

AI AGENTS AND COLLUSION: THE TWO FACES OF AGENTIC AI



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By Giovanna Massarotto



AGENTIC AI'S REGULATORY CONUNDRUM

By Anant Raut



INTER-AI-AGENT COMPETITION

By Stefan Thomas



NAVIGATING THE INCREASING REGULATORY SCRUTINY OF AI-PRICING TOOLS: COMPETITION AND OTHER EMERGING RISKS

By Mark L. Krotoski & Vinny Sidhu



AGENTIC AI, MARKETS AND COMPETITION LAW

By Salil K. Mehra



THE POTENTIAL IMPACT OF AGENTIC AI ON COMPETITION AND MERGER REVIEW

By Cristián Hernández & Gabriella Monahova



ANTITRUST SIMILARITIES AND DIFFERENCES BETWEEN BROWSER COMPETITION AND AI COMPETITION

By Julian Chan, Kayuna Fukushima & Aparna Sengupta



AGENTIC AI BEFORE CADE: THE CURRENT CHALLENGES FACED IN BRAZILIAN ANTITRUST ENFORCEMENT

By Marcela Mattiuzzo, Matheus Barreto & Bárbara Sá Castro



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The digital economy is becoming increasingly automated. Moving beyond traditional machine-learning systems, companies are rapidly adopting AI agents and agentic AI systems capable of autonomously performing complex tasks and streamlining decision-making processes. These technologies promise significant gains in efficiency and consumer welfare. At the same time, a growing body of economic literature suggests that AI agents can learn increasingly sophisticated forms of coordination capable of producing collusive outcomes that challenge traditional methods of detection and proof under U.S. antitrust law. As autonomous AI systems become more prevalent, antitrust law faces a fundamental question: how can competition be preserved in markets increasingly shaped by AI agents? While AI agents can facilitate collusion, antitrust law can be adapted to encourage their deployment in ways that promote competition. Ensuring that AI develops consistently with competitive market principles will be one of the central challenges facing antitrust enforcers in the years ahead.

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The digital economy is becoming increasingly automated. Moving beyond traditional machine-learning systems, companies are rapidly adopting AI agents and agentic AI systems capable of autonomously performing complex tasks and streamlining decision-making processes. These technologies promise significant gains in efficiency and consumer welfare. At the same time, a growing body of economic literature suggests that AI agents can learn increasingly sophisticated forms of coordination capable of producing collusive outcomes that challenge traditional methods of detection and proof under U.S. antitrust law. As autonomous AI systems become more prevalent, antitrust law faces a fundamental question: how can competition be preserved in markets increasingly shaped by AI agents? While AI agents can facilitate collusion, antitrust law can be adapted to encourage their deployment in ways that promote competition. Ensuring that AI develops consistently with competitive market principles will be one of the central challenges facing antitrust enforcers in the years ahead.

I. INTRODUCTION

Since the release of OpenAI's ChatGPT in November 2022, artificial intelligence has become a central topic in antitrust scholarship, enforcement, and policy debates worldwide.² Antitrust agencies increasingly view AI as both a driver of innovation and a potential source of new competitive risks, raising fundamental questions about market power, coordination, data access, and automation in digital markets.³ More recently, growing attention has focused on AI agents: AI systems that, unlike traditional models designed primarily to generate outputs in response to prompts, can act with a degree of autonomy to perform multi-step tasks, including software development, online transactions, research assistance, and conversational interaction.⁴ Because these systems may continuously adapt and improve through iterative feedback and user interaction, they present novel challenges for antitrust law and policy.

One important challenge concerns the risk that AI agents may facilitate collusion harmful to competition, including forms of algorithmic coordination sometimes described as invisible or secret collusion.⁵ While interactions among AI agents may generate significant efficiencies and enable beneficial interoperability across platforms and services, they may also facilitate unintended information sharing, parallel strategic adaptation, or forms of coordination capable of reducing competitive independence. As AI agents increasingly interact autonomously and at scale, these systems may create new pathways for collusive outcomes that are difficult to detect within traditional antitrust frameworks.

This article reviews recent economic papers examining the problem of collusion in the context of AI agents by drawing an analogy with collusion problem with oligopolies. It argues that advancements in AI are requiring the antitrust community to rethink about collusion under Section 1 of the Sherman Act (Section 1).

II. THE RISE OF AI AGENTS

AI agents offer important economic opportunities.⁶ Advances in AI have enabled far more than sophisticated search engines and voice assistants capable of answering increasingly complex questions. Recent developments have given rise to autonomous systems that can interact with one another and dynamically adjust their decision-making in response to the behavior of other agents. These capabilities have led to the emergence of multi-agent systems in which AI agents continuously learn, adapt, and coordinate their actions within shared environments.⁷

AI agents are like 'autopilots' capable of performing a variety of tasks on behalf of users with significant autonomy. Agentic AI systems exhibit agency through persistent memory, strategic adaptation, and autonomous decision-making, enabling them to understand and perform tasks effectively.

2 Giovanna Massarotto, *The Meaning of AI and Its Implications for Antitrust Law*, 56 Seton Hall L. Rev. 1557 (2026); Daniel A. Crane, *Antitrust After the Coming Wave*, 99 N.Y.U. L. Rev. 1187, 1188–89, 1240 (2024); Erik Hovenkamp, *AI, Data, and Leveraging Strategies: Implications for Antitrust*, Network L. Rev. (2025) <https://www.networklawreview.org/hovenkamp-ai-antitrust/>; Press Release, Fed. Trade Comm'n, *FTC Launches Inquiry into Generative AI Investments and Partnerships* (Jan. 25, 2024), <https://www.ftc.gov/news-events/news/press-releases/2024/01/ftc-launches-inquiry-generative-ai-investments-partnerships>; European Commission, *Commission Publishes Policy Brief on Competition in Generative AI and Virtual Worlds* (Sep. 19, 2024), <https://digital-strategy.ec.europa.eu/en/news/commission-publishes-policy-brief-competition-generative-ai-and-virtual-worlds>; Foo Yun Chee, *EU Antitrust Chief Meets Google, Meta, OpenAI, Amazon CEOs Amidst AI Scrutiny*, Reuters (Mar. 24, 2026), <https://www.reuters.com/legal/litigation/eu-antitrust-chief-meets-google-meta-openai-amazon-ceos-amidst-ai-scrutiny-2026-03-24/>.

3 *Ibid.*

4 Anna Gutowska, *What Are AI Agents?*, IBM <https://www.ibm.com/think/topics/ai-agents>

5 Summeet Ramesh Motwani, Mikhail Baranchuk, Martin Strohmeier, Vijay Bolina, Philip H.S. Torr, Lewis Hammond & Christian Schroeder de Witt, *Secret Collusion AI Agents: Multi-Agent Deception via Steganography* (Feb. 2024), <https://arxiv.org/abs/2402.07510>.

6 Noam Kolt, *Governing AI Agents*, 101 Notre Dame L. Rev. 1, 4 (2025).

7 Lewis Hammond et al., *Multi-Agent Risks from Advanced AI* (Feb. 19, 2025), <https://arxiv.org/pdf/2502.14143>.

Importantly, agentic AI is no longer a theoretical concept. Leading AI companies have begun deploying AI agents, such as OpenAI's *Operator*, which is designed to autonomously navigate digital environments and perform tasks on behalf of users. Anthropic launched the AI agent feature *Computer Use* for Claude.⁸ Most AI agent prototypes possess an 'act-like-a-human architecture.'⁹ These AI agents perform human interactions, including clicking or typing just like a person would. They are revolutionizing how consumers interact with devices, such as smartphones, and raising a number of legal and ethical issues.¹⁰ In the antitrust context, these systems raise a fundamental question: are AI agents capable of learning sophisticated forms of collusion that generate collusive outcomes while leaving little evidence of agreement as traditionally antitrust law requires? The short answer is, Yes.

III. AI TACIT COLLUSION

Renowned economists and antitrust scholars studied collusion through AI for about a decade.¹¹ Already in 2015, Professors Ariel Ezrachi & Maurice E. Stucke raised a red flag about companies developing pricing algorithms that leverage advancements in AI. Although AI-driven pricing algorithms can make price setting more efficient and lowering search costs for consumers, they may also facilitate price coordination and collusive outcomes that result in supracompetitive prices harmful to consumers.¹² Ezrachi & Stucke identified four models of algorithmic collusion that are still valid today: i. Messenger; ii. Hub and Spoke; iii. Predictable Agent; iv. and the Digital Eye.¹³ The first model — the Messenger — is the simplest one, implying an algorithm that advances existing human collusion.

In 2015, for instance, the U.S. Department of Justice Antitrust Division charged David Topkins with price fixing by means of pricing algorithms for the sale of certain posters.¹⁴ The defendant instructed an algorithm to set prices in conformity with an agreement.¹⁵ Topkins pleaded guilty, and the case served as an early warning that the use of pricing algorithms does not shield firms from liability for price-fixing conspiracies. However, the case involved a relatively conventional form of collusion in which the algorithm merely facilitated coordinated pricing.

A more challenging scenario occurs when companies perform the other three models of algorithmic collusion. The second model — the 'Hub and Spoke' conspiracy — implies a firm acting as a central intermediary (the "hub"), which facilitates coordination among competing firms (the "spokes"). For instance, on August 23, 2024, the Department of Justice and several states, including California and Colorado, filed a suit against the software company RealPage Inc., which provided revenue-management software generating rental pricing recommendations for landlords.¹⁶ The Department of Justice alleged that RealPage facilitated a 'Hub and Spoke' conspiracy by aggregating competitively sensitive information from competing landlords and using that information to generate pricing recommendations. According to the plaintiffs, this arrangement contributed to coordinated pricing in violation of Section 1 of the Sherman Act. The government also alleged claims under Section 2, arguing that RealPage engaged in conduct to help maintain its dominant position in the market for revenue-management software.¹⁷ Ultimately, the case was settled and the court missed the opportunity to clarify what algorithmic collusion is and how it could manifest through similar AI algorithms.

The third model that Ezrachi & Stucke identified is the 'Predictable Agent,' which imply pricing algorithms acting as predictable agents that constantly monitor and adapt each other's prices and data. The Predictable Agent facilitates what is commonly referred to as tacit collusion,

8 Anthropic, *Introducing Computer Use, a new Claude 3.5 Sonnet, and Claude 3.5 Haiku* (Oct. 22, 2024), <https://www.anthropic.com/news/3-5-models-and-computer-use>.

9 See Friso Bostoen & Jan Krämer, *How Future-Proof is the DMA? A Case Study of AI Agents*, J. Competition L. & Econ. 1, 3 (2026).

10 Kolt, *supra* note 6, at 4.

11 Martin Bichler, Julius Durmann & Matthias Oberlechner, *Algorithmic Pricing and Algorithmic Collusion*, 67 Bus. & Info. Sys. Eng'g 971, 975 (2025); Ariel Ezrachi & Maurice E. Stucke, *Virtual Competition: The Promise and Perils of the Algorithm-Driven Economy* (Harv. Univ. Press 2016).

12 See Ezrachi & Stucke, *Virtual Competition*, *supra* note 11, at 5-10; Ariel Ezrachi & Maurice E. Stucke, *Artificial Intelligence & Collusion: When Computers Inhibit Competition*, 2017 U. Ill. L. Rev. 1775.

13 Ezrachi & Stucke, *Virtual Competition*, *supra* note 11, at 36-37.

14 Press Release, U.S. Dep't of Just., *Former E-Commerce Executive Charged with Price Fixing in the Antitrust Division's First Online Marketplace Prosecution* (Apr. 6, 2015), <https://www.justice.gov/archives/opa/pr/former-e-commerce-executive-charged-price-fixing-antitrust-divisions-first-online-marketplace>.

15 *Ibid.*

16 Press Release, U.S. Dep't of Just., *Justice Department Sues RealPage for Algorithmic Pricing Scheme that Harms Millions of American Renters* (Aug. 23, 2024), <https://www.justice.gov/archives/opa/pr/justice-department-sues-realpage-algorithmic-pricing-scheme-harms-millions-american-renters>.

17 *Ibid.*

where firms adjust their prices by observing each other's pricing behavior rather than through explicit communication.¹⁸ Lastly, the fourth model is probably the most problematic from a legal perspective and relevant for our discussion on AI agents. It concerns computers learning on how to optimize profit, find ways to engage in anticompetitive behavior that presently evade detection, by leaving no evidence of anticompetitive intent or agreement, which Section 1 of the Sherman Act requires.¹⁹

The DOJ warned about the use of AI systems to collude on several occasions, acknowledging the importance of academic studies in the area.²⁰ The seminal work of Calvano, Calzolari, Denicolò & Pastorello emphasized the possibility that AI algorithms (Q-learning agents) may achieve coordinated, supracompetitive outcomes through repeated interaction. Their findings demonstrated that algorithms could learn to sustain such outcomes without direct communication: therefore to engage in what economists typically refer to as tacit collusion.²¹ They specifically noted the emergence of strategies involving the monitoring of competitors' prior prices, punishment of defections, and the maintenance of coordinated outcomes through reward-and-punishment mechanisms.²² Similarly, Klein examined how Q-learning agents behave in a sequential pricing environment. His study demonstrates that, when the set of discrete prices is limited, these algorithms can learn to converge toward collusive pricing equilibria.²³

The study by Banchio & Mantegazza revealed that reinforcement-learning algorithms can sustain supracompetitive outcomes through recurring patterns of cooperation and deviation without reward-and-punishment schemes. They identified a mechanism they termed 'spontaneous coupling,' whereby an endogenous statistical linkage in the algorithms' estimates leads to correlated behavior without explicit communication. Their study complemented earlier experimental findings in the economics literature by identifying spontaneous coupling as a mechanism capable of sustaining collusive outcomes in both prices and market shares.²⁴ Similar findings have also been reported in the context of large language model ("LLM") agents. Fish, Gonczaronski & Shorrer identified comparable coordination risks and mechanisms among LLM-based agents.²⁵ They found that LLM-based pricing agents can autonomously sustain collusive outcomes in oligopolistic markets through repeated strategic interaction, resulting in higher prices and consumer harm.²⁶ They further observed that prompt design can significantly influence the extent of coordination, with certain prompts increasing the likelihood of collusive outcomes detrimental to consumers.²⁷

Some economic studies have examined the collusive behavior of AI agents in specific sectors. For instance, Wei Dou, Goldstein and Ji examined price formation and market efficiency in financial markets characterized by asymmetric information, noise trading, and strategic interaction among market participants. Their analysis focused on how AI agents can learn strategically from the behavior of other market participants and adapt their conduct accordingly, even in the absence of communication, agreement, or intention. They specifically identified two algorithmic mechanisms through which collusive outcomes emerge: price-trigger strategies and over-pruning bias in learning. The authors showed that both mechanisms can sustain collusive outcomes and correspond to established game-theoretic equilibrium concepts.²⁸

The main insight emerging from these economic studies is that AI agents are capable of engaging in tacit collusion, which, at least under current U.S. antitrust law, remains lawful because Section 1 of the Sherman Act requires proof of an agreement. In *Monsanto* (1984), the Supreme Court reaffirmed that parallel conduct alone is insufficient to establish a violation and that plaintiffs must present evidence from which

18 Ezrachi & Stucke, *Virtual Competition*, *supra* note 11, at 37.

19 *Ibid.* at 71. See also, Steven Van Uysel, *The Algorithmic Collusion Debate: A Focus on (autonomous) Tacit Collusion* 1, 6 in Steven Van Uysel, Salil Mehra & Yoshitery Uemura, *Algorithms, Collusion and Competition Law* (2023).

20 U.S. Dep't of Just., *Acting Deputy Assistant Attorney General for Criminal Enforcement Daniel Glad Delivers Remarks at the Antitrust West Coast Conference* (May 14, 2026), https://www.justice.gov/opa/speech/acting-deputy-assistant-attorney-general-criminal-enforcement-daniel-gladd-delivers#_ftnref7.

21 Emilio Calvano, Giacomo Calzolari, Vincenzo Denicolò & Sergio Pastorello, *Artificial Intelligence, Algorithmic Pricing, and Collusion*, 110 Am. Econ. Rev. 3267 (2020).

22 *Ibid.*

23 Timo Klein, *Autonomous Algorithmic Collusion: Q-Learning Under Sequential Pricing*, 52 RAND J. Econ. 538 (2021).

24 Martino Banchio & Giacomo Mantegazza, *Artificial Intelligence and Spontaneous Collusion* (Sept. 2023) (working paper), <https://arxiv.org/abs/2202.05946>.

25 Sarah Fish, Yannai A. Gonczaronski, & Ran I. Shorrer, *Algorithmic Collusion by Large Language Models* (Mar. 2026) (working paper), <https://arxiv.org/abs/2404.00806>.

26 *Ibid.*

27 *Ibid.* at 4.

28 Winston Wei Dou, Itay Goldstein & Yan Ji, *AI-Powered Trading, Algorithmic Collusion, and Price Efficiency*, NBER Working Paper No. 34054, at 1, 6, 42 (2025), <https://www.nber.org/papers/w34054>.

an agreement may reasonably be inferred.²⁹ More recent court's rulings have reinforced the importance of evidence supporting an inference of agreement under Section 1. In *In re Text Messaging Antitrust Litigation* (2015), Judge Richard A. Posner observed the absence of a "smoking gun" of express collusion.³⁰ Similarly, in *Kleen Products*, Judge Diane P. Wood emphasized that plaintiffs had failed to produce sufficient evidence from which an agreement could reasonably be inferred. Together, these cases illustrate the continuing difficulty of distinguishing unlawful concerted action from lawful parallel conduct.³¹ The issue of tacit collusion engaged courts, economists, and lawyers for about a century, particularly in the context of oligopolistic markets, offering important lessons for contemporary antitrust debates with AI.

IV. LESSONS FROM OLIGOPOLIES

Historically, the debate about tacit collusion centered on oligopolistic markets, where a small number of firms interact repeatedly and collusion may emerge simply from competitors observing and responding to one another's conduct, even in the absence of an explicit agreement. Consider gas stations that are close to each other and can easier set the same price for gas, even without an explicit agreement. The main problem with prosecuting tacit collusion is that observing competitors is rational in a competitive context and courts do not aim to prosecute rational business conduct.

Economic theories are often limited in distinguishing explicit from tacit collusion because they typically focus on equilibrium outcomes rather than the process through which coordination is achieved. While economic models can explain how firms sustain supracompetitive prices, they are generally incapable of determining whether those outcomes result from an agreement or from lawful interdependent conduct.³² Another important challenge concerns the identification of what injunction or remedy would be capable of addressing tacit collusion effectively in a way that courts do not restrain competition. Importantly, prosecuting tacit collusion would imply judges defining what a competitive price is by *de facto* becoming price regulators when enforcing Section 1.³³

In Germany, § 47k of the German Competition Act established a fuel market transparency system requiring gas stations to report price changes. The provision was adopted in response to concerns about persistent parallel pricing and high fuel prices in an oligopolistic market, even where competition authorities lacked sufficient evidence to establish a cartel infringement. It can be understood as an attempt to address competitive concerns arising from coordinated market outcomes in the absence of provable collusion.³⁴ Similar remedies in oligopolistic markets can be defined through merger control.³⁵

Economists such as George A. Hay argued that facilitating practices may help firms achieve and sustain collusive outcomes and can therefore provide evidence supporting an inference of agreement.³⁶ Similarly, Joseph Harrington, leading economist in this field, emphasized that collusion often relies on mechanisms that enable firms to communicate intentions, coordinate expectations, and monitor compliance, even in the absence of traditional cartel meetings.³⁷ Nevertheless, courts have generally required proof of an explicit agreement rather than relying solely on facilitating practices or economic theories of coordination.³⁸

29 *Monsanto Co. v. Spray-Rite Svc. Corp.*, 465 U.S. 752, 760–64, 768 (1984). See also, Giovanna Massarotto, *Detecting Algorithmic Collusion*, 86 Ohio St. L. J. 818, 826 (2025).

30 *In re Text Messaging Antitrust Litig.*, 782 F.3d 867 (7th Cir. 2015).

31 *Kleen Prods. LLC v. Georgia-Pacific LLC*, 910 F.3d 927, 931 (7th Cir. 2018). The Seventh Circuit ruled again on the "fine line between agreement and tacit collusion, or, put another way, conscious parallelism." *Id.*

32 Joseph E. Harrington, *Posted Pricing as a Plus Factor*, 7 J. Competition L. & Econ. 1, 2 (2011).

33 See Donald F. Turner, *The Definition of Agreement under the Sherman Act: Conscious Parallelism and Refusals to Deal*, 75 Harv. L. Rev. 655, 669 (1962).

34 Francisco Beneke & Mark-Oliver Mackenrodt, *Remedies for Algorithmic Tacit Collusion*, 9 J. Antitrust Enforcement 152, 153-154 (2020).

35 *Ibid.*

36 George A. Hay, *The Meaning of Agreement under the Sherman Act: Thoughts from the Facilitating Practices Experience*, 16 Rev. Indus. Org. 113 (2000).

37 Harrington, *supra* note 32, at 15.

38 See *supra* notes 29, 30, 31.

V. CONCLUDING REMARKS

The present AI collusion discussion revives a century long debate about tacit collusion from which important lessons can be drawn. Although the underlying technology of markets has changed, the problem remains largely the same. The rise of AI and AI agents in particular urges U.S. antitrust law to rethink of collusion and the agreement requirement. If oligopolistic coordination was once largely confined to a limited set of concentrated industries, AI pricing systems have the potential to scale similar coordination mechanisms across the broader economy. The challenge for antitrust law is therefore no longer confined to a handful of markets. It is whether competition law can continue to preserve competitive independence in an age increasingly governed by autonomous AI agents.



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