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A CRITIQUE OF RECENT REMEDIES FOR THIRD-PARTY PRICING ALGORITHMS AND WHY THE SOLUTION IS NOT RESTRICTIONS ON DATA SHARING

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ABSTRACT

A growing antitrust challenge is competitors using a pricing algorithm supplied by the same data analytics company. Although there can be procompetitive efficiencies in outsourcing pricing, the risk of anticompetitive harm in having a common agent influence competitors' prices is severe. To deal with this challenge, a remedy has recently been proposed in the United States at the federal level and is being adopted at the local level. This remedy prohibits a third party's use of nonpublic competitor data. If firms A and B both subscribe to the same third party, that third party is prohibited from using the nonpublic data of firm B in the pricing algorithm that recommends prices to firm A. The contribution of this paper is to critically examine this remedy. First, it is explained the remedy creates inefficiencies that need to be recognized. Second, and more importantly, it is shown the remedy may not prevent the harm it is intended to prevent. More specifically, a workaround is developed whereby a third party can result in firms charging supracompetitive prices while not using nonpublic competitor data. The problem is that the remedy focuses on shared data when the source of harm is shared objective.

I. INTRODUCTION

One of the implications of Big Data and advances in algorithms, including artificial intelligence (AI), is that it is more attractive for a firm to use the assistance of a third party in their pricing. A data analytics or software company is likely to have better pricing algorithms than a firm would develop on its own because it has access to more data, more expertise and experience,

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and stronger incentives to invest in their development (as the pricing algorithm can be licensed to many firms). Offsetting the efficiencies from outsourcing pricing are concerns that a third party advising competitors could facilitate coordinated pricing. The OECD has expressed that "concerns of coordination would arise if firms outsourced the creation of algorithms to the same IT companies and programmers."[1] The United Kingdom's Competition & Markets Authority has warned: "If a sufficiently large proportion of an industry uses a single algorithm to set prices, this could result in a... structure that may have the ability and incentive to increase prices."[2] The German Monopolies Commission has noted that a third party, when selling a pricing algorithm, possibly "knows or accepts [it] could contribute to a collusive market outcome [and] it is even conceivable that [they] see such a contribution as an advantage, as it makes the algorithm more attractive for users interested in profit maximization."[3] And, in testimony before the U.S. Congress, a former Assistant Attorney General of the U.S. Department of Justice's Antitrust Division (DOJ) opined as an area of concern: "Companies avoiding price competition by using the same third-party vendor to collect data on supply and demand and 'recommend' pricing or output behaviors that facilitate price coordination."[4]

There is some evidence that these concerns have manifestedthemselves. Data analytics companies A2i Systems and Kalibratedeveloped pricing algorithms to assist retail gasoline companies in their pricing. After the wide adoption of such pricing software in Germany, a study by Assad *et al.* [2024] found higher margins from adoption and, consistent with it facilitating coordinated pricing, margins were higher in duopoly and triopoly markets only when all stations adopted. A recent study by Calder-Wang and Kim [2024] offers evidence for both procompetitive and anticompetitive effects. Pricing algorithms not only enhanced efficiency by making prices more sensitive to market conditions—"buildings with the software increase prices during booms and lower prices during busts, compared with nonadopters in the same market"[5]—but also evidenced supporting rents being set to maximize joint profits, which led to higher markups. [6] Based on these and other studies, the Council of Economic Advisers [2024] expressed concern that third-party pricing algorithms were fueling higher rents and exacerbating the housing crisis.

With *ex ante* concerns by competition authorities about anticompetitive harm and some supportive *ex post* empirical evidence, it is not surprising there has been growing activity in terms of private litigation and public investigations. In the market for apartments, data analytics companies RealPage and Yardi are being sued in separate litigation for violating Section 1 of the Sherman Act. Quoting from two complaints:

> RealPage provides software and data analytics to Lessors [and] serves as the mechanism by which Lessors collude and avoid competition, increasing lease prices to Plaintiffs.[7]

[1] OECD, "Algorithms and Collusion—Background Note by the Secretariat," DAF/COMP(2017)4, 9 June 2017, ¶ 68.

[2] United Kingdom Competition and Markets Authority [2018], "Pricing Algorithms: Economic Working Paper on the Use of Algorithms to Facilitate Collusion and Personalised Pricing," 8 October 2018, ¶ 5.21.

[3] German Monopolies Commission [2018], XXII. Biennial Report, Chapter on "Algorithms and Collusion," 2018, ¶ 263.

[4] Written Testimony of Bill Baer, U.S. Senate Committee on the Judiciary, Subcommmittee on Competition Policy, Antitrust, and Consumer Rights, Hearings on "The New Invisible Hand? The Impact of Algorithms on Competition and Consumer Rights," December 13, 2023, p. 2. < https://www.judiciary.senate.gov/imo/media/doc/2023-12-13_pm_-_testimony_-_baer.pdf> (downloaded January 17, 2024)

[5] Abstract of Calder-Wang and Kim [2024].

[6] For theoretical research exploring the third party's design of a pricing algorithm, see Harrington [2022 2025a b], Hickok [2024], and Sugaya and Wolitsky [2025].

[7] *Bason, et al. v. RealPage, Inc., et al.*, No. 3:22-cv-01611-WQH-MDD, U.S. District Court, Southern District of California, October 18, 2022, ¶ 5.

> Defendant Yardi and the Operator Defendants collectively used Yardi's "RENTmaximizer" software to coordinate on setting supracompetitive pricing on multifamily properties across the nation.[8]

There are also many class action suits in the market for hotels rooms where the defendants are third parties Rainmaker and IDeAS and subscribing hotel chains. Quoting from two complaints:

> Defendant Hotel Operators... on the Las Vegas Strip have replaced their independent pricing and supply decisions with a shared set of pricing algorithms [from Rainmaker] that allow the Hotel Operators to collect supracompetitive prices for their hotel rooms.[9]
> [B]y agreeing to use the pricing recommendations generated by the shared algorithm, Operator Defendants have agreed and conspired to outsource their independent pricing decision-making to a single, common pricing manager—IDeaS, which has willingly facilitated and enforced the conspiracy.[10]

Competition authorities are also starting to get into the action. The DOJ has filed its own complaint against RealPage and its subscribers.[11] In the market for gasoline, the Competition Bureau in Canada is investigating Kalibrate [12] and CADE in Brazil is investigating data analytics company Aprix.[13]

Lying behind this array of concerns, litigation, and investigations, there are three possible sources of anticompetitive harm. The first and most egregious form is a price-fixing agreement involving a third party and subscribing firms, as is being claimed by plaintiffs in private litigation in the U.S. markets for apartments and hotels. Although there may be challenges in detecting and proving the existence of such an agreement, it falls squarely under competition law as a *per se* (or by object) offense. A second source of anticompetitive harm is that a third party and subscribing firms have an information exchange agreement. This is the legal approach taken by the DOJ in its case against RealPage and subscribing firms.[14] Such an agreement is not *per se* illegal and will be evaluated under the rule of reason, which means the DOJ will need to prove there is an information exchange agreement and it is anticompetitive. The third and final source of harm is unilateral conduct by a third party. To increase the value of its services, a third party may have its pricing algorithm produce supracompetitive prices without the request, approval, or knowledge of the subscribing firms. Although harmful, it is not clear it is a violation of competition law, as noted by the German Monopolies Commission.

8 *Duffy, et al v. Yardi System, Inc., et al,* No. 23-cv-01391, U.S. District Court, Western District of Washington at Seattle, September 8, 2023, ¶ 1.

9 *Richard Gibson, et al. v. MGM Resorts International, et al.*, No. 2:23-cv-00140, U.S. District Court, District of Nevada, January 25, 2023, ¶ 2-4.

10 *Hanson Dai, et al v. SAS Institute, Inc., et al*, No. 3:24-cv-02537, U.S. District Court, Northern District of California, April 26, 2024, para. 9.

11 *United States of America v. RealPage, Inc.* (1:24-cv-00710), District Court, M.D. North Carolina, January 7, 2025

12 "Competition Bureau advances an investigation into Kalibrate's gas pricing services," Competition Bureau Canada Press Release, July 24, 2024 < https://www.canada.ca/en/competition-bureau/news/2024/07/competition-bureau-advances-an-investigation-into-kalibrates-gas-pricing-services.html >

13 "CADE launched an administrative proceeding to examine if the use of algorithms influences the adoption of concerted practices in the Brazilian fuel market. The anticompetitive practices stem from an algorithmic pricing tool used at petrol stations in a number of Brazilian cities.", "CADE investigates algorithmic pricing in fuel market", CADE Press Release, November 21, 2024 < https://www.gov.br/cade/en/matters/news/cade-investigates-algorithmic-pricing-in-fuel-market >

14 *United States of America v. RealPage, Inc.* (1:24-cv-00710), District Court, M.D. North Carolina, January 7, 2025, ¶ 263. The DOJ is also claiming that the defendants have aligned (not coordinated) rents: "The agreement by a landlord to use AIRM or YieldStar is an agreement to align users' pricing processes, strategies, and pricing responses." ¶ 277

> [L]iability gaps can open up if the IT service provider brings about a collusive market outcome without the approval of the parties involved. It is possible that several users use pricing algorithms whose use leads to collusive pricing. However, users may not be able to recognize this collusive market outcome themselves—for example, due to the complexity of the product or the market conditions—and therefore may not form a joint intention necessary to create a cartel. At the same time, however, the IT service provider that provided the pricing algorithms may be well aware of the possibility of collusive pricing and may also approve of it. In such a case, the situation ... cannot or only with difficulty be addressed pursuant to Article 101.[15]

Although there is debate whether there is a "liability gap," it would clearly be challenging to convict a third party of an antitrust offense without proving an agreement with subscribing firms.[16]

A takeaway from all this activity is that the unique features of competitors outsourcing pricing to a common data analytics company may require new laws. A law could simply prohibit competitors from using the services of the same third party. In light of the efficiencies that data analytics delivers, such a draconian solution has, rightfully, not been pursued. Indeed, that is the conundrum any remedy faces: How does one allow firms to avail themselves of the efficiencies of data analytics without risking anticompetitive harm? Section II places this challenge in the context of a broader competition policy issue: information sharing among competitors. Section III then describes recent efforts in the United States where bills have been put forth at the federal level and laws have been adopted at the local level. The contribution of this paper is to critically examine this class of remedies. Two points are made in Section IV. First, these remedies create inefficiencies that need to be recognized and taken into account when evaluating them. Thus far, the debate surrounding them has failed to do so. Second, and more importantly, these remedies are unlikely to prevent the harm they are intended to prevent. This I show through "proof of concept" by designing a workaround whereby a third party, if it wanted to set supracompetitive prices, could achieve that end without violating the law. Although the workaround is specific in its design, it illustrates a broader critique. As discussed in Section V, the current legal approach is misguided in viewing the source of harm as shared data, when it is instead shared objective. I explain how shared data are neither necessary nor sufficient for anticompetitive harm and that a remedy should focus on shared objective.

II. THIRD-PARTY PRICING ALGORITHMS AND INFORMATION SHARING

A data analytics company collects past data from subscribing firms to train a pricing algorithm and then uses that algorithm to make recommendations based on current data. To set the stage for presenting and critiquing recent remedies, it is useful to situate the practices of data analytics companies in the broader context of information sharing between competitors. In reviewing information sharing, the discussion will focus on practices most relevant to the setting at hand, which means firms share information through a third party (rather than directly) and the output of that third party is exclusively for the firms sharing information.[17]

Information sharing by competitors can involve a wide array of variables. First and foremost are prices that can mean past prices, current prices, and even future prices (though the latter is relatively uncommon because it is almost surely a competition law violation). Then there is the

15 German Monopolies Commission's Report on "Algorithms and Collusion", supra note 3, at ¶ 266.

16 For a further discussion of the harms and challenges of third-party pricing algorithms, see Harrington [2024].

17 For a more comprehensive treatment of information sharing among competitors, see Kühn [2001], Bennett and Collins [2010], and OECD [2011]. Though it will not be relevant to our discussion, there is a developed doctrine regarding how third parties—in particular, trade associations—should anonymize and aggregate data and delay their sharing.

sharing of sales, production output, and inventories, for example, past sales and planned future production. Firms may also share their costs, capacities, production metrics (for example, output at different stages of the production process), and performance metrics (for example, price-cost margins).

All of this information is commercially sensitive, which means a firm does not share it without the anticipation of some substantive benefit. A central competition policy concern is whether those benefits have the collateral effect of helping or harming consumers. One procompetitive benefit is that information sharing makes firms better informed when they make price, production, investment, and other decisions. For example, the sharing of past prices and sales will allow for improved demand estimation and that will lead to prices being better tailored to market conditions. A second type of procompetitive benefit is improved efficiencies through benchmarking. Information sharing can allow firms to compare their practices and performance, which has the potential for firms to lower cost and through other means deliver higher profit with better value for consumers. Turning to the dark side, competitors sharing information, even through a third party, run the risk of anticompetitive effect. Sharing current prices can facilitate firms making coordinated price decisions, whereas sharing past prices can provide the means to monitor and then discipline firms who price aggressively.

Given that background, let us consider some classes of third parties who engage in information sharing. In doing so, it is useful to address three questions: 1) What information does a participating firm provide to the third party?; 2) In return, what information does the third party provide to a participating firm?; and 3) What information provided by the third party is commonly shared with all participating firms?

One class of third parties shares price data among competitors. A firm provides its current prices and, consequently, a data set of past prices is accumulated. A third party shares either that raw price data or summary statistics with all participating firms, so it is common information. This information sharing can allow firms to be better informed of market conditions but can also be the basis for them to coordinate on supracompetitive prices.[18] Informed Sources is a third party in Australia that collects and then shares real-time price data from participating retail gasoline companies (see Bryne *et al.* [2024]). In the hotel sector, Smith Travel Research collects data from subscribing hotel chains on room revenue, rooms sold, and rooms available, and then aggregates them to deliver revenue per available room along with other measures such as the occupancy rate.[19] In the market for polyvinyl chloride pipe, the Oil Price Information Service collects prices from converters and distributors on a daily basis and then returns a weekly report with "low," "midpoint," and "high" prices.[20] In addition to or instead of handling price data, there are third parties that collect extensive production and sales-related data. A notable example is Agri Stats, which serves the broiler chicken, pork, and turkey industries. In the broiler chicken industry, firms provide data such as feed costs, plant workers' wages, number of breeder chickens, average flock age, along with many other variables. Agri Stats anonymizes and aggregates the data in a monthly report that it delivers to all subscribing firms. This information can be useful for benchmarking purposes though there are claims of it having resulted in coordinated conduct to reduce competition.[21]

[18] Harrington and Leslie(2023) provide a comprehensive analysis of competitors sharing prices, either directly or through a third party.

[19] *Jeanette Portillo et al v CoStar Group, Inc. et al*, Class Action Complaint, U.S. District Court for the Western District of Washington at Seattle, Case 2:24-cv-00229, February 20, 2024.

[20] *Blake Wrobbel v Atkore, Inc. et al*, Class Action Complaint, U.S. District Court – Northern District of Illinois, Eastern Division, Case No. 24-8012, September 3, 2024.

[21] For details on the services provided by Agri Stats and the associated litigation, see Sappington and Turner [2023].

With that brief overview of information sharing by competitors through a third party, let us consider third parties who are supplying a pricing algorithm. What information does a participating firm provide to the third party? A firm delivers prices and sales where prices are conditioned on product traits when the good is not a commodity (compare apartments and hotels with gasoline). Other information may be provided such as costs and capacities. What information does the third party provide to a participating firm? A firm will receive product-specific price recommendations. What information provided by the third party is commonly shared with all participating firms? Generally, no information is commonly shared, as these price recommendations are private between a firm and the third party. [22] Though the third party collects prices and sales, none of that data are shared with competitors. However, one could argue a firm's price recommendations are informative of other firms' data because those recommendations are generated by a pricing algorithm trained on all firms' data. In its case against RealPage and subscribing apartment owners, the Antitrust Division of the U.S. Department of Justice takes such a view: "Landlords... that compete with each other in the relevant markets alleged have agreed... to exchange nonpublic, competitively sensitive data... through RealPage's revenue management software."[23] In contrast, a judge in the case against Rainmaker and subscribing hotels takes a different view: "Using data across all your customers for research does not plausibly suggest that one customer has access to the confidential information of another customer."[24] Consistent with the latter view, it would seem extremely difficult to infer other firms' shared data from price recommendations. Although recommending a significant price increase (decrease) is consistent with most firms delivering data that suggest demand is stronger (weaker), that falls far short of a firm being able to infer rivals' data from the price recommendations it receives. On the other hand, if subscribing firms believe their recommendations are highly correlated then a firm may be learning a lot about competitors' price recommendations when it learns its own. That is more of a reason for concern.

In assessing the potential effects of information sharing in association with a third-party pricing algorithm, we have the procompetitive benefit of the third party having more precise demand estimates due to having the past prices and sales of many suppliers. At the same time, the information that is shared does not support benchmarking and thus will not produce better firm practices. On the anticompetitive side of the ledger, a third party could use its price recommendations to coordinate firms to set higher prices and is well placed to monitor competitors' prices for compliance. In addition, if information sharing is generating efficiencies, say through improved demand estimation, the third party has a lever to discipline noncompliant firms by denying them access to that efficiency. Interestingly, a procompetitive effect of information sharing becomes a facilitating factor for anticompetitive harm.[25]

III. CURRENT APPROACH TO A REMEDY FOR THIRD-PARTY PRICING ALGORITHMS

On January 30, 2024, Senator Amy Klobuchar introduced the "Preventing Algorithmic Collusion Act of 2024" in the U.S. Senate.[26] The bill has three features. First and foremost, it prohibits

[22] A third party who shared price recommendations with all subscribing firms is sharing price intentions and thus the associated parties are committing a *per se* or by object offense. Such information sharing facilitates coordinated conduct with no countervailing procompetitive benefits and, therefore, should be prohibited.

[23] United States of America et al. v RealPage, Inc. et al., United States District Court for the Middle District of North Carolina, Case No. 1:24-cv-00710-LCB-JLW, Amended Complaint, January 7, 2025, ¶ 263.

[24] Richard Gibson, et al., v. Cendyn Group, et al, United States District Court for the District of Nevada, Case No. 2:23-cv-00140-MMD-DJA, Order, May 8, 2024, page 10.

[25] As support for this faciliating factor, Harrington [2025b] and Sugaya and Wolitsky [2025] show the supracompetitive markup caused by a third-party's pricing algorithm is increasing in the efficiency the third party delivers.

[26] Preventing Algorithmic Collusion Act of 2024, S.3686, 118th Cong.https://www.congress.gov/bill/118th-congress/senate-bill/3686/text

the use of a pricing algorithm using nonpublic competitor data, the details of which are described below. Second, and for the purpose of enforcing that prohibition, it gives the U.S. Department of Justice's Antitrust Division and U. S. Federal Trade Commission (FTC) the authority to audit a firm's pricing algorithm. Third, it requires a firm to share certain information with customers and other market participants toward providing transparency regarding its pricing algorithm.

Section 4 of the bill states: "It shall be unlawful for a person to use or distribute any pricing algorithm that uses, incorporates, or was trained with nonpublic competitor data." In unpacking this prohibition, a "pricing algorithm" is defined as "any computational process, including a computational process derived from machine learning or other AI techniques, that processes data to recommend or set a price or commercial term." Nonpublic data are "information that is not widely available or easily accessible to the public ... regardless of whether the data are attributable to a specific competitor or anonymized," and a competitor is someone who "competes in the same market ... or a related market." Nonpublic data exclude "information distributed, reported, or otherwise communicated in a way that does not reveal any underlying data from a competitor, such as narrative industry reports, news reports, business commentaries, or generalized industry survey results."

The bill draws on existing antitrust laws in more precisely defining unlawful conduct. Parties have an agreement in violation of Section I of the Sherman Act and have engaged in an unfair method of competition in violation of Section 5 of the FTC Act when it is established that

> (1) the defendant distributed the pricing algorithm to two or more persons: (A) with the intent that the pricing algorithm be used to set or recommend a price or commercial term...; or (B) and two or more persons used the pricing algorithm to set or recommend a price or commercial term...; or (2) (A) the defendant used the pricing algorithm to set or recommend a price or commercial term...; and (B) the pricing algorithm was used by another person to set or recommend a price or commercial term....

Part (1) applies to a third party and part (2) applies to firms subscribing to the third party's service.

At the same time as that bill was put forward, one targeted for the rental housing market was also introduced. The stated objective of the "Preventing Algorithmic Facilitation of Rental Housing Cartels of 2024"[27] is "to prohibit the use of algorithmic systems to artificially inflate the price or reduce the supply of leased or rented residential dwelling units in the United States." It is similar in design in that the bill proposes to make it a *per se* violation of Section 1 of the Sherman Act for a rental property owner to contract with

> any person that operates a software or data analytics service that performs a coordinating function," where a coordinating function means: "(A) collecting historical or contemporaneous prices, supply levels, or lease or rental contract termination and renewal dates of residential dwelling units from two or more rental property owners; (B) analyzing or processing of the information described in (A) using a system, software, or process that uses computation, including by using that information to train an algorithm; and (C) recommending rental prices, lease renewal terms, or ideal occupancy levels to a rental property owner.

[27] Preventing Algorithmic Facilitation of Rental Housing Cartels Act of 2024, S.3692, 118th Cong. https://www.congress.gov/bill/118th-congress/senate-bill/3692

Although the two Senate bills are yet to pass (and have not even come to a vote),[28] laws pertaining to rental housing markets have been put in place in the cities of San Francisco (effective October 2024)[29] and Philadelphia (effective February 2025).[30,31] The San Francisco law defines an "algorithmic device" as

> revenue management software that uses one or more algorithms to perform calculations of nonpublic competitor data concerning local or statewide rents or occupancy levels, for the purpose of advising a landlord on whether to leave a unit vacant or on the amount of rent that the landlord may obtain for that unit.

As noted, the algorithm only comes under the law if it uses nonpublic competitor data, which are defined as "information that is not available to the general public, including information about actual rent prices, occupancy rates, lease start and end dates, and similar data." It then prohibits the sale and use of such software. Pertaining to a third-party supplier, it makes it "unlawful to sell, license, or otherwise provide to San Francisco landlords any algorithmic device that sets, recommends, or advises on rents or occupancy levels..." As regards users, it is "unlawful for a landlord to use an algorithmic device... when setting rents or occupancy levels..."

The Philadelphia law borrows the definition of "nonpublic competitor information" from the San Francisco law and then defines the prohibited conduct as "price coordination for residential rental units in the City." Price coordination is defined to have occurred when both of the following acts take place:

> (a) collecting historical or contemporaneous nonpublic competitor information concerning prices, price changes, supply levels, occupancy rates, or lease or rental contract termination and renewal dates of residential rental units from two or more real estate lessors...; and (b) recommending or suggesting rental prices, fees, rental terms, or occupancy levels to a real estate lessor based on such information, including when such recommendation involves the analysis or processing of information using a computational or algorithmic system, software, or process.

Distilling these bills and laws, they are all based on a common approach to restricting the conduct of third parties who are supplying pricing algorithms and the conduct of firms in a market who are using a third party's pricing services. They prohibit a third party, such as a software or data analytics company, from providing a service to two or more firms in a market that involves recommending prices to a firm based on an algorithm that has been trained on or conditions on nonpublic data from competitors to that firm. A recommended price to a firm can only depend on private data provided by that same firm, public data, and other data collected by the third party through sources other than that firms' competitors. They also prevent firms from using a pricing algorithm based on nonpublic competitor data.

Interestingly, this type of restriction was purportedly agreed to between RealPage and apartment property owner AvalonBay, where the latter

> insisted on a contractual provision .... that prohibited [RealPage] from (1) using any data [used in determining the rent recommended to AvalonBay] other than AvalonBay's own data

28 The "Preventing Algorithmic Collusion Act" was reintroduced on January 23, 2025.

29 City and County of San Francisco, File No. 240766, Ban on Automated Rent-Setting, July 29, 2024.

30 City of Philadelphia, Bill No. 240823, Amending Chapter 9-800 ("Landlord and Tenant") to add prohibitions and penalties related to anticompetitive rental practices.

31 A similar law has gone into effect in Berkeley, California and is to go into effect in Minneapolis in March 2026.

> and publicly available data; and (2) using AvalonBay's data or disclosing the ... recommendations made by AvalonBay to any other [RealPage] client.[32]

Presumably in response to litigation, RealPage has now provided this option for its clients: "All customers have the ability to remove nonpublic data from the calculation of rent recommendations if they choose."[33]

The trend is to "fix" the potential anticompetitive problem of a third party by prohibiting the use of nonpublic competitor data. In the next section, I explain the problems with this approach.

IV. CRITIQUE OF THE REMEDY

A. Introduction

The primary critique of the remedies that have been proposed and implemented is that they are unlikely to prevent the harm they are intended to prevent. Toward establishing that claim, a workaround is described in Section C, which leads to substantively supracompetitive prices. Of course, one could respond that the remedy is still worth pursuing because it *might* work—in that third parties may not design such a workaround or the workaround may not be as effective in terms of charging supracompetitive prices—and if it does not work then there is no harm. However, there is harm. As described in Section B, the remedy interferes with the efficiencies made possible by data analytics. But there is a more fundamental reason why this class of remedies should not be pursued, which is that it does not get at the core of the anticompetitive problem. As I discuss in Section V, the source of anticompetitive harm is not shared data but shared objective, and a remedy should focus on preventing it.

B. Remedy will create inefficiencies

As there is no evidence that these data analytics companies were founded to facilitate coordinated pricing among competitors, we should presume they were created for the purpose of using data analytics to assist firms in making better decisions. At the same time, the provision of this legitimate service to competitors runs the risk of entering into anticompetitive territory. The recognition of data analytics as a legitimate service is crucial to understanding the incentives and intent of a third party and to ensure efficiencies are taken into account when assessing a remedy.

The problem before a firm is how best to price to maximize its profit. What will allow it to be more effective is better estimation and better optimization. More specifically, better estimation means being better informed of its demand function and thus how prices affect profits. With that knowledge, better optimization means being better skilled to identify the most profitable prices given that estimated profit function.[34]

A third party is likely to be more effective in both estimation and optimization. Estimation is improved with more data and better methods. A third party will have more data than any individual firm for two reasons. First, it will have the data from all subscribing firms, which encompass firms not only in the same market but also in different geographic markets with the same product or service. Second, compared with an individual firm, it is more incentivized to create new data, such as by conducting surveys of consumers or running experiments. An individual firm benefits from new data in terms of improving its own pricing but a third party

32 *In re RealPage, Inc., Rental Software Antitrust Litig.*, 2023 U.S. Dist. LEXIS 230199, at *27 (M.D. Tenn. Dec. 28, 2023).

33 "RealPage Offers its Revenue Management Software Customers the Ability to Remove Use of Nonpublic Data," RealPage Press Release, September 5, 2024. https://www.realpage.com/news/realpage-offers-its-revenue-management-software-customers-the-ability-to-remove-use-of-nonpublic-data/

34 Some learning algorithms, such as reinforcement learning, learn how prices affect profits without separately estimating the firm's demand function. Thus, estimation and optimization are not separate modules.

reaps such benefits many times over as it can use those data to improve the pricing of all subscribing firms. Larger benefits means a willingness to engage in more investment. A third party compounds its advantage in data with better estimation methods. There is a fixed cost to adopting or developing new estimation procedures, which a third party is more willing to incur because it can be applied to improving many firms' pricing. Plus, there are likely to be scale economies in having a staff of economists, data scientists, and software engineers. Consequently, a third party will have better estimation procedures than individual firms, in addition to having more data. For analogous reasons, a third party will have better optimization procedures.

The currently proposed and implemented remedies harm the efficiencies delivered by a third party because they reduce the amount of data it has, and data are the essential ingredient in data analytics. More specifically, a subscribing firm will no longer benefit from what a third party can learn from the private data of other subscribing firms. One might say that is the purpose of the remedy but, actually, its purpose is to prevent coordinated pricing, not make a firm less effective in its pricing. Let me provide three concrete examples of how a prohibition of the sharing of nonpublic competitor data results in less profitable pricing when firms price independently.

The first example pertains to distinguishing between firm-specific and market-wide changes in demand. Suppose a firm experiences a decline in its demand. If it believes there has been a shift in its demand function, its appropriate response will depend on whether this decline is specific to it or has been experienced by its competitors, too. If it is specific to it then it will not expect competitors to be lowering their prices—as they do not see themselves having weaker demand—and that will limit how much the firm should lower its price. Now suppose a firm learns that its competitors have also experienced a slide in their demand. It will then expect them to also lower their prices, which means this firm will need to lower its price more—compared with when its competitors are not lowering their prices—to remain competitive. Thus, the appropriate price response will depend on knowing what is happening with other firms' demand functions. By preventing the sharing of nonpublic competitor data, a third party will not be able to distinguish between firm-specific and market-wide changes in demand when it is recommending prices to a firm. As a result, prices are less responsive to market conditions. For example, prices will not fall as fast when there is a market-wide weakness in demand (nor rise as fast when there is market-wide strengthening in demand).

A second inefficiency coming from this remedy is that new firms are more disadvantaged and this could weaken potential competition by deterring entry or making entry less effective. In the absence of this remedy, a firm that enters a market served by a third party could immediately avail itself of the accumulated knowledge of the third party, which is embodied in the pricing algorithm it has developed using incumbent firms' data. More effective pricing means more profit and that will make entry more profitable and, therefore, likely. However, if nonpublic competitor data cannot be used in recommending prices to this new firm, the third party's pricing algorithm will be significantly less effective. It will take time to build a data set for the new firm and train the pricing algorithm. A third party that is able to use all of its subscribing firms' data will then equalize firms' proficiency when it comes to pricing, which, under independent pricing, should result in better market outcomes.

A third, and related, inefficiency is that the remedy will create a differential advantage due to firm size. The inability of a third party to draw on competitors' data in developing a firm's pricing algorithm is less detrimental to a larger firm with its more expansive data set. Consequently, the presence of a third party is less effective at leveling the playing field between small and large firms. Or what could happen is that large firms forego using a third party and instead internally develop their pricing algorithm on the grounds that the remedy has reduced the incremental value of using a data analytics company. That could ultimately kill the market if there is not sufficient demand for a third party's services, which would put small firms at an even greater disadvantage.

The takeaway is that a third party is delivering an efficiency to subscribing firms through the use of data analytics, and the remedy interferes with that efficiency.[35] This is not to say the remedy should not be pursued because that cost may be more than exceeded by the benefit of reducing anticompetitive harm from the third party facilitating coordinating pricing. However, as I explain next, the remedy is unlikely to prevent such anticompetitive harm as a third party can design a workaround that achieves supracompetitive prices.

C. Remedy will not prevent anticompetitive harm

Let us assume the third party has the objective of maximizing subscribing firms' joint profits and the current remedy is in place so it cannot use nonpublic competitor data. To be clear, I am not claiming that third parties are, as a rule, trying to facilitate coordinated pricing. Rather, I want to explore how the remedy affects a third party's ability to produce supracompetitive prices should that be its objective.

Adherence to the restrictions imposed by the remedy means the prices a third party recommends to, say, firm A cannot be the output of a pricing algorithm trained on data that include nonpublic data of firm B, and the pricing algorithm cannot condition on nonpublic data of firm B. This not only restricts data sharing but also prohibits joint optimization by the third party. For suppose the third party estimates a demand function for firm A using only public data and firm A's private data and estimates a demand function for firm B using only public data and firm B's private data. Next, suppose the third party chooses prices for firms A and B to maximize their joint profits (or some weighted average of their profits or some other collective function that is increasing in both firms' profits) where a firm's profit is based on the estimated demand function. An implication of joint optimization is that firm A's recommended price will depend on firm B's estimated demand function, which means it depends on the nonpublic data for firm B that were used in estimating firm B's demand function. That would violate the prohibition. The remedy's restriction on data sharing then implies a prohibition on joint optimization.

How can a third party recommend supracompetitive prices for its subscribers without using nonpublic competitor data? I will address this question in the context of the third party using an estimation-optimization algorithm, though the broader conclusions apply to other types of learning algorithms. An estimation-optimization algorithm has two modules. The estimation module uses data to estimate an agent's environment, which here is a firm's demand and profit function. The optimization module then solves for actions to maximize its objective in light of the estimate of the environment, which here means finding prices to maximize the estimated profit functions.

The third party's task is to recommend supracompetitive prices while estimating each subscribing firm's demand function and choosing prices for them that do not depend on other firms' nonpublic data. Toward that end, each firm shares its data set, which comprises past prices and past quantities. As would typically be the case, past quantities are nonpublic data and past prices are public data. (There may be other nonpublic data such as inventories and capacities but such are ancillary to the analysis and thus will be ignored.) To meet the conditions of the remedy, it must then be the case that the third party's recommended price for a firm cannot depend on competitors' past quantities. If the third party uses a firm's past quantities to estimate its demand then a firm's recommended price cannot depend on the estimated demand for another firm and, by the argument above, firms' recommended prices cannot be co-determined as part of a joint optimization routine.

[35] For further discussion of the inefficiencies that these remedies may cause, see Ezrielev [2024].

Let me begin with a baseline procedure that respects the remedy and, under certain conditions, converges to competitive prices. The following steps are conducted in each period for which firms are choosing prices.

Step 1 (demand estimation): For each firm, estimate its demand function using the firm's past quantities and all firms' past prices.
Step 2 (price optimization): Using a firm's estimated demand function along with its self-reported cost, solve for a firm's profit-maximizing price assuming rival firms price the same as in the previous period.
Step 3 (price convergence): Iterate steps (1) and (2) until firms' prices converge (that is, the difference between their prices in adjacent periods is below some tolerance level).

This is a standard learning algorithm. It has the third party estimate each firm's demand function using past quantities (private data to the firm) and all firms' past prices (public data). That delivers an estimate of the firm's profit function. Of course, a firm's profit-maximizing price will depend on rival firms' prices and here it is assumed they will price the same as in the previous period. Although it is generally not going to be true that rival firms will price the same, the price solved for a firm in step 2 will be close to the profit-maximizing price as long as rival firms' prices are not changing price too much. Under certain conditions, this procedure will converge on competitive prices. That is, each firm's price maximizes its expected profit given other firms' prices, and that holds for all firms.

Let us start with a simple but not very effective workaround to the remedy. Replace Step 2 with Step 2':

Step 2' (price optimization): Using a firm's estimated demand function along with its self-reported cost, solve for a firm's profit-maximizing price assuming rival firms price the same as in the previous period and then inflate that price by w percent.

Under certain conditions, this procedure will converge on supracompetitive prices, which exceed competitive prices.[36] However, this obvious workaround is unlikely to be very effective, especially when firms are different, because a third party will not know how high to set w. If it sets it to high, it could cause prices to exceed monopoly levels and result in lower profit because of significantly lower sales. This risk is accentuated with asymmetric firms as it is more likely that at least some firm's demand is sufficiently adversely affected that its profits are lower. To avoid such an outcome, a third party could be conservative and set w rather low to be confident that all firms' profits are higher. But then the supracompetitive markup may not be at a level to create much of a concern.

The problem with that workaround is that a third party is arbitrarily setting the supracompetitive markup w—which I will refer to it as the inflator—without any information to guide it. Let us now consider a learning algorithm that allows the third party to learn how to set the inflator, along with learning how to set prices. This description is nontechnical and, consequently, is not precise. A formal description is provided in the appendix.[37]

[36] Note that prices will exceed competitive prices by more than w percent. A firm will price higher by w percent when rival firms price the same. However, those rival firms are also pricing higher by w percent. Consequently, a firm's demand is stronger, which causes the third party to price higher than w percent.

[37] It is assumed all firms in the market are subscribing to the third party though the ensuing analysis can be extended in a straightforward manner should that not be so.

Step 1 (demand estimation): For each firm, estimate its demand function using the firm's past quantities and all firms' past prices.
Step 2 (price optimization): Using a firm's estimated demand function along with its self-reported cost, solve for a firm's profit-maximizing price assuming rival firms price the same as in the previous period.
Step 3 (application of inflator): Proportionally increase a firm's best response price in step (2) by the inflator.
Step 4 (price convergence): Iterate steps (1)–(3) until firms' prices converge. Upon convergence, go to step 5.
Step 5 (adjustment of inflator): If average profit under the current inflator exceeds the average profit under the previous inflator then raise a firm's inflator. Otherwise, fix a firm's inflator at its current value.
Step 6 (inflator convergence): Iterate (1)–(5) until all firms' inflators are fixed.

This learning algorithm estimates each firm's demand function and then determines a firm's profit-maximizing price assuming rival firms' prices equal those from the previous period. All firms start with a common and small inflator, call it $w(1)$. Each firm's best response price is then increased by that inflator. Given those prices, firms realize sales, which then leads to repeating steps (1)–(3) in the following period. This process continues until firms' prices settle down so the amount by which they change over the most recent two periods is below some tolerance level. At that point, the algorithm moves to step 5, which has the inflator increased by a small amount to $w(2)$ and then steps (1)–(4) are repeated until again prices converge. Once that happens the algorithm moves to step 5 when it compares each firm's average profit under inflator $w(2)$ with its average profit under $w(1)$. If the former is larger for a firm then the inflator for that firm is increased by a small amount to $w(3)$, otherwise the inflator is fixed at $w(2)$. Hence, if all firms experienced higher average profit then all will get a higher inflator $w(3)$. This process continues until all firms' inflators have converged.

In the appendix, more structure is added to produce precise results. There the analysis focuses on the optimization module by assuming the third party knows firms' demand functions so the iterative procedure involves steps 2–6. Under some simplifying assumptions—two symmetric firms, linear demand, constant marginal cost—it is shown the algorithm converges to **monopoly prices without the third party using competitors' nonpublic data**.

When firms are asymmetric, prices may not get to the monopoly level but prices can still be well above competitive levels. To illustrate, Table 1 reports results when firms have different costs.[38] Reported are the competitive (Nash equilibrium) prices, the prices to which the third party's algorithm converges, and monopoly prices.[39] For example, consider when firm 1's cost is 0 and firm 2's cost is 40. Competitive prices are 72 and 88 for firm 1 and 2, respectively, whereas their monopoly prices are 100 and 120. The third party's workaround achieves prices of, approximately, 90 for firm 1 and 108 for firm 2. Thus, the third party is able to raise firm 1's price by 25 percent and firm 2's price by 22 percent above competitive levels, which compares well with the monopoly markup of 39 percent for firm 1 and 36 percent for firm 2.

The process by which supracompetitive prices arise is simple. The third party begins by calculating the price for a firm that maximizes the firm's profit based on rival firms choosing the prices they chose in the previous period. If it were to recommend those prices then such

38 The functional forms for demand and cost functions can be found in the appendix. The demand parameters used in Table 1 are $a_1 = a_2 = 100$, $b_1 = b_2 = 1$, $d_1 = d_2 = .5$. Results when costs are the same and a_1 and a_2 differ—so firms have asymmetric demand—are similar.

39 A firm's "monopoly price" is defined as the price associated with a common inflator for firms, which maximizes that firm's profit. Asymmetric firms will then have different monopoly prices.

Table 1. Prices

Cost		**Competition**		**Third party**		**Monopoly**	
Firm 1	**Firm 2**	**Firm 1**	**Firm 2**	**Firm 1**	**Firm 2**	**Firm 1**	**Firm 2**
0	0	66.67	66.67	100.00	100.00	100.00	100.00
0	10	68.00	72.00	96.58	101.43	100.00	105.00
0	20	69.33	77.33	93.77	103.22	100.00	110.00
0	30	70.67	82.67	91.50	105.33	100.00	115.00
0	40	72.00	88.00	89.68	107.74	100.00	120.00
20	20	80.00	80.00	110.00	110.00	110.00	110.00
40	0	88.00	72.00	107.74	89.68	120.00	100.00
40	10	89.33	77.33	110.75	97.13	120.00	105.00
40	20	90.67	82.67	113.80	104.66	120.00	110.00
40	30	92.00	88.00	116.88	112.29	120.00	115.00
40	40	93.33	93.33	120.00	120.00	120.00	120.00

a process would converge to competitive (Nash equilibrium) prices. Instead, the third party inflates those calculated prices by some factor, say 1 percent, which is recommended to firms. To be clear, there is no joint optimization and a firm's price depends only on its own data and rival firms' past prices, which are presumed to be public information. The third party iterates on this process—each period, recalculating a firm's profit-maximizing price based on rival firm's previous period's price and inflating it—until firms' prices have settled down. Those prices will exceed competitive prices by slightly more than 1 percent. At that point, the third party increases the inflator for all firms from 1 percent to, say, 2 percent. Again it iterates the process until prices settle down. Now, it compares a firm's average profit during the periods with the 2 percent inflator with its average profit during the periods with the 1 percent inflator. If the latter is higher then it keeps the inflator at 2 percent. If the former is higher then it raises the inflator to, say, 3 percent. Thus, some firms' inflators may become fixed (if their profit is not higher), and others are still being increased. This process continues until all firms' inflators are fixed.

As originally mentioned, a simpler scheme is for the third party not to adjust the inflator but to simply specify a fixed value for it, say, 10 percent. The problem here is twofold. First, it may prove to be too high in that the resulting prices exceed monopoly prices and could cause firms to earn lower, not higher, profit. Second, it may prove to be too low, leaving prices well below monopoly prices. Without sharing nonpublic competitor data, the use of a fixed inflator is a risky and probably ineffective approach by the third party. The advantage to this algorithm is that the third party gradually learns about how high it can set the inflator from the perspective of maximizing firms' profits. As a result, anticompetitive harm is greater.

Though the workaround may result in supracompetitive prices without the use of nonpublic competitor data, is it lawful? When the third party programs an inflator into the pricing algorithm, is it engaging in a facilitating practice in violation of competition law? Jurisprudence has established that a facilitating practice may be presented as evidence of a concerted practice or agreement or may itself be a concerted practice or an agreement (for example, an information exchange agreement).[40] Almost always, it is the colluding firms who are accused of engaging

[40] "[A] horizontal price-fixing agreement may be inferred on the basis of conscious parallelism, when such interdependent conduct is accompanied by circumstantial evidence and plus factors such as defendants' use of facilitating practices.... Information exchange is an example of a facilitating practice that can help support an inference of a price-fixing agreement." *Todd v. Exxon Corp.,* 275 F.3d 191, 198 (2d Cir. 2001) "There is a closely related but analytically distinct type of claim... where the violation lies in the information exchange itself—as opposed to merely using the information exchange as evidence upon which to infer a price-fixing agreement. This exchange of information is not illegal *per se*, but can be found unlawful under a rule of reason." *Todd v. Exxon Corp.,* 275 F.3d 191, 198 (2d Cir. 2001).

in a facilitating practice, some times along with a third party. In the current context, this would mean showing subscribing firms are complicit in the third party's use of an inflator, which may be difficult to prove and, in fact, not be true. Alternatively, the third party's unilateral adoption of a facilitating practice could be pursued as a standalone infringement. However, there is not much precedent for doing so. It does not come under Section 1 of the Sherman Act, which requires two or more compliant parties though perhaps could be a Section 2 violation with its prohibition on monopolization. It could possibly be viewed as a concerted practice under Article 101 of the Treaty of the Functioning of the European Union (TFEU) or it could fall into the "liability gap" noted by the German Monopolies Commission.[41] All this leads to an interesting open question: If a third party's practice results in supracompetitive prices without the use of nonpublic competitor data, is that practice necessarily a violation of competition law?

Putting aside the question of the workaround's legality, its existence means that competition agencies would have to remain vigilant under this remedy. It would not be enough for a third party to silo data—so as to avoid using a competitor's nonpublic data—and to set up firewalls—so as to prevent joint optimization. Even when those conditions are satisfied, a third party could still produce supracompetitive prices for subscribing firms. Thus, enforcement would remain a challenge under this remedy.

V. SOURCE OF ANTICOMPETITIVE HARM FROM A THIRD-PARTY'S UNILATERAL CONDUCT

A. Harm comes from shared objective, not shared data

It has been shown that a third party can produce supracompetitive prices without relying on nonpublic competitor data. Such a workaround puts into doubt the efficacy of the current remedy that is being considered and implemented. Although this result is of intrinsic value, it is also the basis for two broader points related to designing an effective remedy. The first point is that any proposed remedy should come with an explanation for why one thinks it will be effective. Just as much as a condemned practice needs to be supported by a theory of harm, a recommended remedy needs to be supported by a *theory of cure*. In the case of the current remedy, why do we think prohibiting the use of nonpublic competitor data would prevent a third party from recommending supracompetitive prices and subscribing firms from implementing them? What is the theory of harm by which the data are being used to produce anticompetitive effect and how would the prohibition address it? To my knowledge, those questions have not been asked and answered in the debate pertaining to remedies. As we move forward and consider placing restrictions on third parties and firms, we should always explain how the restrictions would actually prevent the harm they are intended to prevent.

The second point offers guidance for finding candidate remedies. In searching for a remedy, it is critical to keep in mind one fundamental point: the source of harm is shared objective, not shared data. A third party is said to have "shared objective" when, in designing its pricing algorithm, it takes into account the common interest of subscribing firms. That is, when recommending prices for firm A, it internalizes the effect of firm A's prices on firm B's profit and, analogously, in recommending prices for firm B, it internalizes the effect of firm B's prices on firm A's profit. Consequently, it will recommend higher prices than would occur if prices were set independently. That is the source of harm, and shared data are neither necessary nor sufficient for there to be harm. I have already shown sharing nonpublic competitor data are not necessary

[41] When they made the statement quoted in Section I, I suspect the German Monopolies Commission was thinking of an explicit scheme involving data sharing and joint optimization, not one as subtle as the workaround. If it is problematic for the former to be a competition law violation then it is surely so for the latter.

for harm. Let me now explain how it is not sufficient in that harm need not result when sharing nonpublic competitor data.

Suppose a third party collects subscribing firms' prices, sales, inventories, capacities, and other information, and uses it to estimate each firm's demand function. With that data—which involves sharing nonpublic competitor data—it estimates each firm's demand function and, along with cost information, its profit function. With those estimated profit functions, it solves for a collection of prices such that each firm's price maximizes that firm's profit given the selected prices for the other firms. In other words, the third party solves for competitive (or Nash equilibrium) prices, not joint profit-maximizing prices. Under this hypothetical, competitive prices emerge with or without a third party though those prices are not the same because they are based on different information. The competitive prices generated by the third party come out of more precisely estimated demand functions due to the sharing of competitor data. The literature on information sharing has explored the associated welfare effects and there it is found that consumers could be better or worse off from the additional information used to determine firms' prices, as it depends on the specifics of the market environment.[42]

Harm emanates from a third party's shared objective with subscribing firms to charge supra-competitive prices. Though sharing nonpublic competitor data is not the source of harm, it could exacerbate the effects of shared objective because more data generally make accomplishing one's objective more effective. For example, such data would be useful in taking account of firm asymmetries. When firms are symmetric, a common price increase will raise all firms' profits as long as price remains below the monopoly level. That is not the case when firms have different demand functions or costs. A common percentage increase in prices could lower the profits of those firms whose demand is more price-elastic while raising other firms' profits. A third party with shared objective would be more likely to identify higher prices that would raise all firms' profits if it is able to use nonpublic competitor data to better estimate firms' demand functions and jointly optimize. By way of example, the prices produced by the workaround fall short of monopoly prices when firms are asymmetric, whereas the use of nonpublic competitor data (specifically, joint optimization) would result in higher prices.

B. Why the focus has been on shared data

That the proposed remedies have focused on information sharing can be attributed to drawing on past approaches to addressing unlawful collusion. In doing so, there is a failure to recognize how a third party's unilateral conduct differs from firms' coordinated conduct. To make this point, let me begin by reviewing the legal approach to collusion and why it takes the form it does.

Jurisprudence established that firms violate Section 1 of the Sherman Act when they have an *agreement to restrain competition* (literally, to "unreasonably restrain trade"). The U.S. Supreme Court defines an agreement as when firms have a "unity of purpose or a common design and understanding, or a meeting of minds"[43] and "a conscious commitment to a common scheme designed to achieve an unlawful objective".[44] These terms focus on the same mental state: mutual understanding among firms that they will restrict competition in some manner.[45] As

42 "[T]he welfare effects of information sharing on consumer and total surplus... depend on two main features of the market. First, the type of decision variable (price or quantity) matters.... Secondly, the type of uncertainty (common value versus private value) matters.... These underlying effects generate a relatively complex picture of the impact of information sharing on welfare and consumer surplus. Fine tuning of competition policy to take into account the welfare impact found in this literature appears to be a formidable task.", Kühn and Vives [1994], pp. 37-38.

43 *Am. Tobacco Co. v. United States*, 328 U.S. 781, 810 66 S. Ct. 1125 (1946)

44 *Monsanto Co. v. Spray-Rite Serv. Corp.*, 465 U.S. 752,765 104 S. Ct. 1464 (1984)

45 This perspective has been echoed by the E.U. General Court in conjunction with a violation of Article 101 of the TFEU. An agreement is defined as or as requiring "joint intention" (Judgment of the Court of 15 July 1970. *ACF Chemiefarma NV v Commission of the European Communities* Case 41-69.) or a "concurrence of wills" (Judgment of the Court of First Instance of 26 October 2000. *Bayer AG v Commission of the European Communities).*

a manager's mental state is not directly observable, courts have accepted forms of evidence which facilitate or reflect such a mutual understanding. The most clear evidence is express communication, such as when one firm invites a rival firm to limit competition and the invitation is accepted by that firm, or firms privately meet and verbally announce their intentions to set a common price.[46] Another form of evidence is the use of some facilitating practice, which refers to conduct that aids firms in coordinating or implementing a common plan to restrain competition. Of particular relevance to our discussion is an information exchange whereby firms share commercially sensitive information. This is viewed as evidence supporting an agreement because it would not be in the individual interests of a firm to share this information unless it was part of a reciprocal arrangement to share and then use that information to soften rather than intensify competition.

Given this treatment of information sharing in the context of collusion, it is not surprising that the approach taken to restricting third parties has been to prohibit the sharing of nonpublic competitor data. However, this analogy only goes so far and ultimately is leading the search for a remedy down the wrong path. To begin, prohibiting information sharing between competitors is far more likely to be effective in preventing them from coordinating on supracompetitive prices than in preventing a third party from recommending supracompetitive prices. Without the sharing of prices or pricing intentions, firms will need to coordinate through distinctly more subtle and less effective methods such as advance price announcements or price signaling. As opposed to when information is privately shared between firms—whereby the intent is clear that it is to serve common cause among competitors—a firm's prices or price announcements are public and could be construed as intended for customers and thereby fail to be seen by rival firms as an invitation for them to produce the intended coordinated price increase. Thus, communication can be significantly hampered without information sharing so a remedy that prohibits information sharing may well prove beneficial. In contrast, a third party who is supplying an algorithm to competitors can coordinate price increases even if information sharing is prohibited, as was shown in Section IV.C. In sum, the efficacy of a prohibition on information sharing as a remedy in the context of collusion is unlikely to carry over to when a third party is supplying pricing algorithms to competitors.

That was the bad news and now for the good news. The inability to directly prohibit firms from having a shared objective—as reflected in a "conscious commitment to a common scheme" to constrain competition—does not carry over to prohibiting a third party from having a shared objective with subscribing firms to charge supracompetitive prices. As previously explained, an unlawful agreement is a "meeting of minds," which is a mental state among firms' managers, and mental states cannot be directly observed and thus cannot be prohibited. Consequently, the courts have instead prohibited the communication that is the cause or consequence of a shared objective. However, it may be possible to restrict a third party so it does not have shared objective. I will have more to say on this matter in the near future.

In concluding, it is worth emphasizing that supracompetitive prices are not inevitable when competitors use a common third party's pricing algorithm. Harrington [2022, 2025a] finds there is no supracompetitive markup when a third party designs its pricing algorithm to maximize its profit from licensing it. In that case, the third party is interested in enhancing a firm's willingness to pay for the pricing algorithm—which is a firm's profit from adopting minus its

[46] It is common for courts to view this communication as the agreement but that is inconsistent with how the courts define agreement. The courts define an agreement as a "meeting of minds" but firms can verbally say one thing and believe another. For example, firms could verbally communicate to each other that they will raise price by 10 percent but one (or both) could have no intention of doing so because it does not believe the other firm will do so. Clearly, there is no "conscious commitment to a common scheme" though there is an *expressed* commitment to such a scheme. The verbal expression is accepted as sufficient evidence to establish a Section I violation.

profit from not adopting—as doing so raises the fee it can charge firms for using its pricing algorithm. A third party does not build in a supracompetitive markup because doing so would lower a firm's willingness to pay, as it raises the profit from not adopting more than it raises the profit from adopting. However, when instead the third party designs the pricing algorithm to maximize subscribing firms' profits—so there is shared objective—Harrington [2025a, b] and Sugaya and Wolitsky [2025] show supracompetitive prices emerge.

VI. CONCLUDING REMARKS

The era of firms outsourcing pricing to data analytics companies has arrived. Although firms have long used third parties to assist them—whether it is an information aggregator to collect and process data, an operations research company to supply optimization routines, or a management consulting firm to recommend a new pricing strategy—what is different now is the extent to which a firm is delegating the task of pricing to a third party. Although a third party can deliver many efficiencies in performing that task, concerns about the risk of harm are justified when competitors in a market are being supplied by the same third party. The challenge for competition law and enforcement is to prevent the possible anticompetitive harm from third-party pricing algorithms without unduly interfering with the delivery of legitimate services to companies. Laissez faire is not an option for it would invite the creation of third parties who deliver higher profits to subscribing firms through coordinated pricing rather than efficiencies.

This paper contributes to the discussion on how best to address this challenge. To begin, it provides a critical evaluation of the proposed (and, in some jurisdictions, implemented) remedy to prohibit a third party from using nonpublic competitor data when recommending prices. I have explained there are two problems with this remedy. To begin, it interferes with procompetitive efficiencies as competitor data are useful for informing competitive prices. Of course, that cost may well be warranted if the remedy is effective in preventing anticompetitive harm. That leads to the more innovative contribution, which is to develop a workaround to the remedy: a pricing algorithm resulting in supracompetitive prices without using nonpublic competitor data. Consequently, it is not at all clear the remedy will prove effective in preventing anticompetitive harm. Turning to a more constructive contribution, I then seek to redirect the search for a remedy by focusing on the actual source of harm: a third party has a shared objective with subscribing firms to produce supracompetitive prices. A remedy should focus on prohibiting that shared objective, rather than shared data.

VII. TECHNICAL APPENDIX

Here, I formally describe an algorithm that results in the third party coordinating subscribing firms in the setting of substantively supracompetitive prices while not using nonpublic competitor data. Admittedly, the algorithm has not been shown to be "street ready" as there are issues of the speed of convergence and performance in light of stochastic demand and cost shocks. Nevertheless, it is proof of concept that, at least for a simplified setting, an algorithm can outsmart the remedy. I suspect a properly incentivized and clever data analytics company could devise something far better than is described here.

A. General case

For firm $i \in \{1, 2, ..., n\}$, define p_i^t as its price, q_i^t as its quantity, and w_i^t as its inflator, in period $t \in \{1, 2, ...\}$. A series of increasing base inflators $\{w(r)\}_{r=1}^{\infty}$ is specified at the start of the procedure where $w(r) = r\varepsilon$ and ε is positive and small. The base inflators will follow this series with the period at which it switches to the next value in the series being determined by the algorithm. Letting $\tau(r)$ denote the final period in which the base inflator is $w(r)$ then the inflator is $w(1)$

over periods $1, ..., \tau(1)$, $w(2)$ over periods $\tau(1) + 1, ..., \tau(2)$, and so on. I will refer to a round r as comprising the periods for which the base inflator is $w(r)$. A firm's inflator will equal the base inflator until some period at which the firm's inflator is fixed where it is said to have converged. Let $\Gamma(r) \subseteq \{1, 2, ..., n\}$ denote the set of firms whose inflators have not converged as of the start of round r.

Initiation: An initial price vector $\left(p_1^0, ..., p_n^0\right)$, data set of firms' past prices and quantities, series of increasing base inflators $\{w(r)\}_{r=1}^{\infty}$, and $\Gamma(1) = \{1, 2, ..., n\}$.

Step 1 (demand estimation): For each firm, estimate its demand function using the firm's past quantities and all firms' past prices.

In period t, firm i's data set is $\left\{\left(q_i^h, p_1^h, ..., p_n^h\right)\right\}_{h=1}^{t-1}$, along with any data before period 1. The estimate of firm i's demand function is denoted $\widehat{D}_i^t\left(p_1, ..., p_n\right)$.

Step 2 (price optimization): Using a firm's estimated demand function along with its self-reported cost, solve for a firm's (pre-inflated) profit-maximizing price assuming rival firms price the same as in the previous period.

In period t, firm i's (pre-inflated) profit-maximizing price is

$$\phi_i^t\left(p_1^{t-1}, ..., p_{i-1}^{t-1}, p_{i+1}^{t-1}, ..., p_n^{t-1}\right) \equiv \arg\max_{p_i}\left(p_i - c_i^t\right)\widehat{D}_i^t\left(p_1^{t-1}, ..., p_{i-1}^{t-1}, p_i, p_{i+1}^{t-1}, ..., p_n^{t-1}\right)$$

where c_i^t is its reported cost.

Step 3 (application of inflator): Proportionally increase a firm's (pre-inflated) profit-maximizing price by its inflator w_i^t. This is the price the firm charges in period t.

$$p_i^t = (1 + w_i^t)\phi_i^t\left(p_1^{t-1}, ..., p_{i-1}^{t-1}, p_{i+1}^{t-1}, ..., p_n^{t-1}\right).$$

Step 4 (price convergence): Iterate Steps (1)–(3) until firms' prices converge.

Specify a tolerance level $\eta > 0$. If $\max\left\{\left|p_1^{t-1} - p_1^{t-2}\right|, ..., \left|p_n^{t-1} - p_n^{t-2}\right|\right\} < \eta$ is not satisfied then go back to Step (1). Otherwise go to Step (5). (Note: Prices are used from the previous two periods so this criterion depends only on public data.)

Step 5 (adjustment of inflator): If a firm's inflator has not converged then raise a firm's inflator if average profit under the current inflator exceeds the average profit under the previous inflator.

If $i \in \Gamma(r)$ and

$$\left(\frac{1}{\tau(r) - \tau(r-1)}\right)\sum_{t=\tau(r-1)+1}^{\tau(r)}\left(p_i^t - c_i^t\right)q_i^t > \left(\frac{1}{\tau(r-1) - \tau(r-2)}\right)\sum_{t=\tau(r-2)+1}^{\tau(r-1)}\left(p_i^t - c_i^t\right)q_i^t$$

then $w_i^{t+1} = w_i^t + \varepsilon = w(r+1)$ and $i \in \Gamma(r+1)$. If

$$\left(\frac{1}{\tau(r)-\tau(r-1)}\right)\sum_{t=\tau(r-1)+1}^{\tau(r)}\left(p_i^t - c_i^t\right)q_i^t \leq \left(\frac{1}{\tau(r-1)-\tau(r-2)}\right)\sum_{t=\tau(r-2)+1}^{\tau(r-1)}\left(p_i^t - c_i^t\right)q_i^t$$

then $w_i^{t+1} = w_i^t = w(r)$ and $i \notin \Gamma(r+1)$.

- If $i \notin \Gamma(r)$ then $w_i^{t+1} = w_i^t$ and $i \notin \Gamma(r+1)$.

Step 6 (inflator convergence): Iterate Steps (1)–(5) until all firms' inflators converge; that is, $\Gamma(r) = \varnothing$.

B. Special case

To prove results for the optimization module, let us put aside the demand estimation module by assuming firms' demand functions are fixed and known to the third party, as is firms' cost functions. To simplify on notation, it is assumed there are just two firms and, for tractability, demand and cost are linear functions. Firm *i*'s demand function is $a_i - b_i p_i + d_i p_j$ and its cost is c_i. Assume $a_i - b_i c_i > 0$ and $b_i > d_i \geq 0$ and firms are not too different so that the algorithm always delivers an interior solution with both firms having positive demand.

Given there is no random component to demand, we can replace the average of profits over a round in Step (5) with the final period's profit in a round.

Step 5 (adjustment of inflator): If $i \in \Gamma(r)$ and

$$\left(p_i^{\tau(r)} - c_i\right)q_i^{\tau(r)} > \left(p_i^{\tau(r-1)} - c_i\right)q_i^{\tau(r-1)}$$

then $w_i^{t+1} = w_i^t + \varepsilon = w(r+1)$ and $i \in \Gamma(r+1)$. If

$$\left(p_i^{\tau(r)} - c_i\right)q_i^{\tau(r)} \leq \left(p_i^{\tau(r-1)} - c_i\right)q_i^{\tau(r-1)}$$

then $w_i^{t+1} = w_i^t = w(r)$ and $i \notin \Gamma(r+1)$. If $i \notin \Gamma(r)$ then $w_i^{t+1} = w_i^t$ and $i \notin \Gamma(r+1)$.

Under these assumptions, I show in Section 6.2.1 that prices converge for fixed inflators. Assuming symmetric firms, it is shown in Section 6.2.2 that prices and inflators converge and result in monopoly prices.

1. Convergence of prices for a fixed inflator

Given firm *i*'s profit function is $\left(p_i - c_i\right)\left(a_i - b_i p_i + d_i p_j\right)$, then its best response function is

$$\phi_i\left(p_j\right) \equiv \arg\max_{p_i}\left(p_i - c_i\right)\left(a_i - b_i p_i + d_i p_j\right) = \frac{a_i + b_i c_i + d_i p_j}{2b_i}.$$

Define an inflated best response function:

$$\widetilde{\phi}_i\left(p_j\right) \equiv \left(1 + w_i\right)\phi_i\left(p_j\right),$$

where $w_i \geq 0$. Under two assumptions, the unique equilibrium for these inflated best response functions,

$$\begin{aligned} p_1^*(w_1,w_2) &= (1+w_1)\,\phi_1\left(p_2^*(w_1,w_2)\right) \\ p_2^*(w_1,w_2) &= (1+w_2)\,\phi_2\left(p_1^*(w_1,w_2)\right), \end{aligned}$$

is

$$\begin{aligned} p_1^*(w_1,w_2) &= \frac{(1+w_1)\left(2b_2(a_1+b_1c_1)+d_1(1+w_2)(a_2+b_2c_2)\right)}{4b_1b_2-d_1d_2(1+w_1)(1+w_2)} \\ p_2^*(w_1,w_2) &= \frac{(1+w_2)\left(2b_1(a_2+b_2c_2)+d_2(1+w_1)(a_1+b_1c_1)\right)}{4b_1b_2-d_1d_2(1+w_1)(1+w_2)}. \end{aligned} \tag{1}$$

The first assumption is

$$4b_1b_2-d_1d_2(1+w_1)(1+w_2)>0, \tag{2}$$

which is required for second-order conditions to hold. The second assumption is

$$\begin{aligned} a_1-b_1p_1^*(w_1,w_2)+d_1p_2^*(w_1,w_2) &> 0 \\ a_2-b_2p_2^*(w_1,w_2)+d_2p_1^*(w_1,w_2) &> 0, \end{aligned} \tag{3}$$

which is required for both firms to have positive demand and thus the solution to be interior. The first assumption holds if w_1 and w_2 are not too high and the second assumption holds if the distance between (a_1,b_1,c_1,d_1) and (a_2,b_2,c_2,d_2) is sufficiently small; that is, firms are not too different.

Define the dynamic so prices in period t are inflated best responses to the rival firm's price in period $t-1$:

$$\begin{aligned} p_1^t &= \widetilde{\phi}_1\left(p_2^{t-1}\right) = (1+w_1)\left(\frac{a_1+b_1c_1+d_1p_2^{t-1}}{2b_1}\right) \\ p_2^t &= \widetilde{\phi}_2\left(p_1^{t-1}\right) = (1+w_2)\left(\frac{a_2+b_2c_2+d_2p_1^{t-1}}{2b_2}\right). \end{aligned}$$

By [Vives, 1999, p. 51], $\left(p_1^*(w_1,w_2),p_2^*(w_1,w_2)\right)$ is a locally stable point for these difference equations when

$$\begin{aligned} \left|(1+w_1)\frac{\partial\phi_1(p_2)}{\partial p_2}\right|\left|(1+w_2)\frac{\partial\phi_2(p_1)}{\partial p_1}\right| &< 1 \Leftrightarrow \\ \left(\frac{(1+w_1)d_1}{2b_1}\right)\left(\frac{(1+w_2)d_2}{2b_2}\right) &< 1 \Leftrightarrow \\ 4b_1b_2-d_1d_2(1+w_1)(1+w_2) &> 0, \end{aligned}$$

which holds by assumption. By [Vives, 1999, p. 54], if the equilibrium of a supermodular game with continuous payoffs is unique then it is globally stable. To establish supermodularity, let us derive the payoff function that produces $\widetilde{\phi}_i\left(p_j\right)$. First note

$$\begin{aligned}(1+w_i)\left(\frac{a_i+b_ic_i+d_ip_j}{2b_i}\right) &= \frac{(1+w_i)a_i+(1+w_i)b_ic_i+(1+w_i)d_ip_j}{2b_i}\\ &= \frac{\widetilde{a}_i+(1+w_i)b_i\widetilde{c}_i+(1+w_i)\widetilde{d}_ip_j}{2b_i},\end{aligned}$$

where

$$\widetilde{a}_i \equiv (1+w_i)a_i,\ \widetilde{c}_i \equiv (1+w_i)c_i,\ \widetilde{d}_i \equiv (1+w_i)d_i.$$

Defining

$$\widetilde{\pi}_i \equiv \left(p_i-\widetilde{c}_i\right)\left(\widetilde{a}_i-b_ip_i+\widetilde{d}_ip_j\right),$$

the best response is

$$\frac{\widetilde{a}_i+b_i\widetilde{c}_i+\widetilde{d}_ip_j}{2b_i}=\frac{(1+w_i)a_i+(1+w_i)b_ic_i+(1+w_i)d_ip_j}{2b_i}.$$

Thus, we need supermodularity of $\widetilde{\pi}_i$,

$$\frac{\partial^2\widetilde{\pi}_i}{\partial p_i\partial p_j}\geq 0 \Leftrightarrow \widetilde{d}_i\geq 0 \Leftrightarrow (1+w_i)d_i\geq 0,$$

which is true.

To summarize, if (2)–(3) hold then the system

$$\begin{aligned}p_1^t &= (1+w_1)\left(\frac{a_1+b_1c_1+d_1p_2^{t-1}}{2b_1}\right)\\ p_2^t &= (1+w_2)\left(\frac{a_2+b_2c_2+d_2p_1^{t-1}}{2b_2}\right)\end{aligned}$$

converges and

$$\lim_{t\to\infty}\left(p_1^t,p_2^t\right)=\left(p_1^*\left(w_1,w_2\right),p_2^*\left(w_1,w_2\right)\right).$$

2. Convergence of inflators: symmetric firms

In the symmetric case, if there is price convergence at each round then the inflator is bounded above by the value that results in the monopoly price, for once it reaches that value then the inflator-adjustment process stops.

The monopoly price is

$$p^m \equiv \arg\max_p \left(p - c\right)\left(a - (b-d)p\right) = \frac{a + (b-d)c}{2(b-d)}.$$

The convergent price for firms is

$$p_1^*(w,w) \equiv p^*(w) = \frac{(1+w)\left(2b(a+bc) + d(1+w)(a+bc)\right)}{4b^2 - d^2(1+w)^2} = \frac{(1+w)(a+bc)}{2b - d(1+w)}.$$

Solve for the inflator that results in the monopoly price:

$$p^*(w) = p^m \Leftrightarrow \frac{(1+w)(a+bc)}{2b - d(1+w)} = \frac{a+(b-d)c}{2(b-d)} \Leftrightarrow w^m \equiv \frac{d(a-(b-d)c)}{(2b^2-d^2)c + 2ab - d(a+bc)}.$$

If price convergence occurs for each inflator then the algorithm results in the inflator being bounded above by w^m. Price convergence occurs when (2) holds, which implies a restriction on the inflator:

$$4b_1b_2 - d_1d_2(1+w_1)(1+w_2) > 0 \Leftrightarrow 4b^2 - d^2(1+w)^2 > 0 \Leftrightarrow w < \frac{2b-d}{d}.$$

For prices to converge for all inflators not exceeding w^m, we need

$$\frac{d(a-(b-d)c)}{(2b^2-d^2)c + 2ab - d(a+bc)} < \frac{2b-d}{d} \Leftrightarrow$$

$$(2b-d)\left((2b^2-d^2)c + 2ab - d(a+bc)\right) - d^2(a-(b-d)c) > 0 \Leftrightarrow$$
$$4b(b-d)(a+bc) > 0,$$

which is true. Thus, with symmetric firms, the algorithm converges to the monopoly price.

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