Pricing Algorithms and Antitrust Risk: Lessons from RealPage

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I. Introduction

The adoption of AI and machine learning models to support pricing decisions has become widespread across industries. Property management, hospitality, retail, ride-sharing, and airline revenue management all now rely on algorithmic tools that process large volumes of data to generate pricing recommendations. These tools can create genuine efficiencies: they reduce the information burden on individual firms, allow faster responses to market conditions, and can improve resource allocation. But they also introduce a structural antitrust risk that traditional frameworks were not designed to address.

The federal government's antitrust action against RealPage illustrates that risk with clarity. RealPage's revenue management software recommended rental prices to competing landlords. What made it legally significant was not the sophistication of the algorithm but the information it used: real-time, nonpublic data pooled from thousands of competing properties. That information structure, not the AI component itself, is what gave rise to antitrust liability. The case establishes a principle with broad application: when a pricing algorithm is trained on aggregated private data from competing firms, and the resulting recommendations flow back to those same competitors, independent price competition may be compromised regardless of whether any two competitors communicated directly.

This article summarizes the RealPage case, explains the theory of harm, and identifies the practical implications for firms deploying or evaluating algorithmic pricing tools. A companion paper, "Platform Pricing, Information Asymmetry, and Antitrust Risk," addresses additional antitrust risks in multi-sided platform markets. These include platforms' exploitation of buyer-side information for price discrimination and the coordination risks that arise from widely adopted pricing algorithms.

II. Background: The RealPage Case and the DOJ Settlement

RealPage is a Texas-based property technology company acquired by private equity firm Thoma Bravo in 2021 for approximately $10.2 billion.[1] Its revenue management software, formerly known as LRO (Lease Rent Options), uses algorithmic models to recommend optimal rent prices to property managers and landlords.[2]

The controversy began in October 2022, when ProPublica published an investigation revealing how the software pooled nonpublic, competitively sensitive lease data from thousands of competing apartment properties to generate pricing recommendations. Landlords who adopted the software were effectively allowing a common algorithm fed by their rivals' private data to set their prices.[3] The story triggered a wave of private class-action lawsuits[4] and eventually prompted action by state attorneys general and the DOJ.[5]

On August 23, 2024, the DOJ filed a civil antitrust lawsuit against RealPage in the Middle District of North Carolina, alleging violation of Section 1 of the Sherman Act.[6] The complaint, joined by eight state attorneys general, alleged that competing landlords shared nonpublic data with RealPage, whose algorithm used that pooled data to generate recommendations that replaced independent price competition with algorithm-mediated coordination.

A January 2025 amended complaint added six major landlord companies as defendants (Greystar, Camden, Cushman & Wakefield/Pinnacle, LivCor, Willow Bridge, and a Greystar affiliate), alleging they were active participants in the scheme, not merely software customers.[7]

On November 24, 2025, the DOJ announced a proposed consent decree resolving its claims against RealPage. Key terms include:[8]

- **Ban on nonpublic competitor data:** RealPage may not use nonpublic, competitively sensitive information from competing landlords when generating floor-plan- or unit-level rent recommendations. Pricing outputs may only be based on a given landlord's own data and publicly available information.
- **12-month aging requirement for training data:** Any nonpublic data used to train RealPage's algorithms must be at least 12 months old (i.e., historical, backward-looking data). Current lease and occupancy data from competitors may not be used.
- **Independent compliance monitor:** A court-approved compliance monitor — selected by the DOJ — will have broad access to review RealPage's source code, model training documentation, and how the software generates pricing recommendations in real time to verify ongoing compliance. The monitor's costs are borne by RealPage, and the monitor may hire independent technical experts.
- **Seven-year term:** The consent decree is effective for seven years from entry, though the DOJ may seek to terminate it after four years if it determines the decree is no longer necessary or in the public interest.

While the DOJ's claims against RealPage were resolved by the November 2025 consent decree, the State plaintiffs so far have not settled the DOJ's cases against certain landlords, and suits in other circuits brought by private plaintiffs remain unresolved.[9]

III. The Theory of Harm: Information Aggregation Across Competing Sellers

The central lesson of RealPage is about information aggregation by a third party that serves as a hub for conspiracy. This section examines three areas: how pooled private data functions as a coordination mechanism, why machine learning amplifies the concern, and how courts have analyzed comparable arrangements under Section 1 of the Sherman Act.

A. Pooled Private Data as the Coordination Mechanism

In a functioning market, each firm sets prices based on its own costs, capacity, and its interpretation of publicly observable market conditions. Rivals' nonpublic information, including their real-time occupancy rates, lease terms, and pricing strategies, remains private. That separation of information is part of what makes competition work: each firm must independently decide how to set prices, without knowing exactly what rivals are doing.

A pricing algorithm changes this norm when it is trained on aggregated data contributed by competing firms. Each firm's private data, fed into a shared model, effectively becomes available to all participants through the pricing recommendations that the model generates. The algorithm acts as a clearing house for competitive intelligence that would otherwise remain siloed. No bilateral communication between competitors is needed. The data flows through the intermediary, and the recommendations flow back.

This is the structure that RealPage built: landlords in the same market shared real-time occupancy and lease data with RealPage; the algorithm used that pooled data to generate recommendations for each participant; and the recommendations, derived from the collective's private information, effectively coordinated pricing across the market. The DOJ's theory was that this structure suppressed the independent decision-making that competition law requires, even without any direct communication among competing landlords.

B. Why AI Amplifies the Risk

Machine learning models trained on large datasets can identify market signals and pricing patterns that no individual firm could detect from its own data alone. This is precisely what makes AI-assisted pricing valuable. But it also implies that when the training data includes nonpublic information from competing firms, the model encodes competitive intelligence at a level of granularity and recency that human analysts could not match.

The speed and opacity of algorithmic systems compound the concern. Because pricing recommendations are generated automatically and updated in real time, the coordination that they produce is faster and harder to detect than traditional price-fixing arrangements. Firms may not even appreciate that their pricing decisions are being influenced by rivals' nonpublic data. The compliance monitor provision in the DOJ consent decree reflects the emerging regulatory recognition that meaningful oversight of algorithmic pricing requires technical examination of source code, training data, and how the software generates pricing recommendations in real time.

C. The Legal Framework: Hub-and-Spoke Under Section 1

Section 1 of the Sherman Act prohibits contracts, combinations, and conspiracies in restraint of trade. The central challenge in algorithmic coordination cases is establishing the agreement element, since competing firms using a shared pricing tool do not communicate directly with each other. Courts have addressed analogous situations through the hub-and-spoke conspiracy doctrine. Under this framework, a horizontal agreement among competitors (the spokes) can be inferred when each competitor knew or should have known that others were participating in the same arrangement. The intermediary (the hub) facilitates coordination without itself being a competitor.[10]

RealPage is a straightforward application of this doctrine. Each landlord that shared data with RealPage and adopted its recommendations had reason to know that competitors in the same market were doing the same. The algorithm's use of pooled competitor data made each participant's pricing decisions dependent on rivals' private information, producing the functional equivalent of a horizontal agreement through contracts with a common intermediary.

IV. Practical Implications

The DOJ's investigation and consent decree establishes a compliance baseline for firms that develop, deploy, or use algorithmic pricing tools. The following implications are worth highlighting.

- **Training data should not include pooled nonpublic competitor information.** The competitively sensitive nature of the data is the critical factor. Real-time occupancy, pricing, and lease terms from competing firms present high risk. Historical or publicly available data presents substantially lower risk, though market structure and concentration still matter.
- **Recommendations should be based on the firm's own data and public market information.** When a model injects rivals' nonpublic data into a recommendation, the output cannot be characterized as independent decision-making, even if the firm never communicated directly with any competitor.
- **Assess the tool's market penetration, not just its design.** Even a well-designed algorithm creates coordination risk if adopted by a large share of competitors in a concentrated market. Firms should evaluate not just their own deployment but the prevalence of the same tool among rivals.
- **Communications about adoption rates require scrutiny.** Disclosing to participants how many competitors have accepted a pricing recommendation can function as a focal point for tacit coordination. This practice elevates legal risk independently of the algorithm's data inputs.
- **Maintain documentation sufficient for technical audit.** The compliance monitor provision in the DOJ consent decree sets the expectation that firms deploying AI pricing tools be prepared to open model inputs, training methodology, and recommendation logic to substantive examination.

Firms seeking to assess the antitrust risk profile of a specific AI pricing tool should engage both legal counsel with antitrust expertise and economic experts with experience in algorithmic pricing. The interaction between model design, market structure, and competitive effects is highly fact-specific and cannot be reliably assessed through generalized checklists alone.

V. Conclusion

The RealPage case offers a concrete answer to a question that has grown more urgent as AI pricing tools proliferate: at what point does algorithmic coordination become an antitrust violation? The answer turns not on the sophistication of the technology but on the structure of information flows — specifically, whether competing firms share nonpublic data through a common intermediary in ways that suppress independent pricing decisions. Courts and regulators are still refining the analytical frameworks for these cases, creating uncertainty for firms operating at the frontier of algorithm-assisted pricing.

Looking forward, the RealPage case is unlikely to be an isolated enforcement action. Algorithmic pricing is expanding rapidly into sectors beyond multifamily housing — including hotel and airline revenue management, ride-sharing surge pricing, online retail, and healthcare billing. As AI pricing tools become more capable and more widely adopted, antitrust regulators and private plaintiffs will develop more sophisticated tools for detecting and proving algorithmic coordination. Expert economic analysis — including review of model architecture, training data, and market-level effects — will be central to both prosecution and defense.

Sources

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