test of each category of coordination against the agreement requirement. Part V places the Indian position within comparative context, examining recent developments in the United States, the European Union, and California. Part VI engages directly with the CCI's own 2025 findings. Part VII considers consumer welfare implications, and Part VIII proposes regulatory reforms. Part IX summarises findings, Part X offers suggestions, and Part XI concludes.

II. THE ARCHITECTURE OF ALGORITHMIC PRICING: FROM HUMAN CARTELS TO MACHINE-MEDIATED COORDINATION

Competition scholars conventionally classify pricing algorithms that raise collusion concerns into four types: monitoring algorithms, parallel algorithms, signalling algorithms, and self-

learning algorithms.[10] Monitoring algorithms scrape competitor prices and function as messengers or data-collection tools; they enable coordination but do not themselves set prices. Parallel or "hub-and-spoke" algorithms arise where multiple competitors licence pricing recommendations from a common third-party vendor, which pools competitively sensitive data across its client base. Signalling algorithms respond to market conditions through sophisticated statistical models capable of tacitly communicating pricing intentions without any explicit agreement. Self-learning algorithms, typically built on deep reinforcement learning, operate with the sole objective of profit maximisation and are capable of discovering collusive strategies as an emergent property of repeated market interaction, without being programmed to collude and often without their operators understanding why a particular price was set.[11]

For the purposes of a Section 3 analysis, it is more useful to reorganise this typology around the degree of human intent involved, since intent or its conspicuous absence is precisely what Indian doctrine treats as decisive.

A. Category 1: Algorithm as Implementation of an Existing Human Agreement

In the simplest case, two or more competitors first reach an explicit human agreement to fix prices say, at ₹1,000 per unit and then use algorithms merely to implement and monitor compliance with that pre-existing agreement. Here, the algorithm is doctrinally irrelevant: the human agreement supplies the illegality, and the algorithm is simply the mechanism of execution, no different in principle from a cartel that uses a shared spreadsheet or a trade association circular to police compliance. Existing Section 3 doctrine applies to this category without modification.

B. Category 2: Hub-and-Spoke Coordination through a Shared Third-Party Algorithm

Here, competing firms independently licence pricing software from the same third-party vendor. The vendor's algorithm ingests each client's non-public pricing and occupancy or inventory data, pools it across the client base, and returns pricing recommendations calibrated to what the whole market is doing. No client firm need ever communicate directly with a rival; the vendor's algorithm performs the function a human intermediary would perform in a classic

[10]Ariel Ezrachi & Maurice E. Stucke, The Role of Secondary Algorithmic Tacit Collusion in Achieving Market Alignment, Univ. of Tenn. Legal Studies Research Paper CCLP(L)54 (2023); OECD, Algorithmic Competition, OECD Roundtables on Competition Policy Papers No. 296 (2023).
[11]CCI AI Study, supra note 3, at 49–51.

hub-and-spoke cartel. This is precisely the fact pattern that has driven a wave of litigation in the United States against real-estate and hospitality pricing vendors such as RealPage and Cendyn Group's Rainmaker software, discussed in Part V.

C. Category 3: Signalling Through Independently Deployed, Non-Communicating Algorithms

In this category, competitors deploy separate, independently designed algorithms not a shared vendor product that nonetheless read public or semi-public signals from one another (posted prices, promotional patterns, inventory levels) and adjust rapidly. No data pooling occurs and no vendor sits in the middle; the algorithms simply react to each other's observable market conduct at a speed and with a consistency no human pricing team could match. The Supreme Court's decision in *Samir Agrawal v. Competition Commission of India* concerned an allegation of precisely this kind against Ola and Uber, discussed in Part III.[12]

D. Category 4: Autonomous Algorithmic Collusion

The most conceptually difficult category involves self-learning algorithms that, through iterative exposure to market data and a reward function tied solely to their own firm's profit, independently discover that sustained higher prices outperform aggressive competition, and thereafter maintain elevated prices as an emergent equilibrium. Experimental studies using Q-learning agents in simulated Bertrand and Stackelberg competition have repeatedly demonstrated this outcome under laboratory conditions.[13] Whether this laboratory phenomenon translates reliably into real-world markets, where noise, differentiated products, and imperfect information are far greater than in a simulated Bertrand duopoly, remains empirically contested a point to which this paper returns in Part VII but the CCI's own market study now treats it as a live regulatory concern for the Indian economy rather than a purely theoretical one.[14]

It is this fourth category no meeting, no phone call, no email, no shared vendor, and no human agreement of any kind that supplies the central research problem of this paper: autonomous

[12]Samir Agrawal v. Competition Comm'n of India, Civil Appeal No. 3100 of 2020 (S.C., decided Dec. 15, 2020) (India).
[13]Calvano et al., supra note 4; Timo Klein, Autonomous Algorithmic Collusion: Q-Learning Under Sequential Pricing, 52 RAND J. Econ. 538 (2021); Martino Banchio & Giacomo Mantegazza, Artificial Intelligence and Spontaneous Collusion, arXiv:2202.05946 (2023).
[14]CCI AI Study, supra note 3, at 49 ("Though self-learning algorithms as well as signaling algorithms may not have been designed to achieve collusion, they may still reach collusive outcomes on their own depending upon the market conditions.").

algorithmic collusion under Section 3 of the Competition Act, 2002.

III. THE DOCTRINAL PROBLEM: TACIT COLLUSION AND THE CONCEPT OF "AGREEMENT" UNDER SECTION 3

A. The Statutory Text and the Rejection of Parallelism Simpliciter

Section 3(1) of the Act prohibits any "agreement" that causes or is likely to cause an appreciable adverse effect on competition within India. Section 2(b) defines "agreement" expansively to include "any arrangement or understanding or action in concert," whether or not formal, in writing, or intended to be enforceable by legal proceedings.[15] Section 3(3) creates a presumption of appreciable adverse effect for horizontal agreements among competitors that fix prices, limit production, share markets, or engage in bid rigging. On its face, the phrase "action in concert" appears capacious enough to reach informal, tacit coordination.

In practice, however, the CCI and appellate authorities have been markedly cautious about inferring an agreement from parallel conduct alone. In the cement cartel proceedings, the Commission found extensive circumstantial evidence including near-identical price movements coordinated through the Cement Manufacturers' Association, exchange of output and dispatch data, and a pattern of price increases despite falling input costs and only on the strength of this combination of parallel pricing *plus* institutional facilitation did it find a Section 3 violation.[16] The Supreme Court's subsequent decision in *Rajasthan Cylinders and Containers Ltd. v. Union of India* confirmed this "plus factor" approach in the clearest terms, holding that parallel pricing behaviour, standing alone, is "consistent with a wide swath of rational and competitive market behaviour," and that something more evidence of communication, exchange of sensitive information, or an underlying facilitating structure is required before an inference of concerted action becomes sustainable.[17] This is doctrinally significant for present purposes: it means Indian law, like its American and European counterparts, has already confronted and rejected the proposition that mere price parallelism, without more, can ground liability. Algorithmic tacit collusion of Category 4 is, definitionally, parallelism *without* the "more" that *Rajasthan Cylinders* requires there is no association facilitating exchange, no shared data pool, and frequently no direct evidence of communication at all, because none

[15]Competition Act, 2002, No. 12 of 2003, § 2(b) (India).
[16]Builders Ass'n of India v. Cement Manufacturers' Ass'n, Case No. 29 of 2010 (CCI Aug. 31, 2016) (India) (imposing penalties aggregating over ₹6,700 crore on eleven cement manufacturers).
[17]Rajasthan Cylinders & Containers Ltd. v. Union of India, (2018) 16 SCC 413, ¶¶ 36–42 (India).

occurred.

B. Samir Agrawal and the Limits of the Existing Framework

The Supreme Court's decision in *Samir Agrawal v. Competition Commission of India* is the closest Indian precedent squarely on algorithmic pricing, and its limitations illustrate the gap this paper identifies. The informant alleged that Ola and Uber, through their respective surge-pricing algorithms, facilitated a "hub-and-spoke" cartel among individual drivers, with each platform acting as the hub coordinating otherwise-competing drivers as spokes. The Court upheld the CCI's dismissal of the allegation, reasoning that drivers on a platform do not independently determine prices in competition with one another in the relevant sense, and that the platforms' pricing algorithms served a legitimate function of matching supply with demand rather than facilitating horizontal coordination between competing undertakings.[18] *Samir Agrawal* is therefore best read narrowly: it resolved a vertical platform-driver dynamic, not a horizontal case of two independent competing firms each deploying their own self-learning pricing algorithm against the other. It leaves entirely open rather than answers the harder question this paper poses: whether two horizontally competing firms whose independent, non-communicating algorithms converge on a coordinated price can be said to have entered an "agreement" or "action in concert" within the meaning of Section 2(b).

C. The 2023 Amendment and Its Hub-and-Spoke Proviso

The Competition (Amendment) Act, 2023 inserted a new proviso to Section 3(3), extending the presumption of an appreciable adverse effect to an enterprise that, "although not a party to any such agreement," nevertheless "participates or intends to participate" in furtherance of a price-fixing, output-restriction, market-sharing, or bid-rigging agreement between competitors.[19] This was a direct legislative response to the hub-and-spoke gap exposed by cases like *Samir Agrawal* and by earlier CCI orders that had struggled to bring a non-competing intermediary (a trade association, a common vendor, a platform) within the reach of Section 3 where that intermediary was not itself a horizontal competitor of the parties it coordinated.[20]

[18]Samir Agrawal v. Competition Comm'n of India, Civil Appeal No. 3100 of 2020, ¶¶ 14–22 (S.C., decided Dec. 15, 2020) (India).
[19]Competition (Amendment) Act, 2023, No. 9 of 2023, § 3(a) (India), inserting the second proviso to § 3(3) of the Competition Act, 2002.
[20]See In re Alkem Laboratories Ltd., Case No. 1 of 2021 (CCI) (India) (early articulation of hub-and-spoke concerns under the pre-amendment framework).

Category 2 coordination in the typology developed in Part II competitors coordinating indirectly through a shared third-party pricing algorithm now falls squarely within this amended text: the vendor supplying the common algorithm "participates" in furthering the arrangement between its competing clients even though it is not itself a competitor of any of them.

But the 2023 amendment does not solve the harder problem. Its proviso still requires an underlying "such agreement" among the horizontal competitors it merely extends liability outward to a facilitating third party, rather than dispensing with the need for horizontal agreement altogether. Category 3 (independently deployed signalling algorithms) and Category 4 (autonomous algorithmic collusion) involve no shared vendor and no facilitating hub at all: two competitors each build or licence entirely separate algorithms, and coordination emerges purely from repeated market interaction between the two systems. There is no hub for the proviso to reach, and, per *Rajasthan Cylinders*, no plus factor beyond the parallelism itself. The 2023 amendment therefore closes the hub-and-spoke gap while leaving the autonomous-collusion gap entirely untouched confirming H2.

IV. CAN AUTONOMOUS ALGORITHMIC COORDINATION SATISFY SECTION 3? A DOCTRINAL STRESS-TEST

This Part applies the agreement/concerted-practice standard developed in Part III to each category identified in Part II, in order to answer RQ2 and RQ3 directly.

Category 1:

(algorithm as implementation) satisfies Section 3 without difficulty: the human agreement supplies the illegality and the algorithm is evidentiary surplus indeed, in practice, algorithmic logs of an agreed price schedule make such cases *easier* to prove than traditional cartels, since the algorithm creates a persistent digital record of what was agreed and when.

Category 2:

(hub-and-spoke via shared vendor) now satisfies Section 3(3) under the 2023 proviso, provided the informant or the Commission can establish (a) an underlying agreement or concerted practice among the client-competitors to follow the vendor's recommendations, and (b) the vendor's knowing participation in furthering that arrangement. This tracks the approach

taken by United States courts in the RealPage litigation, discussed in Part V, and is consistent with the CCI's own market study, which explicitly flags common third-party algorithms as a coordination risk warranting scrutiny.[21]

Category 3:

(independent signalling algorithms) is considerably harder. *Samir Agrawal* suggests the Commission will look for evidence that the platforms or firms in question specifically designed their algorithms to read and respond to a rival's pricing signals with anti-competitive intent, rather than to optimise unilaterally against demand conditions. Absent such evidence, rapid, algorithm-driven price-matching is likely to be treated as sophisticated but lawful unilateral conduct a conclusion reinforced by *Rajasthan Cylinders"* insistence that parallel conduct consistent with rational, independent business judgment cannot ground liability.

Category 4:

(autonomous algorithmic collusion) currently falls outside Section 3 altogether on a strict textual reading. There is no agreement because there is no meeting of minds not even the attenuated, tacit meeting of minds that European law recognises as a "concerted practice" (discussed in Part V.B), because the firms' own executives may not have intended, foreseen, or even understood the coordinated outcome their independently deployed systems produced. This confirms H1 in its strongest form: it is precisely the technological attributes AI introduces continuous monitoring, near-instantaneous response, and the capacity to learn a cooperative strategy without being taught one that generate the enforcement gap, and current Indian doctrine has no answer for it beyond either (a) stretching "action in concert" to include machine-to-machine coordination absent human intent, a move with serious rule-of-law and mens rea implications for a quasi-penal statute, or (b) accepting the gap and looking to ex ante regulatory tools instead of Section 3 liability, which is the position this paper ultimately favours in Part VIII.

V. COMPARATIVE PERSPECTIVES

India is not alone in confronting this problem, and the comparative record much of it generated in just the last two years is instructive both for what has worked and for what remains

[21]CCI AI Study, supra note 3, at 52–54.

unresolved elsewhere.

A. United States: Sherman Act Section 1 and the Agreement Requirement

Section 1 of the Sherman Act prohibits "every contract, combination . . . or conspiracy" in restraint of trade, a textual anchor closely analogous to Section 3's "agreement" requirement, and American courts have historically been just as reluctant as their Indian counterparts to treat parallel conduct alone as sufficient.[22] Two recent, and strikingly divergent, appellate decisions illustrate how far American courts remain from a settled answer. In *Gibson v. Cendyn Group, LLC*, the Ninth Circuit affirmed dismissal of claims that Las Vegas Strip hotels had used a common revenue-management algorithm (Rainmaker) to fix room rates, holding that the plaintiffs had failed to plausibly allege that the hotels agreed to use the algorithm's output *in a coordinated fashion* rather than merely subscribing to the same commercial software independently for their own unilateral advantage.[23] By contrast, the Third Circuit's 2026 decision in *Cornish-Adebiyi v. Caesars Entertainment, Inc.* revived similar claims against Atlantic City casino-hotels using the same Rainmaker system, holding that allegations of shared, competitively sensitive pricing data flowing into a common algorithm that then issued price recommendations the hotels systematically followed were sufficient to plead a hub-and-spoke conspiracy at the motion-to-dismiss stage.[24] The circuit split turns almost entirely on how much is required to infer an "agreement to use the algorithm's output as a coordinating mechanism" from parallel adoption of the same software the exact evidentiary line Indian courts draw through the "plus factor" requirement in *Rajasthan Cylinders*.

The Department of Justice's enforcement action against RealPage, a dominant supplier of algorithmic rent-pricing software to residential landlords, represents the most significant American regulatory response to date. The government's amended complaint alleged that RealPage's software enabled landlords to share non-public rent and occupancy data through a common algorithm that then recommended supracompetitive rents, and, unusually, alleged that human RealPage employees actively pressured landlords to adopt the algorithm's recommendations without deviation reintroducing precisely the human facilitation element that *Rajasthan Cylinders* and the cement cartel cases treat as decisive.[25] The matter settled in

[22]Sherman Act § 1, 15 U.S.C. § 1; see Bell Atl. Corp. v. Twombly, 550 U.S. 544 (2007) (requiring plausible allegations of an actual agreement, not mere parallel conduct, to survive dismissal).
[23]Gibson v. Cendyn Grp., LLC, 148 F.4th 1069 (9th Cir. 2025).
[24]Cornish-Adebiyi v. Caesars Ent., Inc., No. 24-3006 (3d Cir. July 29, 2026).
[25]First Amended Complaint, United States v. RealPage, Inc., No. 1:24-cv-00710 (M.D.N.C. Jan. 2025).

late 2025 with a consent decree requiring RealPage to disclose its pricing methodology, refrain from recommending rents based on pooled competitor data absent adequate anonymisation and aggregation safeguards, and submit to a compliance-monitoring regime a settlement structure that, notably, addresses the problem through algorithmic transparency and design mandates rather than through expanding the definition of "agreement" itself.[26]

B. European Union: Article 101 TFEU and the "Concerted Practice" Standard

European Union competition law offers a doctrinally richer analogue than either the Indian or American frameworks, because Article 101 of the Treaty on the Functioning of the European Union prohibits not only "agreements" but also "concerted practices," a concept the Court of Justice has defined as "a form of coordination . . . which, without having reached the stage where an agreement properly so-called has been concluded, knowingly substitutes practical cooperation . . . for the risks of competition."[27] This standard is significantly more capacious than Section 3's "action in concert," because it can, in principle, be satisfied by conduct falling well short of any communication including, European scholars have argued, conduct where firms merely have foresight of, and accept, the practical effect of adopting a common algorithmic tool that predictably narrows competitive uncertainty between them.[28] Even so, the European Commission has to date proceeded cautiously, and no EU enforcement decision has yet found a pure Category 4 autonomous-algorithmic-collusion violation without some element of prior human coordination or data-sharing; the concerted-practice doctrine remains, at present, a promising conceptual tool rather than a tested one.

C. California's Legislative Response: Assembly Bill 325

Rather than wait for courts to resolve the agreement question, California enacted Assembly Bill 325, effective January 1, 2026, which amends the Cartwright Act to prohibit the use of a common pricing algorithm that relies on the non-public data of two or more competitors, and creates a rebuttable presumption of unlawful coordination where a supplier of such an algorithm coerces or induces multiple competing clients to substantially adopt its

[26]Proposed Final Judgment, United States v. RealPage, Inc., No. 1:24-cv-00710 (M.D.N.C. filed Nov. 2025).
[27]Case 48/69, Imperial Chem. Indus. Ltd. v. Comm'n, 1972 E.C.R. 619, ¶64; Case C-8/08, T-Mobile Netherlands BV v. Raad van Bestuur van de Nederlandse Mededingingsautoriteit, 2009 E.C.R. I-4529.
[28]Ariel Ezrachi & Maurice E. Stucke, Virtual Competition: The Promise and Perils of the Algorithm-Driven Economy 45–62 (2016).

recommended prices.[29] This is, in effect, a legislative codification of the hub-and-spoke theory pressed in *Cornish-Adebiyi*, and it is instructive precisely because it is targeted, evidence-based, and confined to Category 2 California's legislature, like this paper, appears to have concluded that autonomous algorithmic collusion (Category 4) is not yet susceptible to a workable liability rule, and has instead focused reform where the evidentiary picture (shared data, a common vendor, inducement) is clearest.

VI. THE CCI'S OWN RECKONING: THE OCTOBER 2025 AI MARKET STUDY

The Commission's own October 2025 market study is significant less for any single finding than for the fact of its existence: it marks the first occasion on which the CCI has formally acknowledged, in its own institutional voice, that Indian digital markets face a live risk of algorithm-facilitated coordination that existing doctrine may not adequately reach. The study catalogues the same four-part typology developed independently in Part II of this paper, explicitly warns that self-learning and signalling algorithms "may still reach collusive outcomes on their own" even absent any design intent to collude, and flags the "black-box" nature of deep-learning pricing models as an evidentiary obstacle to detection under the Commission's existing investigative toolkit.[30] Notably, the study stops short of recommending any amendment to the statutory text of Section 3 itself; its proposed responses are confined to enhanced market monitoring, encouraging firms to conduct voluntary algorithmic compliance audits, and building internal technical capacity within the Commission to interrogate pricing models submitted in merger review and investigation proceedings.[31] This paper reads that institutional restraint as itself instructive: even the regulator most directly confronted with the problem has concluded that the immediate priority is ex ante regulatory tooling rather than judicial expansion of "agreement" a conclusion Part VIII builds upon rather than displaces.

VII. CONSUMER WELFARE IMPLICATIONS

It is worth pausing on why any of this matters to consumers, since algorithmic pricing is not inherently harmful and indeed carries genuine efficiency benefits: dynamic pricing can clear perishable inventory more efficiently, pass through demand signals faster than static pricing, and, in genuinely competitive markets, can intensify rather than dampen price competition by

[29]Cal. Bus. & Prof. Code §§ 16720.5, 16721.5 (as amended by 2025 Cal. Legis. Serv. ch. 812 (A.B. 325), eff. Jan. 1, 2026).
[30]CCI AI Study, supra note 3, at 49–51.
[31]Id. at 55–58.

enabling firms to undercut rivals in near real time.[32] The consumer harm this paper is concerned with arises specifically where algorithmic adoption *increases* market transparency and the speed of competitive response beyond the point where undercutting remains individually rational precisely the mechanism the German retail-fuel study documented, where algorithmic adoption was associated with a measurable increase in retail margins without any corresponding change in the number of competing stations.[33] Because this harm manifests as elevated prices sustained through tacit coordination rather than through any single dramatic act, it is also comparatively difficult for consumers, journalists, or even competition authorities to detect through casual observation there is no smoking-gun cartel meeting to be exposed, only a pattern of prices that never quite falls as far as unilateral competition would predict. This detection asymmetry is itself a distinct harm: it shifts enforcement costs onto the regulator and makes proactive market studies, of the kind the CCI undertook in 2025, considerably more valuable than complaint-driven enforcement in this specific context.

VIII. REGULATORY OPTIONS FOR INDIA

Four reform options merit consideration, in ascending order of intervention.

A. Enhanced Technical Capacity within the CCI

The most modest and least controversial option is for the Commission to build dedicated technical capacity data scientists and computational economists embedded within the Combinations and Enforcement divisions capable of directly interrogating pricing algorithms submitted or discovered during investigation, including through controlled algorithmic audits that test how a given model responds to simulated rival price changes. This mirrors the approach the CCI's own study recommends and requires no legislative amendment.[34]

B. Mandatory Algorithmic Disclosure for Dominant Pricing Intermediaries

For Category 2 hub-and-spoke arrangements specifically, India could adopt a disclosure obligation modelled on the RealPage consent decree: a vendor supplying pricing algorithms to multiple competing clients in a concentrated market should be required to disclose, on request

[32]OECD, supra note 4, at 12–15 (distinguishing pro-competitive and anti-competitive uses of algorithmic pricing).
[33]Assad et al., supra note 4.
[34]CCI AI Study, supra note 3, at 57.

from the Commission, the categories of data ingested, whether client data is pooled or anonymised, and whether the algorithm is designed to recommend supra-competitive prices when the model detects a client's willingness to forgo short-term volume for margin. This could be implemented through CCI regulations under the existing Section 3 framework without further legislative amendment, since it does not alter the substantive standard for liability but only its evidentiary predicate.

C. A Calibrated, Rebuttable Presumption for Autonomous Coordination

The most difficult category autonomous algorithmic collusion is best addressed not by redefining "agreement" in the abstract, which risks either overreach (capturing genuinely unilateral, procompetitive dynamic pricing) or continued underenforcement (if courts remain anchored to *Rajasthan Cylinders'* plus-factor requirement), but by a narrow, rebuttable statutory presumption triggered only where specific technological plus factors are independently established: (i) each competitor's algorithm is shown to have continuously ingested the rival's real-time pricing data; (ii) the market exhibits sustained supra-competitive margins relative to a plausible but-for competitive benchmark; and (iii) the firms cannot demonstrate that the pricing outcome reflects cost, demand, or capacity conditions rather than strategic interaction with the rival's algorithm. This tracks California's approach in spirit targeted, evidence-anchored, and confined to circumstances where the risk of false positives is lowest while adapting it to the pure autonomous-collusion scenario AB 325 itself does not reach.

D. Regulatory Sandboxes for Dynamic Pricing Innovation

Finally, to preserve the efficiency benefits Part VII identifies, the Commission could operate a voluntary regulatory sandbox in which firms deploying novel self-learning pricing systems in genuinely competitive markets could seek an advisory, non-binding assessment of collusion risk before full-scale deployment, in exchange for algorithmic transparency to the Commission during the sandbox period. This answers RQ4 directly: it allows India to address the collusion risk AI introduces without discouraging the legitimate efficiency gains dynamic pricing can offer to Indian consumers and firms alike.

IX. FINDINGS

First, Section 3 of the Competition Act, 2002, even as strengthened by the 2023 amendment's

hub-and-spoke proviso, adequately addresses Categories 1 and 2 of algorithm-facilitated coordination but not Categories 3 and 4, confirming H2. Second, the technological attributes of self-learning pricing algorithms — continuous monitoring, rapid response, and the capacity to learn cooperative strategies without explicit instruction — are capable of producing stable coordinated pricing outcomes under conditions that remain empirically contingent rather than universal, confirming H1 in a bounded form. Third, the CCI's own October 2025 market study corroborates both propositions from within the regulator itself, and notably favours ex ante regulatory tooling over doctrinal expansion as the appropriate near-term response. Fourth, comparative experience — the U.S. circuit split in *Gibson* and *Cornish-Adebiyi*, the RealPage settlement, the EU's untested concerted-practice standard, and California's targeted legislative fix — shows no jurisdiction has yet resolved the Category 4 problem through adjudication alone; every workable response to date has relied on either regulatory settlement or targeted legislation confined to the hub-and-spoke fact pattern.

X. SUGGESTIONS

This paper suggests that India (1) build dedicated computational-economics capacity within the CCI; (2) introduce, by regulation rather than legislative amendment, algorithmic disclosure obligations for dominant pricing-technology vendors serving multiple competitors in concentrated sectors; (3) enact a narrow, evidence-anchored rebuttable presumption addressed specifically to autonomous algorithmic coordination, confined by the three plus-factors identified in Part VIII.C, so as to avoid chilling legitimate dynamic pricing; and (4) establish a voluntary sandbox mechanism allowing firms to obtain advisory clearance for novel pricing systems before deployment. Together, these measures preserve the efficiency benefits of algorithmic pricing that Part VII identifies while closing the specific doctrinal gap Part IV exposes.

XI. CONCLUSION

The two competitors described at the outset of this paper never spoke to one another, yet their algorithms arrived at exactly the price a cartel would have chosen. Indian competition law, built around the concept of an agreement between human decision-makers, was not designed with this possibility in mind, and the 2023 amendment's hub-and-spoke proviso — however welcome — answers a narrower question than the one autonomous algorithmic collusion actually poses. The honest conclusion is not that Section 3 has failed, but that it was never built to

answer a question this specific, and that the CCI's own 2025 market study is right to look past Section 3 litigation, at least for now, toward the more modest but more achievable project of technical capacity-building, targeted disclosure, and a carefully bounded evidentiary presumption. Whether India ultimately needs to redefine "agreement" itself will depend on how the empirical picture develops over the coming years on whether Category 4 coordination proves to be a genuine and recurring feature of Indian digital markets, or remains, as it has so far in every jurisdiction that has looked for it in adjudicated cases, a well-documented laboratory phenomenon awaiting its first clear real-world test case.