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What About Bob? Revisiting the Intersection of Antitrust Law and Algorithmic Pricing in 2024

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Abstract

Courts have begun to flesh out the relevant questions for when competitors can use the same algorithmic pricing tools as each other. The US DOJ and FTC are intervening to try to push the law in a more plaintiff-friendly direction, showing skepticism when companies use pricing algorithms to capture more of consumers' willingness to pay. But the touchpoint for answering the tricky legal questions seems to be guided by analogies to human decision-making, at least for now. Courts are asking "What About Bob?" – that is, wouldn't this be fine if a human did it? – and that question should therefore guide companies when they consider three risk factors in making or using algorithmic pricing tools: (1) what sort of independent discretion do users of the tool exercise, (2) is the algorithm trained on public or non-public data, and, (3) does the algorithm have the power to manipulate market conditions to "learn" inferences?

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I. Introduction

488. A test offered by Maureen Ohlhausen (one of the authors here), while Acting Chairman of the US Federal Trade Commission (FTC), in a 2017 speech has become a widely cited standard for the legality of using algorithms under the antitrust laws. What has become known as the "Bob" Test is as follows:

> Everywhere the word "algorithm" appears, please just insert the words "a guy named Bob". Is it ok for a guy named Bob to collect confidential price strategy information from all the participants in a market, and then tell everybody how they should price? If it isn't ok for a guy named Bob to do it, then it probably isn't ok for an algorithm to do it either.[1]

489. Seven years – and many technology cycles – later we ask, "What About Bob?" – how have companies been using pricing algorithms, and is the "Bob" Test still a reliable way of judging a business's antitrust risk from using or creating an algorithm? We think the answer is that the test is still apt, and the courts are following it despite plaintiffs' and enforcers' attempts to distinguish it. The US Department of Justice (DOJ), FTC, and private plaintiffs have recently argued that machines are fundamentally distinct from employees – in their view, technological tools that may help businesses more effectively maximize profits should receive special antitrust scrutiny. Some of the typical elements of Section 1 of the Sherman Act case should be relaxed in this context, according to this view.

490. With this heightened level of scrutiny on pricing algorithms, we think the time is right to a provide a roadmap of key factors for evaluating the antitrust risk from algorithmic pricing tools that: (1) have users who compete against each other in their market, (2) ingest large amounts of data (perhaps eclipsing the abilities of "Bob"), or (3) both.

491. The most important factors discussed in case law to date are taken in turn – what sort of independent discretion do users of the tool exercise, is the algorithm trained on public or non-public data, and does the algorithm have the power to manipulate market conditions to "learn" inferences?

II. First Factor: Does the User Exercise Independent Discretion Over the Output of the Algorithm?

492. One factor in assessing antitrust risk when an algorithm is involved in price-setting looks at how the output of that algorithm is used. Are the results of the algorithm mere non-mandatory pricing recommendations? Or have the parties agreed – independently or in coordination with one another – to delegate decision-making authority to the algorithm? Even where competitors have not clearly communicated or agreed, do they face pressure to adopt the pricing recommendations, and how often do they do so in practice?

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1 Maureen K. Ohlhausen, *Should We Fear the Things That Go Beep in the Night? Some Initial Thoughts on the Intersection of Antitrust law and Algorithmic Pricing*, FTC (May 23, 2017), https://www.ftc.gov/news-events/news/speeches/should-we-fear-things-go-beep-night-some-initial-thoughts-intersection-antitrust-law-algorithmic.

493. The answers to these questions determine the binding or non-binding nature of reliance on the algorithm and constitute arguably the greatest risk factor in assessing how the use of an algorithm to set pricing will be scrutinized under an antitrust analysis.

494. At one end of the spectrum of risk, a business might decide to employ technology that cedes independent control of pricing to a third-party algorithm. Investigations and litigations in this area show that binding agreements to price according to an algorithm, whether by contractual agreement or by a less formal agreement, comes with risks.

495. *United States v. Topkins* is an early and relatively straightforward example of how agreeing to be bound by the results of an algorithm can violate Section 1 of the Sherman Act.[2] *Topkins* is commonly cited as the first US Department of Justice (DOJ) case to allege that a pricing algorithm was a tool to further an antitrust violation.[3]

496. In *Topkins*, defendant David Topkins sold posters through Amazon Marketplace, Amazon's Website for third-party sellers.[4] Topkins pleaded guilty to participating in a conspiracy with other poster sellers to fix the prices of certain posters sold on Amazon Marketplace.[5] The DOJ had evidence that Topkins and other poster sellers engaged in pricing discussions with each other during which they agreed to fix the prices of certain posters.[6] To implement these agreements, Topkins and his co-conspirators "agreed to adopt specific pricing algorithms for the sale of the agreed-upon posters with the goal of coordinating changes to their respective prices."[7] According to the DOJ, Topkins actually wrote the computer code that instructed his company's algorithm-based software to set prices of the agreed-upon posters in conformity with the conspirators' agreement.[8] Ultimately, Topkins pleaded guilty to violating Section 1 of the Sherman Act and agreed to pay a $20,000 criminal fine.[9]

497. As *Topkins* shows, an agreement between competitors to be bound by the prices generated by an algorithm is treated no differently from any other hardcore price-fixing agreement that violates Section 1. This is the

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2 U.S. Dep't of Justice, Plea Agreement, United States v. Topkins, 3:15-cr-00201-WHO (N.D. Cal. 2015), https://www.justice.gov/atr/case-document/file/628891/dl; 15 U.S.C. § 1.

3 See, e.g., *AI and Antitrust – When Does an Algorithm Become an Agreement?*, JDSupra (May 19, 2023), https://www.jdsupra.com/legalnews/ai-and-antitrust-when-does-an-algorithm-6819337/.

4 *Id.*

5 U.S. Dep't of Justice, Plea Agreement, *Topkins*, 3:15-cr-00201-WHO, at ¶ 4(b) (N.D. Cal. Apr. 30, 2015).

6 *Id.*

7 *Id.*

8 *Id.* information at ¶ 8(d). *See also* Robert E. Connolly, *The US DoJ Secures the Guilty Plea of a Former E-Commerce Executive Following the Prosecution of the First E-Commerce Price Fixing Case (Topkins)*, e-Competitions April 2015, art. No. 73395. www.concurrences.com/73395

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

original premise of the "Bob" Test after all: if it isn't ok for Topkins to reach pricing agreements with his competitors without an algorithm, it is not ok to do so with an algorithm.

498. This basic concept was a touchpoint of the "Bob" Test and continues to be reinforced in agency positions and actions. For example, a recent FTC blog post reiterated: "[Y]our algorithm can't do anything that would be illegal if done by a real person… When you replace once-independent pricing decisions with a shared algorithm, expect trouble. Competitors using a shared human agent to fix prices? Illegal. Doing the same thing but with an agreed upon, shared algorithm? Still illegal."[10]

499. Moving on to a closer set of cases, agreements to assist, rather than end, independent pricing judgment are being scrutinized by the current Administration as well as private plaintiffs.

500. Recent statements from the FTC and FTC leadership have expressed the position that the use of price-setting algorithms can violate the US antitrust laws even if the competitors using the algorithm never "directly communicated and retained some pricing discretion."[11] So long as competitors "each agree to use [an algorithm] knowing the others are doing the same in concert[,]" the conduct may be scrutinized.[12] These statements show that there is some antitrust risk in using the same algorithm as your competitors, even if there is no separate agreement to be bound by the results of an algorithm, as was present in *Topkins*. We can learn this Administration's position fromits recent Statements of Interest submitted in private litigation.[13] They argue that delegating "key aspects" of pricing to an algorithm could be per se illegal, "even if [parties] retain some authority to deviate from the algorithm's recommendations."[14]

1. In re: RealPage, Inc. Rental Software Antitrust Litigation (No. II)[15]

501. In November 2023, the DOJ filed a statement of interest in *In re: RealPage, Inc. Rental Software Antitrust Litigation (No. II)*, a federal multidistrict litigation out of Tennessee, arguing that an algorithm that

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10 Hannah Garden-Monheit & Ken Merber, *Price Fixing by Algorithm is Still Price Fixing*, FTC Business Blog (Mar. 1, 2024), https://www.ftc.gov/business-guidance/blog/2024/03/price-fixing-algorithm-still-price-fixing.

11 Lina Khan, Twitter (Mar. 29, 2024, 10:45 AM), https://x.com/linakhanFTC/status/1773768439720509738.

12 Garden-Monheit & Merber, *supra* note 10.

13 As this chapter was going to print, the U.S. Department of Justice filed a civil lawsuit directly challenging the practices it criticized in the Statements of Interest we discuss here. See United States v. RealPage, Inc., No. 1:24-cv-00710, Complaint (M.D.N.C. Aug. 23, 2024) ECF No. 1. This development demonstrates that the principles articulated in this chapter are an enforcement priority for the U.S. antitrust agencies, and confirms that this is an important area to watch for businesses using modern pricing technologies.

14 U.S. Dep't of Justice, Statement of Interest of the United States of America, Duffy v. Yardi Systems, Inc., 2:23-cv-01391-RSL, at 3 (W.D. Wash. Mar. 1, 2024), ECF No. 149.

15 The authors' firm, Wilson Sonsini Goodrich & Rosati, represents one of the defendants in the RealPage litigation.

sets non-mandatory prices could still be per se illegal under the US antitrust laws.[16]

502. The *RealPage* litigation began in October 2022 when renters of multi-family residential real estate brought a class action case against RealPage and certain property owners and managers who use RealPage's offerings.[17] RealPage offers a revenue management software that collects property owners' and managers' sensitive pricing and supply data, applies an algorithm across this data, and then generates price recommendations for each rental unit.[18] Plaintiffs allege that by co-mingling their sensitive pricing and supply data within RealPage's revenue management software, property owners and managers – who are horizontal competitors – have been facilitated by RealPage to conspire to fix prices in student and multi-family rental housing markets throughout the United States.[19]

503. In a November 2023 Statement of Interest the DOJ argued that "the alleged scheme [met] the legal criteria for per se unlawful price fixing"[20] because "the common delegation of decision-making to a common entity allows its decisions to affect actual or potential competition – even without any additional subsequent agreement or coordination among the parties."[21] According to the filing, this kind of delegation, even if some deviation or non-conformity with the algorithm's pricing recommendations remained, represented "the joining together of separate actors with separate economic interests characteristic of concerted action that Section 1 of the Sherman Act reaches."[22]

504. Analogizing to the Supreme Court's decision in *State Bar. Goldfarb v. Virginia State Bar* as well as cases holding that fixing advertised list prices is per se unlawful, even if firms are free to ultimately charge lower prices to customers, the DOJ reasoned that fixing non-mandatory prices by way of an algorithm could still be per se illegal.[23]

505. The correct focus – according to the DOJ – is on how the challenged price-fixing scheme "disrupt[s] the competitive process," rather than the ultimate success of the scheme or, in this case, complete adherence to the algorithm's pricing.[24] According to the DOJ, it seems, when a seller uses

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16 U.S. Dep't of Justice, Statement of Interest of the United States of America, In re: RealPage, Inc. Rental Software Antitrust Litigation (No. II), 3:23-md-03071 (M.D. Tenn. Nov. 15, 2023), ECF No. 628.

17 Edward Rogers, Elizabeth Weissert & Haesun Burris-Lee, *Algorithmic Pricing Programs Caught in Antitrust Crosshairs*, Law360 (Feb. 2, 2024, 2:28 PM), https://www.law360.com/articles/1791730/algorithmic-pricing-programs-caught-in-antitrust-crosshairs?copied=1.

18 Memorandum Opinion*, In re: RealPage,* at 2 (Dec. 28, 2023).

19 *Id.*

20 U.S. Dep't of Justice, Statement of Interest of the United States of America, *In re: RealPage*, at 2-3.

21 *Id.* at 5.

22 *Id.* at 5.

23 *Id.* at 22.

24 *Id.* at 20–21.

a pricing algorithm knowing its competitors will also do so, this could subject the party to per se liability even if the seller does not adhere to the prices generated by the algorithm on every occasion, and has made no agreement (with the algorithm provider or with its competitors) to do so.

2. Duffy v. Yardi Systems, Inc.

506. In March 2024, the DOJ – joined this time by the FTC – took this position again even more pointedly in a Statement of Interest filed in a separate class action involving a rent-setting algorithm, *Duffy v. Yardi Systems, Inc*.[25] In *Duffy v. Yardi*, a putative class of renters alleged that Yardi and a group of property management companies that used Yardi's RENTmaximizer revenue management software to "maximize rental income" engaged in price coordination in violation of Section 1 of the Sherman Act.[26]

507. The DOJ and FTC submitted a Statement of Interest specifically "to address an incorrect legal position in defendants' motion to dismiss: that the landlords' retention of some pricing discretion dooms a price-fixing claim."[27] The agencies explained that the case law is "clear" that competitors "may not agree to fix the *starting point* of pricing (e.g., agree to fix advertised list prices) even if the actual charged prices vary from the starting point."[28] Pointing to per se treatment for schemes that "fix advertised *list* prices or sticker prices,"[29] the agencies noted that "[t]he same principle holds in cases involving joint delegation of pricing recommendations to a common algorithm. By altering the starting point of prices, such agreements among competitors are analogous to agreements to fix list prices – distorting the competitive pricing process that the per se rule protects."[30]

508. According to the agencies, adherence to an agreed price is not a condition of per se illegality: "Price deviations don't immunize conspirators… Just because a software recommends rather than determines a price doesn't mean it's legal. Setting initial starting prices or recommending initial starting prices can be illegal, even if conspirators deviate from recommended prices. And even if some of the conspirators cheat by starting with lower prices than those the algorithm recommended, that doesn't necessarily change things."[31]

509. As of the publication of this chapter, no order on defendants' motion to dismiss has been issued in *Duffy v. Yardi*. Yet between the two statements of interest in these ongoing rent-setting algorithm litigations, US antitrust

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25 U.S. Dep't of Justice, Statement of Interest of the United States of America, *Yardi Systems, Inc*.

26 *See* Complaint, *Yardi Systems, Inc.*, 2:23-cv-01391-RSL at 2 (W.D. Wash. Sept. 8, 2023), ECF No. 1.

27 U.S. Dep't of Justice, Statement of Interest of the United States of America, *Yardi Systems, Inc.*, at 2 (internal citation omitted).

28 *Id.* at 2 (internal citation omitted).

29 *Id.* at 4–5.

30 *Id.* at 6.

31 Garden-Monheit & Merber, *supra* note 10.

enforcement agencies have clearly put a stake in the ground for the proposition that "[j]ust because a software recommends rather than determines a price doesn't mean it's legal."[32]

510. While US enforcement agencies have taken the position that using the same algorithm as your competitors to generate non-binding price recommendations may subject a party to per se liability, the few court decisions that analyze this factor have tended to take a softer view – requiring evidence of something more for a per se Section 1 claim to withstand a motion to dismiss. A small (but perhaps growing) body of case law suggests that choosing to use the same third-party algorithm that competitors have used for mere non-binding pricing recommendations does not constitute a per se violation of Section 1 unless paired with evidence: (i) of a direct agreement or communications between competitors, or (ii) that the recommendations were somehow "binding or enforceable."[33]

511. For example, in the January 2024 motion to dismiss opinion in *RealPage*, the court found that multi-family plaintiffs had "not alleged a straightforward conspiracy justifying application of the per se standard."[34] A key defect noted by the court was that, "while Plaintiffs allege that RMS Client Defendants 'delegate[d]' their pricing decisions to RealPage, they also allege that as much as 10–20% of the time, RealPage's clients deviate or override those pricing recommendations."[35] Under these facts, the court could not find the plaintiffs alleged "an absolute delegation of their price-setting to RealPage."[36] While the plaintiffs had alleged "an aggressive scheme created by RealPage to monitor acceptance of its pricing recommendations,"[37] the court found such allegations insufficient without evidence that RealPage could "enforce acceptance of price recommendations" by, for example, "removing an uncooperative member from the conspiracy or applying some other form of punishment."[38] Absent this, the plaintiffs had not sufficiently alleged a per se price-fixing conspiracy.[39]

512. The court noted similar defects in the student plaintiffs' complaint: "the Student Complaint does not allege that the RealPage pricing recommendations were in any way binding or enforceable on Lessors… RealPage's pricing recommendations rel[y] on RealPage's monitoring and Lessors for

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32 *Id.*

33 U.S. Dep't of Justice, Memorandum Opinion*, In re: RealPage,* at 48; *see also* Gibson v. MGM Resorts International, No. 2:23-CV-00140-MMDDJA, 2023 WL 7025996 at *2 (D. Nev. Oct. 24, 2023) ("[T]he Court cannot plausibly infer from the allegations in the Complaint that Hotel Operators are required to accept the recommendations provided by a particular software pricing algorithm. This is a fatal deficiency in the Complaint.")

34 U.S. Dep't of Justice, Memorandum Opinion*, In re: RealPage*, at 45.

35 *Id.* at 46 (cleaned up).

36 *Id.* (cleaned up).

37 *Id.* (cleaned up).

38 *Id.* (cleaned up).

39 *Id.* (cleaned up).

internal enforcement; it does not provide Lessors means to discipline other supposed co-conspirators for failure to adhere to the alleged conspiracy."[40]

513. In late 2023, the court in another ongoing algorithmic pricing litigation came to a similar conclusion. In granting the defendants' motion to dismiss, the court in *Gibson v. MGM Resorts International*, took a similar position on the importance of alleging mandatory pricing recommendations in stating a per se Section 1 claim. The *Gibson* plaintiffs challenged "an unlawful agreement among Defendants to artificially inflate the prices of hotel rooms on the Las Vegas Strip above competitive levels,"[41] alleging that hotel operators "agreed to use a shared set of pricing algorithms" offered by Rainmaker "that recommend supra-competitive prices to the hotel operators."[42]

514. The court reasoned that it could not "plausibly infer from the allegations in the Complaint that Hotel Operators [were] required to accept the recommendations provided by a particular software pricing algorithm."[43] According to the court, this was a "fatal deficiency" to plaintiffs' allegations "as without an agreement to accept the elevated prices recommended by the pricing algorithm, there is no agreement that could either support Plaintiffs' theory or otherwise make out a Sherman Act violation[.]"[44]

515. The reasoning used in both *RealPage* and *Gibson* comports with the well-established principle in cases involving Manufacturer's Suggested Retail Prices that a manufacturer may suggest resale prices to dealers, and no agreement will result if a dealer "independently decides to observe specified resale prices."[45] Manufacturers have generally been permitted to provide suggested price lists to dealers, to advertise suggested resale prices to dealers' customers, and to print suggested resale prices on the product or a price tag without being found to have entered into resale price agreements with dealers.[46] Though these are cases involving vertical restraints, they address directly the question of whether a suggestion can satisfy the element of agreement under Section 1 of the Sherman Act. Where the decision to make a suggestion is a unilateral one, it seems that this crucial element of the Sherman Act may be missing.

516. When faced with the issue of how aggressively the manufacturer can press its dealers to abide by its pricing suggestions, courts have generally found that anything short of coercion – including "exposition, persuasion and

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40 *Id.* at 48.

41 Gibson v. MGM Resorts Int'l, No. 2:23-CV-00140-MMDDJA, 2023 WL 7025996 at *1 (D. Nev. Oct. 24, 2023) (quoting complaint). Accord *Id.* (D. Nev. May 8, 2024) (reaching the same conclusion on motion to dismiss amended complaint).

42 *Id.*

43 *Id.* at *3.

44 *Id.*

45 United States v. Parke, Davis & Co., 362 US 29, 44 (1960); *see also* Isaksen v. Vermont Castings, Inc., 825 F.2d 1158, 1164 (7th Cir. 1987) (fact of adherence does not establish agreement to adhere).

46 *See generally*, American Bar Association, 1-1 Antitrust Law Developments 1D-1-a-(3)(a) (2021).

argument" to encourage dealers to charge the suggested prices – does not constitute the sort of breakdown in independent decision-making that runs afoul of Section 1 of the Sherman Act.[47]

517. While so far the cases involving algorithmic pricing have not relied on a "coercion" standard, they suggest evidence of more than a mere unenforceable recommendation is required.

III. Factor Two: Does the Algorithm Use Non-Public Data to Determine a Price?

518. In addition to considering whether the output of the algorithm is binding on those using it or a mere recommendation not subject to an agreement or enforcement mechanism, investigations and litigations involving pricing algorithms have also focused on whether the algorithm generates pricing recommendations based solely on public information, or whether the algorithm uses non-public, competitively sensitive information provided by groups of competitors.

519. Notably, this public/non-public factor encompasses both what information is *fed into* the algorithm as well as what information *comes out* of the algorithm in each pricing recommendation. For example, even if an algorithm collects non-public pricing data from multiple competitors in a market, it likely makes a difference under a Section 1 analysis whether the pricing recommendation generated for one competitor takes into consideration only that competitor's non-public data, or also considers the pricing data collected from other competitors.

520. Parsing one level further, consider a scenario in which a pricing algorithm collects non-public data from multiple competitors and uses this to observe a demand-side trend – such as softening demand. The algorithm then uses that demand-side trend observation to make an individualized pricing recommendation to one competitor but *does not* use data related to how the other competitors will price in making the recommendation.

521. Despite the fuzzy boundaries and many complications of the public/non-public factor, one principle appears consistent: the "exchange" of non-public information between competitors through an algorithm creates substantial Section 1 risk.[48] This principle again harkens back to our old friend Bob. If it isn't ok for a guy named Bob to exchange non-public information with competitors, then it probably isn't ok for an algorithm to do it either.

522. What is less clear, however, is what exactly it means to "exchange" non-public information by means of an algorithm. Is it enough that multiple competitors feed their non-public information *into* an algorithm, or does Section 1 require that data to be fed into an algorithmic "melting pot" and then *produced out* of the algorithm by way of its pricing recommendations?

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47 Gray v. Shell Oil Co., 469 F.2d 742, 748 (9th Cir. 1972).

48 *See e.g.*, *In re: RealPage,* Memorandum Opinion, at 34 (Dec. 28, 2023).

For a Section 1 "exchange" to have occurred, must the pricing recommendation given by an algorithm to Competitor A be based on the pricing information fed into the system by Competitor B? What if non-public information is combined in training an algorithm to predict the shape of the demand curve in the market, but it does not factor in information about the competitors' plans for supply?

523. The picture emerging from the various cases to consider this factor is that the highest risk involves an algorithm that collects non-public sensitive data from a set of competitors, mixes that data together to forecast supply conditions, and uses it to make individualized recommendations to each competitor. The courts in both *RealPage* and *Gibson* appear to agree that this may constitute an "exchange" of non-public information by means of an algorithm in violation of Section 1.

524. In *Gibson*, for example, the court dismissed the plaintiffs' original complaint on the grounds that their allegations failed to support a hub-and-spoke Section 1 theory. The court explained: "Plaintiffs never quite allege (though they suggest by implication) that Hotel Operators *get* non-public information from other Hotel Operators by virtue of using insufficiently specified algorithmic pricing software."[49] While the plaintiffs alleged

> that confidential information is fed in, but less clearly out, of the algorithms… [plaintiffs do] not explicitly say that one Hotel Operator ever receives confidential information belonging to another Hotel Operator. Moreover, it is unclear whether the pricing recommendations 'generated' to Hotel Operators include that confidential information fed in; perhaps they only get their own confidential information back, mixed with public information from other sources… This does not quite say that the Rainmaker algorithm itself exchanges non-public information.[50]

525. Accordingly, the court found: "Plaintiffs attempt[ed] to create an inference of the exchange of nonpublic information in their Complaint without actually alleging such an exchange."[51]

526. Several months later, the *RealPage* court grabbed on to this distinction, noting this was the "critical difference" between the two cases, and the reason certain claims in *RealPage* survived while all claims were dismissed in *Gibson*. The court noted that unlike in *Gibson*, "[h]ere, the Multifamily Complaint unequivocally alleges that RealPage's revenue management software inputs a melting pot of confidential competitor information through its algorithm and spits out price recommendations based on that private competitor data."[52] The court held this was sufficient

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49 2023 WL 7025996 at *4.

50 *Id.* at *5.

51 *Id.* at *4.

52 *See In re: RealPage*, Memorandum Opinion, at 34 (Dec. 28, 2023).

to allege a plausible "exchange" in violation of Section 1. This exchange of non-public, commercially sensitive information – along with the common motive to conspire – "taken together… support[ed] a 'reasonable expectation that discovery will reveal evidence of [an] illegal agreement.'"[53]

527. Even when the plaintiffs in *Gibson* amended their complaint to include additional allegations that non-public information had improved the algorithm's pricing predictions over time through machine learning, the court rejected that this constituted the sort of coordinated use of a competitor information prohibited by the antitrust laws. The court specifically appealed to a version of the Bob Test in deciding whether a hub having access to confidential information constitutes the illegal exchange of information between the spokes:

> Defense counsel persuasively analogized the pricing algorithms to an attorney's practice at the Hearing. He argued you can think of Plaintiffs' machine learning theory as to GuestRev and GroupRev as no different than an attorney improving her skills over time with the benefit of experience and access to confidential client information she gains with each client engagement. The attorney does not share one client's confidential information with another, but over time, she (ideally) gets smarter because of what she has learned from each client engagement she has successfully completed. And in time, clients seek her out because she has, for example, developed expertise in antitrust law. But that does not plausibly suggest that each new client who seeks out the attorney is entering into an agreement with every client she has ever worked with. How could it? And the same goes for Plaintiffs' machine learning theory. Thus, mere use of algorithmic pricing based on artificial intelligence by a commercial entity, without any allegations about any agreement between competitors – whether explicit or implicit – to accept the prices that the algorithm recommends does not plausibly allege an illegal agreement, or 'raise a reasonable expectation that discovery will reveal evidence of illegal agreement' sufficient to survive the Motion.[54]

528. In short, the courts in both *RealPage* and *Gibson* have not stopped the inquiry with what is fed *into* an algorithm, finding instead that an "exchange" of non-public information by competitors only occurs when there is proof that "the pricing recommendations '*generated*'… include th[e] confidential information fed in."[55] While "melting pot" algorithms present the highest risk, even the act of feeding non-public data to a third-party algorithm operator – without the additional step of the algorithm

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53 *Id.* at 33.

54 Gibson v. MGM Resorts Int'l, No. 2:23-CV-00140-MMDDJA, Slip Op. at 12 (D. Nev. May 8, 2024) (quoting Kendall v. Visa U.S.A., Inc., 518 F.3d 1042, 1047 (9th Cir. 2008)).

55 2023 WL 7025996 at *5 (emphasis added).

mixing that information with competitors' information and using it to inform individualized pricing recommendations – appears to carry some antitrust risk.

529. In fact, for the DOJ, it appears the collection of non-public data alone may be sufficient. This was the focus in the recent *RealPage* Statement of Interest, in which the DOJ argued that when "competitors knowingly *combine* their sensitive, non-public pricing and supply information in an algorithm… with the knowledge and expectation that other competitors will do the same" they have violated Section 1.[56] For the DOJ, that competitors were alleged to have "knowingly *shar[ed]* 'competitively sensitive' and 'non-public' pricing information with RealPage" was sufficient to suggest a per se violation had occurred, without further inquiry into what RealPage ultimately did with the data and how it specifically informed its pricing recommendations.[57]

530. While this position does not yet appear to have been adopted by a court, it is an issue to monitor as the investigations and litigation over this use of data continue to play out in the courts.

531. Offering or using a pricing algorithm that collects and/or uses sensitive, non-public data from multiple competitors carries some amount of antitrust risk. However, the question remains whether an algorithm that collects only public data can also come under scrutiny.

532. The complaint brought against Amazon by the FTC in late 2023 appears to suggest so. The FTC alleges that Amazon created an algorithmic tool codenamed "Project Nessie" that allowed Amazon to track and observe price changes of other online retailers at such high frequency that it could "predict[] the likelihood that the online store or stores offering the lowest price for a given product would follow an Amazon price increase."[58] According to the FTC, Amazon could comfortably raise its own prices and, in doing so, induce other online retailers to raise their prices as well.[59]

533. The FTC complaint does not allege a Section 1 violation,[60] but rather that Project Nessie constitutes an unfair method of competition in violation of the FTC Act.[61] This is an area to watch and one in which the basic premise of the "Bob" Test may reach its limit. Though Bob has always been allowed under the antitrust laws to react to competitors' public price changes, even if the reaction was a "punishment" for deviating from a preferred price by steep (but not predatory) discounting, there remains a question whether the use of a technology tool changes the fundamental

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56 Statement of Interest of the United States of America, *In re: RealPage*, at 15.

57 *Id.* at 20.

58 FTC v. Amazon.com Inc., No. 2:23-cv-01495, Complaint (Public Redacted Version) at 120 (W.D. Wa. Nov. 2, 2023) ECF No. 114.

59 *Id.*at 120.

60 *Id.* at 1.

61 *Id.* at 126–28.

nature of the practice – morphing it into "unfair." On the one hand, Bob cannot do what the technology allegedly does – it is the high frequency nature of the observations and reactions that lessen competitive pressure, according to the FTC. On the other hand, antitrust law has never stood in the way of technology to improve upon human processes before, and the human process of price comparison, and reacting to competitors' publicly available information, is the *sine qua non* of competition.

534. Indeed, all the technologies at issue in the cases we discuss here make their users better at pricing, which means: (1) capturing more of the value that customers are willing to pay – a prize that is fundamental to the profit-motive underpinning a market-based economy, and (2) levelling the playing field among the companies who use the technology – there is no longer a competitive advantage from employing the best price-comparison team to research competitor prices at the most relevant times. Technological shifts always have the risk of levelling playing fields and shifting the vector along which businesses need to compete. Pricing algorithms, when they do not involve agreements among competitors to refrain from striving to out-do one another, are no different.

IV. Factor Three: Does the Algorithm Manipulate Market Conditions On Its Own?

535. Just as an algorithm that only uses public data may raise certain concerns under an antitrust analysis that humans exchanging public data do not raise, some have suggested that certain forms of learning algorithms may violate the antitrust laws in new and unexpected ways and therefore deserve particular scrutiny. While this factor has not yet played out significantly in the case law, it is a concern discussed in academic literature and has been noted as an issue to look for as algorithms become more sophisticated.

536. The technology behind the types of pricing algorithms we see in antitrust cases and investigations has come a long way in the past decade. Some commentators have observed that we may not be far off the point from which an algorithm may *itself* decide to collude without human instruction. For example, the 2023 OECD Competition Policy Roundtable Background Note on Algorithmic Competition stresses the unique risks of self-learning autonomous algorithms, including that such algorithms can "decide to collude (or at least avoid reaching a competitive outcome) without information sharing or explicit coordination."[62]

537. While not yet the subject of case law, this is an area to watch. There have been early accounts of the potential for algorithmic autonomous tacit collusion by legal scholars, and even more recently economists have started to work on this topic.[63] Despite considerable research on algorithmic

62 OECD, *Algorithmic Competition* (2023) 13–14, https://www.oecd.org/en/topics/competition.html.

63 *Id.*

collusion, the OECD Background Note reports that "its feasibility and scale in practice are still relatively unclear. While the adoption of pricing algorithms has grown considerably, they are not yet universal, never mind the use of self-learning pricing algorithms. Even if firms use self-learning pricing algorithms, there is not conclusive evidence that algorithmic autonomous tacit collusion is a significant issue. Nonetheless, competition authorities should remain vigilant."[64]

V. Conclusion

538. When large technology shifts cause businesses to implement new ways of competing and maximizing profit, there are always questions about how antitrust law will apply. The use of algorithms to price using large amounts of data is no different. The antitrust agencies and private plaintiffs have seized on this moment of uncertainty to push new theories for how this use of technology is suspect. Courts are just beginning to grapple with the task of analogizing to analog practices; in short, they are asking, "What about Bob?" During this period of uncertainty, we recommend that businesses assess whether their pricing tools might come under antitrust scrutiny because they perform a function that a human would not be allowed to perform under the antitrust laws, or because they perform a function that no human would be able to accomplish, no matter how much time and diligence they exercised. In particular, businesses should analyze the three factors most important to an antitrust risk profile in this area: does the user retain independent discretion to price, does the algorithm use non-public data, and is the algorithm able to manipulate market conditions?

64 *Id.*