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Antitrust Regulation in the Age of Algorithmic Collusion: Risks, Challenges, and Mitigation Strategies

-- With a Comparative Review of the RealPage Pricing Algorithm Matter and Gibson v. Cendyn Grp.

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ABSTRACT

Algorithmic collusion, leveraging the technological characteristics of deep learning and autonomous decision-making, transcends the established boundaries of traditional antitrust regulation concerning the identification of collusive agreements, the determination of liability, and the collection of evidence. Drawing upon the RealPage Pricing Algorithm matter and the Gibson v. Cendyn Grp. case, this study examines the operational logic and potential legal risks associated with algorithmic collusion, comparing the fundamental differences between the two instances in terms of algorithm functional design and market intervention effects. Addressing the regulatory challenges inherent in algorithmic collusion-specifically concerning the establishment of concertation ('meeting of minds'), evidence gathering, and liability allocation-this paper proposes a core strategy centered on multi-dimensional technical governance. This strategy aims to curb anomalous pricing behavior through mechanisms such as algorithmic 'speed bumps' and pricing constraints, combined with enhanced trace supervision via log recording, real-time monitoring, and the application of explainability techniques. Furthermore, it suggests utilizing an autonomy scoring model to establish a tiered evaluation framework for liability allocation. The study posits that, predicated on the monitoring and identification of anomalous market behavior, the utilization of indirect evidence and economic analysis can be instrumental in revealing the non-competitive character of algorithmic collusion, thereby bolstering the basis for liability determination. Consequently, the establishment of precise stratification, the integration of technical assistance, and the development of clear liability allocation mechanisms are identified as critical approaches for antitrust regulation in the context of algorithmic collusion, crucial for effectively mitigating the adverse impacts of technological misuse on the competitive market process.

KEYWORDS

Antitrust Regulation; Algorithmic Collusion; RealPage's Pricing Algorithm Case; Gibson v. Cendyn Grp. Case.

1. CASE-LAW INQUIRY: A JUXTAPOSITION OF THE REALPAGE PRICING-ALGORITHM LITIGATION AND GIBSON V. CENDYN GROUP

1.1. The Operational Architecture of the Algorithm in the RealPage Matter

The RealPage Pricing-Algorithm case was brought jointly by the U.S. Department of Justice ("DOJ") and several state attorneys general against RealPage, Inc., a provider of property-management

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software. The complaint alleges that RealPage, by means of an algorithmic pricing tool, collected non-public, competitively sensitive rental data from participating lessors, integrated such data into an optimization model that was capable of self-learning, and disseminated uniform rent recommendations, thereby inducing landlords to set rents at anticompetitive levels in violation of Sections 1 and 2 of the Sherman Act of 1890 (as amended Jan. 5, 2010), 15 U.S.C. §§ 1–2.

In the instant matter , RealPage harvested non-public transactional data from landlords using its "LRO" (Lease Rent Options) platform-e.g., apartment rents, occupancy rates, and other lease terms. The data were fed into an algorithmic model that, inter alia, assimilated rival landlords' pricing, convened "user groups" that facilitated the sharing of landlords' individual pricing strategies, and enabled each landlord to monitor competitors' price behavior so as to avoid being undercut. Employing machine-learning techniques, RealPage continuously refined its pricing recommendations on the basis of market inputs and user behavior, furnishing dynamic rent suggestions to participating landlords. Functionally, the scheme utilized (i) market-wide transactional data as inputs, (ii) algorithmic optimization as the analytical mechanism, (iii) the RealPage platform as the coordinating hub, and (iv) iterative machine learning as the backend enhancer, all with the object-and effect-of dampening price competition, elevating overall rent levels, and steering landlords toward convergent pricing strategies, i.e., an "algorithmic pricing cartel." As the algorithm learned and improved, landlords became ever more dependent on its outputs, while RealPage deepened its control over that segment of the market, further constricting the competitive leeway traditionally available to landlords to vie for tenants via price, discounts, or lease terms. The ultimate economic effect was to strip tenants of the benefits that would otherwise have flowed from unfettered competition.

The DOJ and the attorneys general alleged that RealPage held an 80 percent share in the U.S. multi-family residential revenue-management-software market and contractually required participating landlords to furnish non-public data in exchange for pricing guidance. RealPage also arranged periodic "call-arounds" whereby rival landlords could discuss rents and occupancy rates. An "Auto-Accept" feature permitted landlords to adopt algorithmic rent suggestions without human override. In practice, the algorithm produced a "maximize increases / minimize decreases" posture: during favorable demand conditions the LRO system proposed specific rent hikes; when demand softened, it recommended non-price measures (promotions, service enhancements) rather than price reductions-all to the detriment of tenants.

1.2. The Operational Architecture of the Algorithm in Gibson v. Cendyn Group

In Gibson v. Cendyn Group, LLC, plaintiffs Richard Gibson and Roberto Manzo filed a putative class action as consumers against Caesars Entertainment, Inc., certain Blackstone entities, [1]Wynn Resorts, and Cendyn Group, LLC. Plaintiffs alleged that the defendant hotels employed Cendyn's "GuestRev" (individual room pricing) and "GroupRev" (group-booking pricing) algorithms, each of which generates price recommendations on the basis of historical data, demand forecasts, and competitors' publicly available prices. Plaintiffs characterized the arrangement as a "hub-and-spoke conspiracy," with Cendyn occupying the hub position and the hotels constituting the spokes, all purportedly engaged in tacit collusion. Specifically, plaintiffs pointed to (i) license agreements between each hotel and Cendyn, (ii) the algorithms' integration of competitors' prices, (iii) a 2015 software update incorporating such competitor data, (iv) parallel pricing decisions among hotels using the same tool, and (v) default settings that allegedly steered hotels toward the recommended prices.

The litigation remains on appeal, but the U.S. District Court for the District of Nevada dismissed the complaint at first instance. The court reasoned: (1) plaintiffs failed to adduce evidence of an actual price-fixing agreement among the hotels; (2) the data relied upon were publicly available, and no confidential, competitively sensitive information was exchanged; (3) plaintiffs could not show that the hotels invariably adhered to the algorithmic recommendations-hotels retained discretion to override or modify suggestions (e.g., Hard Rock sometimes accepted, sometimes altered prices); and

(4) the hotels' pricing decisions reflected independent business judgment rather than concerted action. Although parallel pricing may produce convergent prices, the court held that such parallelism, absent "plus factors," does not establish collusion. Accordingly, the court found no Sherman Act violation and dismissed the claims.

1.3. Comparative Analysis of Algorithmic Collusion in RealPage and Gibson v. Cendyn Group

Both cases feature allegations that algorithmic pricing tools facilitated collusive conduct (see Table 2), yet they diverge materially with respect to industry context, data collection and integration, and the nature of algorithmic deployment (see Table 3). The decisive distinction lies in evidentiary sufficiency: in the RealPage matter, the DOJ and state attorneys general produced substantial evidence that RealPage and participating landlords used the algorithm to control rental prices, leading to a settlement that left the factual allegations intact. By contrast, in Gibson v. Cendyn Group the plaintiffs' theories of indirect price fixing, market manipulation, and consumer harm failed at the pleading stage, principally because (i) there was insufficient proof of an agreement among hotel operators; (ii) algorithmic recommendations were non-binding; and (iii) plaintiffs could not demonstrate the sharing of non-public, competitively sensitive pricing data.

Table 1. Similarities between the RealPage Pricing-Algorithm Case and the Gibson v. Cendyn Grp. Case

Dimension	RealPage Pricing-Algorithm Case	Gibson v. Cendyn Grp. Case
Core Issue	Whether algorithmic price manipulation caused consumers to pay supra-competitive rents (or, in the hotel context, supra-competitive room rates) and thereby reduced market competition.	Same—whether algorithmic price manipulation caused consumers to pay supra-competitive hotel rates and diminished competition in the marketplace.
Role of the Algorithm	Enterprises employ the algorithm to optimize prices and increase revenues.	Same—hotels employ the algorithm to optimize prices and increase revenues.
Impact on Consumers	Tenants may face higher rents and diminished bargaining power.	Consumers may face higher room rates and fewer lodging alternatives.
Antitrust Risk	Corporate conduct may contravene the Sherman Act, involving price manipulation and restraints of trade.	Same—corporate conduct may violate the Sherman Act, involving price manipulation and restraints of trade.
Involvement of Third Parties	Third-party RealPage supplies data aggregation, analytical services, and algorithmic pricing recommendations.	Third-party Rainmaker Group supplies customer-price recommendations, competitive analytics, group-booking analytics, etc.
Market Share and Monopoly Considerations	RealPage holds roughly 80 percent of the U.S. multifamily residential revenue-management-software market, indicating monopolistic tendencies.	Defendant hotels constitute the principal operators on the Las Vegas Strip and command the overwhelming bulk of market share in that corridor; market concentration is correspondingly high.

Table 2. Differences between the RealPage Pricing-Algorithm Case and the Gibson v. Cendyn Grp. Case

Dimension	RealPage Pricing-Algorithm Case	Gibson v. Cendyn Grp. Case
Relevant Industry (Market)	Multifamily residential sector, principally the apartment-leasing market.	Hospitality sector, specifically luxury and casino hotels on the Las Vegas Strip.
Data Source	Non-public, competitively sensitive data supplied by landlords-rents, occupancy rates, and similar information.	Publicly available hotel pricing data. The algorithm is used chiefly for data aggregation and pricing advice-customer-price recommendations, competitive analytics, group-booking analytics, price coordination-and involves no direct exchange of confidential price information.
Mode of Algorithmic Application	RealPage connects landlords via the algorithm, aggregates data to generate price recommendations; landlords may employ an "auto-accept" feature and participate in user groups to achieve coordinated pricing; machine-learning techniques are used for price optimization and dynamic adjustment.	Hotels employ Rainmaker's suite of algorithms (GuestRev, RevCaster, etc.) for price coordination, focusing on customer-price recommendations, competitive analytics, and group-booking analytics. The system principally monitors the market and public prices and lacks autonomous optimization or self-learning functionality.
Algorithms at Issue	(i) Machine-learning algorithm performing big-data analysis to optimize future pricing strategies; (ii) dynamic-pricing algorithm that adjusts rates in real time to enhance precision and efficacy; (iii) user-interface and user-group coordination algorithms that facilitate landlords' comprehension and acceptance of platform recommendations, thereby bolstering confidence in pricing strategies.	GuestRev (customer-price recommendation algorithm); RevCaster (competitive-analytics algorithm); GroupRev (group-booking analytics and price-forecasting algorithm).

2. REGULATORY CHALLENGES: ALGORITHMIC COLLUSION AND ITS ABILITY TO OUTSTRIP THE CONVENTIONAL BOUNDARIES OF ANTITRUST CONTROL AND SUPERVISION

2.1. Difficulties in Establishing a "Meeting of Minds" and in Interpreting the Notion of "Monopolistic Agreement" under Algorithmic Collusion

Under the Anti-Monopoly Law, collusion is established only where undertakings (competitors) enter into agreements, resolutions, or other concerted practices that exclude or restrict competition, thereby evidencing a subjective intention to collude. [2]Where coordination is not memorialised in facial contractual terms but manifests solely as parallelised conduct, the extant interpretive framework governing "monopolistic agreements" is stretched to its limits.[3] By way of illustration: in "Messenger"-type collusion, the conspirators first reach an express agreement, whereafter algorithms merely execute or police the cartel-thus intent is relatively easy to infer. In the "Hub-and-Spoke" paradigm, the vertical agreements between the hub (algorithm provider) and the spokes (competitors) likewise render concurrence easier to establish. By contrast, "Predictable Agent" collusion arises in highly transparent markets: algorithms adjust prices autonomously in response to market signals, and the resulting coordination may be mistaken for a natural market reaction; in "Digital (Self-Learning)" collusion the algorithm's decision process is a black box, largely beyond the undertakings' control, yet capable of achieving cartel outcomes. The last two categories entail prohibitive enforcement costs, if detection is feasible at all .

Where algorithmic collusion blurs the contours of the "monopolistic agreement," the meeting of minds diverges radically from that in classic cartel law. As Gibson v. Cendyn Grp. illustrates, any uniform-pricing outcome may not reflect the designers' or users' intent; each hotel used a common tool based solely on public data, and the algorithm did not affirmatively push for price convergence, even though parallel pricing ensued.[4] With direct evidence of agreement scarce-and absent a consensus as to whether an intelligent algorithm possesses legal personality-proving a meeting of minds may be impossible in certain scenarios (e.g., tacit algorithmic collusion). One proposed avenue is to dispense with subjective proof and rely on "economic evidence" to establish concerted conduct (Posner, 2003), or alternatively to piece together logically consistent circumstantial evidence sufficient to demonstrate a subjective nexus; both approaches demand urgent scholarly and practical evaluation.

2.2. Difficulties in Evidence Collection and Burden of Proof under Algorithmic Collusion

Advanced algorithms embed highly complex structures, evolving toward self-learning and autonomous decision-making. Undertakings may preset objectives such that the machine, rather than the firm, executes the decision process. Modern algorithms (e.g., neural-network or machine-learning models) display a "black-box" character; hidden variables, model complexity, and data-volume constraints render the causal chain opaque. Even if an enforcement agency secures full access to code and data, the volatility of market inputs and the multiplicity of variables, coupled with real-time data flows, pose formidable technical barriers to tracing how specific outputs are generated. This technological instrumentalism affords undertakings a potential safe harbour from direct liability.[5]

For example, in Gibson the GuestRev and GroupRev products integrated only publicly available data (e.g., competitors' searchable room rates). The algorithm refreshed inputs in real time, exhibiting considerable flexibility and responsiveness; enforcement would require continuous monitoring of each input-output linkage, yet every run could yield a different result. This real-time, feedback-driven paradigm side-steps the communications evidence typically present in classic antitrust cases. Likewise, in RealPage the algorithm digested non-public, sensitive landlord data to generate rent recommendations; use of "Auto-Accept" eliminated human review, and some commentators have argued that the suggestions merely mirrored supply-and-demand dynamics rather than firm-level manipulation-thereby further complicating evidentiary tracing.

2.3. Difficulties in Allocating and Imposing Liability under Algorithmic Collusion

Under the antitrust framework, the undertakings are both the agents and the bearers of liability. In algorithmic collusion, however, the dramatis personae expand to include algorithm developers and, hypothetically, the algorithms themselves. Given wide variance in each algorithm's design objectives, operational role, and degree of autonomy, a monolithic liability regime risks both under-deterrence and over-deterrence-that is, either licensing abuse or unduly stifling efficiency gains.[6] Professor Mehra posits three allocation possibilities: (1) the algorithm itself bears cartel liability; (2) the user bears liability; or (3) no liable person exists.[7]The third outcome obviously conflicts with the core purpose of antitrust law when algorithmic conduct has in fact restricted competition. Yet the traditional liability logic-predicated on an "actor" endowed with volitional capacity-does not map neatly onto scenarios in which an algorithm acquires quasi-autonomous causal efficacy, thereby complicating the liability chain and potentially creating a vacuum.

Academic debate persists as to whether algorithms should be granted separate legal personality for cartel liability. While the "electronic person" or fictive-entity model is forward-looking, algorithms remain human-engineered tools whose outputs predominantly reflect human intent at either the design or operational stage, rather than independent volition. The low transparency and untraceability of algorithmic decision-making further militate against treating the algorithm itself as the sole defendant.

Another dimension of attribution difficulty arises from the cognitive gulf between technology and law. Where an enforcement authority cannot parse each decisional input and output in the causal chain, liability can fracture, and exclusionary conduct may evade effective sanction. Highly abstract, modular code architecture obscures the internal logic of an algorithm; tracing any single result back through the chain of rules and learning models poses formidable procedural obstacles.

3. REGULATORY PARADIGM: PATHWAYS FOR BEHAVIOURAL MONITORING AND LIABILITY ALLOCATION UNDER ALGORITHMIC COLLUSION

3.1. Monitoring and Identifying Anomalous Behavioural Patterns to Assist in Establishing Subjective Concurrence

As previously noted, where two or more undertakings reach an explicit cartel agreement and exchange information through their algorithms to coordinate prices, the algorithm is merely the tool that secures implementation; establishing a "meeting of minds" is therefore relatively straightforward. In tacit algorithmic collusion, however, undertakings achieve a convergence of wills through information-sharing, signalling, and deep-learning techniques: algorithms autonomously adjust strategies, react to market dynamics, or respond to competitors' behavioural traits, all without an overt agreement or direct communications. In such circumstances, subjective intent may be inferred principally by "anomalous behaviour pattern monitoring," supplemented by indirect evidence.

Algorithmic collusion is, at its core, information-exchange-dependent. Although the mode of exchange has changed, information sharing and signal coordination remain central. To preserve algorithmic efficacy, undertakings must obtain competitors' pricing, demand fluctuations, and historical data, and recalibrate their own strategies accordingly. Hence, regulators should begin by monitoring the frequency and type of information shared. Algorithmic collusion often relies on rapid, automated exchanges among firms, and high-frequency exchange may accelerate price synchronisation. If multiple firms' algorithms repeatedly adjust prices or strategies within the same time window, the behaviour can be flagged as suspect. Particular attention should be paid to exchanges involving pricing, demand forecasts, or rival pricing strategies; where algorithms draw on similar data sources in the absence of any direct agreement, price coordination may ensue. A classification and analytical mechanism should therefore be instituted to subject "strategic" information to heightened scrutiny and to avert non-transparent algorithmic coordination.

Not all information, of course, is equally conducive to collusion. Regulators must distinguish publicly available data from competitively strategic information, the latter being far more likely to trigger collusion. For example, an undertaking's disclosure of future pricing strategies or demand forecasts can directly affect rivals' conduct; once such information spreads algorithmically, other firms may automatically adopt comparable pricing. U.S. antitrust law differentiates between unlawful information exchange, "facilitating practices," and "invitations to collude," examining whether an implicit understanding or unilateral signalling is present.[8]

Where direct evidence (e.g., written agreements or communications) is unavailable, economic evidence may be deployed to identify "unnatural" conduct under competitive conditions. Regulators can construct an evidentiary chain by proceeding from market outcomes to the mutual corroboration of "unnatural behaviour" and "collusive intent." Step one is to confirm abnormal market results-e.g., using a Price Transmission Model to test whether retail prices track cost movements in an atypically synchronous way; or applying the Herfindahl–Hirschman Index (HHI) to detect sustained high concentration and entry barriers; or invoking a Kuznets-type analysis to show that consumer surplus has plummeted despite modest cost increases. Step two is to mine behavioural patterns for coordination indicators-e.g., uniformity in frequency, magnitude, or timing of price changes; excessive reliance on historical or rival data-thereby ruling out independent decision-making. Step three is to examine algorithmic interaction and data-sharing possibilities through big-data tracing tools, assessing the logic of algorithm use and the nature of data exchanged. Step four is to eliminate pro-competitive explanations (demand shocks, cost changes, etc.). Only when "unnatural" market phenomena defy competitive logic does "algorithm-facilitated collusion" remain as the sole reasonable hypothesis.

3.2. Employing Indirect and Economic Evidence to Detect Algorithmic Collusion

Where no direct proof of express collusion is available, courts may rely on circumstantial evidence-analysing firms' conduct, market structure, and algorithmic design to infer conspiracy.[9] If a platform's technical architecture enables instantaneous dynamic pricing and compels multiple undertakings to observe and internalise market price changes, thereby depressing the profitability of independent pricing, the undertakings are more likely to reach an implicit consensus. Even absent written traces, such synchronised behaviour may be interpreted as "facilitated collusion." Not all parallel conduct, however, equates to collusion. In Theatre Enterprises, distributors' refusal to grant first-run rights to a small cinema was grounded in legitimate commercial reasons; the Supreme Court declined to infer conspiracy.[10]Hence, courts must still ask whether an independent, rational explanation exists.

Economic evidence can corroborate the inference. If, after algorithm adoption, prices, output, or utilisation rates converge in ways that normal competition cannot explain, the regulator should treat this as prima facie evidence. To rule out seasonality or entry/exit effects, one may employ control–treatment splits, regression analysis, or difference-in-differences models: firms not using the algorithm serve as the control group, those using it as the treatment group. Significant and persistent differences-after controlling for confounds-provide indirect support for a finding of algorithmic collusion. Typically, random unilateral conduct cannot sustain elevated cartel profits or reduced competitive pressure; uniform pricing that materially raises profitability or dampens competition is strong circumstantial proof of joint price control.

3.3. Liability Allocation in Gradations, Based on Algorithmic Role and Autonomy Scoring

Given blurred responsibility in algorithmic collusion, liability should be apportioned along two axes: (1) "algorithmic role," to identify the conspirators; and (2) "data provenance and decision autonomy," to calibrate responsibility.[11]

3.3.1. Algorithmic Role and Identification of Responsible Actors

The conventional antitrust framework examines the "developer–platform–user" triad to ascertain price-fixing or restraint of trade. In algorithmic settings, multiple actors design, provide, or use the algorithm, risking a liability vacuum or break in the causal chain. The veil must therefore be pierced, assessing each actor's substantive position, freedom of decision, and degree of control or dependence. In RealPage, the company acted as developer and platform operator, aggregating non-public, sensitive landlord data and facilitating peer exchange-behaviour analogous to an "organiser" or "intermediary" of collusion, far beyond pure technical supply. In Gibson v. Cendyn Group, by contrast, Cendyn's tools relied mainly on public data, and hotels could ignore or override recommendations; Cendyn therefore resembled a "passive facilitator," less amenable to "active organiser" status. Where the developer also operates the platform (RealPage), it possesses panoramic oversight of algorithmic logic and data flows and actively accelerates collusion (e.g., auto-accept, call-around). Such a platform should be the primary addressee of liability. Conversely, when the provider merely offers an optional tool (Gibson), with no evidence of coerced uniform pricing, the provider acts only as a supporting vendor.

3.3.2. Data Provenance and Decision Autonomy as Determinants of Liability

To avoid a “responsibility vacuum” created by technological asymmetry, a tiered, dynamic allocation should consider data provenance and the user’s decision autonomy.

First-tier liability: non-public data collection and sharing. If the data originate from sensitive, non-public competitor information (e.g., rents, occupancy, lease terms in RealPage), the collector/aggregator (developer or platform) occupies the first-tier. Data misuse here is intrinsically anticompetitive. Obligations of data protection and use limitation should be imposed, requiring disclosure of data sources and algorithmic logic.

Second-tier liability: processing of public data and algorithmic outputs. If public data are lawfully gathered yet the platform fails to implement safeguards against uniform-pricing outputs (indirect facilitation), attention shifts to whether the model’s optimisation process fosters anticompetitive effects. Developers must file technical compliance reports detailing whether learning models embed price-convergence incentives.

Third-tier liability: data recipients’ use decisions. Recipients (landlords, hoteliers) directly access outputs and may benefit competitively yet lose pricing independence. Their liability turns on decision autonomy, dependency, and market effects. Where the algorithm merely advises and recipients freely modify prices (Gibson), independence is preserved; where recipients rely entirely on auto-accept features (RealPage), their conduct may be deemed passive, tacit collusion.

4. SUMMARY

By examining the RealPage’s Pricing Algorithm case and the Gibson v. Cendyn Grp. case, this study illustrates how algorithmic collusion operates in different contexts and exposes gaps in regulatory oversight. Building on the analysis of the challenges involved in identifying and governing algorithmic collusion, it proposes a two-way convergence of technological governance and legal frameworks to address issues of data sharing and the transparency and traceability of algorithmic decision-making. Accordingly, it advocates the introduction of algorithmic decelerators and price-restriction mechanisms to intervene in high-frequency price-adjustment behaviors; the use of log recording, real-time monitoring, and explainability techniques to support law enforcement in tracing algorithmic operations and detecting anomalies; and the adoption of an autonomous scoring model to demarcate liability boundaries, thereby clarifying the distinct legal obligations of developers, users, and platform providers. Meanwhile, combining anomaly detection with economic modeling helps build an evidentiary chain that enables logical inferences from market phenomena to collusive intent, filling the void left by traditional antitrust enforcement measures. Ultimately, such measures aim to ensure fair competition and robust consumer protection within the digital economy ecosystem.

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