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In this article we examine the impact of adoption of AI-driven algorithmic pricing software. Most of the recent academic work has studied this question from a theoretical or experimental perspective. We describe the first empirical analysis of the consequences of wide-scale adoption of algorithmic pricing software, focusing on Germany's retail gasoline market, where, according to trade publications, software became widely available in 2017. The evidence suggests that adoption increased margins and more so in competitive markets, indicating that it may have softened competition.

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I. INTRODUCTION

In recent years, algorithms employed by companies to aid with price setting have become more sophisticated, evolving from rule-based to AI-driven. The latter can absorb huge quantities of data and autonomously engage in quick and accurate price determination. Crucially, AI-driven algorithms are able to experiment and learn from previous pricing decisions. The development of AI-driven algorithmic pricing has provoked fear regarding its potential impact on competition. The possibility that algorithms might facilitate collusion has been raised by competition-law experts, economic organizations, and antitrust authorities.² The main fear is that, by being able to better monitor and rapidly respond to rival price changes, algorithms might learn to implement collusive pricing strategies that would *reward* companies for following the collusive agreement and *punish* them for undercutting, giving rise to coordination on a joint-profit maximizing outcome.

In this article we summarize findings from our examination of the impact of adoption of algorithmic pricing.³ This work (henceforth “Assad et al 2023”) represents the first empirical analysis of the consequences of wide-scale adoption of algorithmic pricing software. Its focus is the German retail gasoline market, where trade publications suggest that AI-pricing became widely available in 2017. Algorithmic pricing is especially problematic in retail gasoline markets, where a number of countries, including Germany, France, and Spain, have introduced price-disclosure policies that provide the opportunity for algorithms to gather training data and to perfectly monitor prices. Our analysis leverages the data provided by the transparency regime to study the impact of adoption of algorithmic pricing on station margins, and to investigate whether the observed increases in margins can be linked to anti-competitive strategies.⁴

II. ALGORITHMIC COLLUSION

Developers of algorithmic pricing software provide little information regarding the nature of their algorithms. However, their promotional materials indicate that their software applies *artificial intelligence* and *machine learning*. They also explain that their algorithms have the capacity to incorporate information on a variety of variables, such as market conditions, prices (own and competitor), sales volumes, and costs. The algorithms begin by training on historical observations of these variables and then continuously absorb real-time data into decision making as they seek to maximize profits. Next the algorithms evaluate the sales outcomes arising from the chosen prices and plug this new information back into the algorithm as further inputs before the process begins again. Many of these algorithms will use reinforcement learning techniques that employ strategies that have performed effectively historically with higher probability in the future. Importantly, the software developers also state that a large majority of adopters allow the algorithms to operate autonomously, without human intervention.

If companies repeatedly interact, it may be possible for them to coordinate on elevated prices through a reward and punishment mechanism, whereby competitors that maintain high prices are rewarded, while those that undercut are punished. Whether or not such coordination is sustainable depends on the speed with which companies are able to detect competitor defection and to punish deviations. Algorithms may be able to facilitate collusion by helping companies monitor the pricing decisions of their rivals, and then quickly detect undercutting and punish defectors.⁵ If algorithms speed up the ability of companies to react to defection, then the period during which higher profits are earned will be very short before prices collapse. As a result, companies will be less likely to defect and undermine the collusive arrangement.

An additional problem arises if multiple companies operating in the same market adopt the exact same algorithmic software. Then, *hub-and-spoke* arrangements may develop. An algorithm drawing in data from all the companies using it and providing this information to each of them, would be performing the role of *hub* facilitating coordination or collusion amongst its *spokes* – the adopters of the software. The collu-

2 See for instance OECD (2017), “Algorithms and Collusion: Competition Policy in the Digital Age”; United Kingdom Digital Competition Expert Panel (2019), “Unlocking Digital Competition”; Autorité de la Concurrence & Bundeskartellamt (2019), “Algorithms and Competition”; and Ezrachi, A. & M. Stucke (2016), “How Pricing Bots Could Form Cartels and Make Things More Expensive,” *Harvard Business Review*, October 2016.

3 This article is based on our academic paper: Assad, S., R. Clark, D. Ershov & L. Xu (2023), “Algorithmic pricing and competition: Empirical evidence from the German retail gasoline market,” forthcoming, *Journal of Political Economy*.

4 Legal disclaimer: This article analyses the impact of adoption of AP on competition strictly from an economic point of view. We base our understanding of the facts on publicly-available data on prices from the German Market Transparency Unit for Fuels. To our knowledge, there is no direct evidence of anticompetitive behavior on the part of any algorithmic-software firms or gasoline brands mentioned in this paper.

5 See Ezrachi, A. & M. Stucke (2015), “Artificial Intelligence and Collusion: When Computers Inhibit Competition,” University of Tennessee, Legal Studies Research Paper Series #267, 2015; Mehra, S.K. (2015), “Antitrust and the Robo-Seller: Competition in the Time of Algorithms,” *Minnesota Law Review*, 100.

sion-facilitation role of *third-parties* has been documented in the literature, pointing out that they may allow cartels to overcome difficulties related to coordination and information-sharing required for the successful functioning of cartels.⁶

Recent academic work has offered theoretical and experimental evidence that coordination may develop when pricing algorithms are employed.⁷ A number of articles have demonstrated that reinforcement algorithms can, in time, learn to coordinate on high prices, by punishing deviations for finite numbers of periods. The literature has also noted that different algorithms, or combinations of different algorithms adopted by rival companies, may result in different outcomes and, as a result, can be either pro- or anti-competitive.⁸ Therefore, there is no consensus at this time in the theoretical literature regarding whether coordination will emerge following adoption of algorithmic pricing. Furthermore, the extent to which algorithms may intensify or soften competition could be a function of the learning protocols they use.⁹

Empirical work investigating the effect of algorithmic pricing is therefore necessary, but faces three important challenges. The first is that adoption decisions are usually not publicly observed. The second is that adoption is endogenous, since adoption decisions are correlated with factors that may not be observed by researchers. The final challenge is that, should adoption be causally linked to higher prices or margins, it still would not be clear that the resulting changes can be assigned to collusion rather than to alternative causes, such as improved price discrimination.

To address the first challenge, Assad et al (2023) tests for structural breaks in pricing behaviours that are typically associated with AI-driven algorithmic pricing: (i) the number of daily price changes, (ii) the speed of response to competitors' price changes, (iii) the responsiveness of shocks to crude oil prices, and (iv) the responsiveness to local weather shocks. Leading software providers describe their algorithms as being capable of "rapidly, continuously and intelligently" reacting to the conditions of the market. For each of these metrics, Assad et al (2023) identifies structural breaks at each station. The best-candidate structural break in each metric for a given station is the week with the highest F-statistic. Since stations might break in a single metric for a variety of reasons, the paper classifies stations as algorithmic-pricing adopters if they feature best-candidate breaks in at least two of the four markers within a short time frame (four weeks). Approximately 20 percent of stations are found to experience best-candidate breaks in multiple metrics within a four-week window. Reassuringly, most breaks occur in the summer of 2017, when promotional materials by software providers suggest that commercial gasoline-retail algorithmic pricing tools became widely available in Germany.

The next step is to determine the impact of adoption on retail prices and margins; however, adoption decisions may be correlated with station/time specific unobservables, implying the existence of a selection bias and diverging outcomes between non-adopters and adopters before their adoption date. To overcome this problem, Assad et al (2023) adopts an instrumental variable approach, instrumenting for a station's adoption decision using the adoption decision by the station's brand (i.e. by brand headquarters). The idea is that brands may provide support (possibly in the form of subsidies) to stations to defray the costs of adoption. Such support has been offered in the past by brands to their affiliated stations when other technologies (e.g. electronic payment) have been introduced. Because brands' decisions to support adoption are not observed, Assad et al (2023) employs a proxy based on the share of a brand's stations that have adopted algorithmic pricing. Using this instrumental variable approach, findings suggest that adoption increases margins by roughly 15 percent. Reassuringly these estimates are in line with the profit gains claimed by software developers following adoption in other settings.

These findings offer causal evidence that adoption of algorithmic pricing increases margins, but not that the channel through which margins increase is through collusion. For this, Assad et al (2023) investigates whether the impact of adoption varies with market structure. The impact of adoption in monopoly and non-monopoly markets are compared. The effect of adoption should be stronger in non-monopoly markets if adoption influences competition. The findings suggest this to be the case. Assad et al (2023) finds a much stronger impact of adoption in non-monopoly markets than in monopoly markets.

To further confirm that adoption facilitates collusion, Assad et al (2023) focuses on small oligopoly markets – markets with just two or three stations. It investigates whether the impact of adoption varies depending on whether no stations adopted, a subset adopted, or all stations

6 See Clark, R., I. Horstmann & J-F. Houde (2023), "Hub-and-spoke collusion: Theory and evidence from the grocery industry"; Garrod, L., J. Harrington, and M. Olczak (2021), *Hub-and-Spoke Cartels: Why they form, how they operate, and how to prosecute them*, MIT Press.

7 See Calvano, E., G. Calzolari, V. Denicolo & S. Pastorello (2020), "Artificial Intelligence, Algorithmic Pricing and Collusion," *American Economic Review* 110, 3267-3297; Klein, T. (2021), "Autonomous Algorithmic Collusion: Q-Learning Under Sequential Pricing," *RAND Journal of Economics* 52, 538-558.

8 See Miklos-Thal, J. & C. Tucker (2019), "Collusion by Algorithm: Does Better Demand Prediction Facilitate Coordination Between Sellers?" *Management Science* 65, 1552-1561; Brown, Z & A. MacKay (2023), "Competition in Pricing Algorithms," *American Economic Journal: Microeconomics* 15, 109-156.

9 See Asker, J., C. Fershtman & A. Pakes (2021), "Artificial Intelligence and Pricing: The Impact of Algorithm Design," forthcoming *Journal of Economics and Management Strategy*.

adopted. The findings suggest that, relative to markets where none of the stations adopted, markets in which all stations adopted experienced margin increases of almost 40 percent. The size of the observed margin increases are in line with estimates from the literature studying the impact of coordination in retail gasoline markets.¹⁰

Assad et al (2023) also study the pricing behaviour that arises in markets where all stations adopt. It find that following adoption, a station is more likely to respond to a competitor's price decrease by immediately decreasing its own price. In contrast, there is no change in the likelihood of responding to a competitor's price increases. Such immediate punishment of price reductions by algorithmic rivals is somewhat analogous to anti-competitive trigger punishment strategies or price-matching strategies.

III. COMPETITION POLICY

The evidence in Assad et al (2023) is particular to retail gasoline markets in Germany, where high frequency pricing data are available, but algorithmic pricing software is being adopted in gasoline retail markets around the world. At a minimum, the results suggest that competition authorities in Germany and elsewhere should undertake a census of retail-gasoline pricing software to understand the market structure of the algorithmic software market and the extent of adoption. Such a census can help separate whether the main effect of algorithmic pricing software on competition comes from multiple stations in a market adopting the same or different algorithms. Which algorithm competitors adopt is not directly observed and the two possibilities have different implications for regulators and policy-makers.

Moreover, while the empirical focus of Assad et al (2023) was on the retail gasoline market, custom-made and “off-the-shelf” algorithmic pricing software is widely available to use for online and offline retailers in many markets. Adoption of such algorithms is growing: Brown and MacKay (2022) present evidence of algorithmic pricing by pharmaceutical drug retailers online. *Vendavo*, an AI based retail pricing software reports over 300 global deployments in manufacturing, chemicals, distribution, and high-tech industries ([Vendavo.com](https://www.vendavo.com)).¹¹ In the U.S., more than 20 lawsuits have been launched in 2022 and 2023 against Realpage Inc., an algorithmic pricing software developer for multifamily residential properties ([Reuters](https://www.reuters.com/legal/litigation/realpage-antitrust-lawsuits-over-rent-prices-consolidated-tennessee-2023-04-10/)).¹² The plaintiffs claim that the software allowed owners to coordinate on higher prices. Another similar class action lawsuit was launched in January 2023 against Las Vegas hotel operators who allegedly used Rainmaker, a revenue management software, to coordinate on high prices ([Bloomberg.com](https://www.bloomberg.com/news/articles/2023-01-26/hagens-berman-las-vegas-hotel-operators-sued-for-alleged-scheme-to-illegally-inflate-hotel-room-rates-to-record-highs)).¹³ The language in the lawsuits is akin to hub-and-spoke collusion, with the algorithm serving as the coordinator.

The findings in Assad et al (2023) have potentially important implications for competition policy. Multiple antitrust authorities and economic organizations have released reports on algorithmic collusion and its implications for competition law. According to these reports, addressing situations where companies explicitly agree to collude via algorithmic pricing would not require any changes to existing competition laws. However, it is important to note that existing theoretical and empirical evidence suggests that collusion in this context is tacit. It develops without explicit communication between competitors / algorithms. Therefore, as currently defined, the unilateral adoption of algorithmic pricing software would not violate the competition statutes of most jurisdictions. When determining liability in instances of non-algorithmic collusion, competition authorities have concentrated their attention on explicit communication between competitors, instead of on the rules underpinning the collusive arrangement or on outcomes, such as elevated prices, that arise under collusion.¹⁴ This is because it is challenging to determine with certainty that high prices are caused by collusive behavior, and because when humans engage in coordination, the collusive pricing rules are latent.

The UK Digital Competition Expert Panel states that with “further evidence ... of pricing algorithms tacitly co-ordinating of their own accord, a change in the legal approach may become necessary” (p.110, 2019). What might a new approach look like? When prices are set using algorithms, there is no communication between companies, but consumers could still be confronted with elevated (collusive) prices. Some economists have suggested that, rather than targeting explicit communication, in the context of algorithm pricing it may be necessary for antitrust authorities to focus their attention on the collusive pricing rules written into the algorithms (see Harrington 2018 and Calvano et al 2020). Unlike

10 See Clark, R. & J-F. Houde (2013), “Collusion with asymmetric retailers: Evidence from a gasoline price-fixing case,” *American Economic Journal: Microeconomics* 5, 97-123; Clark, R. & J-F. Houde (2014), “The Effect of Explicit Communication on pricing: Evidence from the Collapse of a Gasoline Cartel,” *The Journal of Industrial Economics* 62, 191-228; Byrne, D. & N. de Roos (2019), “Learning to Coordinate: A Study in Retail Gasoline,” *American Economic Review* 109, 591-619.

11 <https://www.vendavo.com/customers>.

12 <https://www.reuters.com/legal/litigation/realpage-antitrust-lawsuits-over-rent-prices-consolidated-tennessee-2023-04-10/>.

13 <https://www.bloomberg.com/press-releases/2023-01-26/hagens-berman-las-vegas-hotel-operators-sued-for-alleged-scheme-to-illegally-inflate-hotel-room-rates-to-record-highs>.

14 For more detailed discussion on these points see Harrington, J. (2018), “Developing Competition Law for Collusion by Autonomous Artificial Agent,” *Journal of Competition Law & Economics* 14, 331-363; Calvano, E., G. Calzolari, V. Denicolo & J. Harrington (2020), “Protecting Consumers from High Prices due to AI,” *Science* 370, 1040-1042.

with human-based collusion, pricing rules are not latent in the case of algorithms. Rather they are directly specified in the code. Should particular rules be identified that make collusion more likely, then authorities could insist that these be avoided by algorithms. This might be especially relevant for companies that have adopted the same algorithmic pricing software.

In Germany, the Federal Cartel Office (“Bundeskartellamt”) is the competition authority charged with regulating and protecting competition.¹⁵ Germany also has an independent advisory board, the Monopoly Commission (“Monopolkommission”), tasked with advising the German Federal Government on competition related issues.¹⁶ The Monopolkommission’s 2018 report on competition issues in Germany included a discussion on the issue of algorithms and collusion. The report states that further monitoring and evidence is needed to determine whether changes need to be made. If evidence does arise that algorithms lead to the further development of collusive markets, the report suggests that potential revisions could include (i) in cases of prohibited competitive behaviour, imposing the burden of proof that algorithmic usage has not contributed to infringement, and (ii) supplementation of the liability regimen under Article 101 of the Treaty of the Functioning of the European Union to include review and potential regulation of third parties (i.e. those that contribute IT expertise to algorithms) in cases of collusive behaviour.

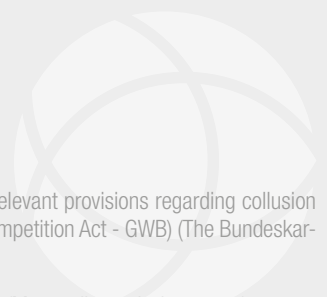
Alternative potential approaches to mitigating the risk of collusive algorithms could include competition authorities or regulators testing algorithms of concern *ex ante* with simulated scenarios. These tests could help to identify the strategies that algorithms use and whether or not they are anti-competitive. For example, an algorithm that responds with a trigger strategy to competitor price decreases in order to maintain high prices would be flagged. Such *ex ante* tests could be useful complements to *ex post* investigations into potential anti-competitive conduct.

IV. CONCLUSION

A key challenge for policy makers is how to balance the fact that companies should be encouraged to make use of all available data when setting their prices, with the possibility that doing so may encourage tacit coordination or even collusive behavior and result in sustained periods of higher prices and margins. Algorithms can aid companies to incorporate a wider range of information and to more efficiently set prices. Determining which parts of a pricing algorithm’s code take a company across the line of better data accumulation and information extraction into collusion facilitation is critical if we are to leverage the positives from this new technology without severely limiting competition.

¹⁵ The Bundeskartellamt’s tasks are carried out in accordance with legal provisions provided on both a national and European level. Relevant provisions regarding collusion are articles 101 and 102 of the Treaty on the Functioning of the European Union (“TFEU”) and the Act against Restraints of Competition (Competition Act - GWB) (The Bundeskartellamt, 2020).

¹⁶ The tasks of the Monopolkommission are regulated by a number of legislative acts including sections 42(5) and 44 to 47 of the GWB (Monopolkommission, 2020).



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