Algorithmic Pricing in Horizontal Merger Review: An Initial Assessment

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With the rapid progress in Machine Learning (ML) and Artificial Intelligence (AI) in the last decade, sophisticated algorithmic pricing has become common.[1] Increasingly, more firms have in-house data science teams that leverage AI technologies to optimize prices and make other strategic decisions. There are also many third-party providers of AI-powered pricing algorithms for different applications (e.g., Competera, Eversight, Intelligence Node, Perfect Price, Remi, and Wise Athena, to name a few).

Pricing algorithms, especially those powered by AI, can automatically set and frequently update the prices of many products. With sufficient computational power, such algorithms *could* leverage detailed data on consumer characteristics and behavior, competitor prices, economic indicators/events, and other information that influences customers' willingness to pay, to predict the demand for firms' products. At least in theory, firms could also use AI to try to predict competitors' responses to the firm's prices, which could be built into the pricing algorithm.

While the possibility of algorithmic price discrimination and algorithmic collusion in conduct cases has been extensively discussed in the global antitrust community in recent years,[2] there has been much more limited discussion in the context of mergers. In this article, we aim to fill this gap by discussing some potential implications of algorithmic pricing on market definition, unilateral effects, coordinated effects, and remedies. Specifically, we discuss the following topics and related questions:

- **Market definition.** How to account for algorithm-enhanced market/customer segmentation and identify relevant antitrust markets when prices are set by a "blackbox" algorithm.[3]
- **Unilateral effects.** How to use merging parties' pricing algorithms to conduct merger simulations.
- **Coordinated effects**. How the recent scholarship can inform analysis of potential coordinated effects in merger investigations.
- **Remedies.** Why data compatibility and collusion risk are important considerations when analyzing the divestiture of a merging parties' pricing algorithm.

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A Primer on Pricing Algorithms

An algorithm is a process or set of rules used to perform calculations. A simple pricing rule that sets the price of a product at 5% above production cost or 5% above a cost index are examples of pricing algorithms. However, with the advances in ML and AI, pricing algorithms can be much smarter. These smart algorithms take as inputs a variety of external information and *learn* how to price "optimally" (say, to maximize profits) without instruction by human decision makers. The learning stage of an algorithm is also known as the "training" stage of an algorithm. Examples of external information that firms can use in the training stage include data on the firm's prices, profits, and variables that affect their financial outcomes. These latter variables may include the firm's marginal costs, competitors' prices, and variables that affect the demand for the firm's products. Other types of pricing algorithms, especially those based on the so-called Reinforcement Learning (RL) techniques, could in theory also learn by extensive experimentation, such as the one implemented in a recent academic study by Calvano et al. (2020).[4] Readers can find a nontechnical introduction to machine learning including RL for the antitrust audience in Deng (2018).[5]

A critical component in any algorithm is its "objective," *i.e.*, what the algorithm is designed to accomplish. For example, an algorithm may be designed to maximize a firm's short-term profits (a myopic algorithm) or to maximize the expected present value of future profits (a forward-looking algorithm). But profit maximization does not have to be the only objective for a pricing algorithm. An algorithm can also be designed to optimize any combination of performance indicators, such as profits, sales, customer satisfaction, or customer retention.[6] Intuitively, including a diverse set of performance metrics in the objective enables the algorithm to incorporate forward-looking considerations (e.g., if my customers like today's prices, they are more likely to purchase tomorrow) or serve as a "fail-safe" mechanism that prevents the algorithm from recommending prices that might upset customers, preventing damage to the firm's reputation, customer backlash, or other detrimental consequences.[7]

Market Definition

The Issue of Potentially Dealing with a Large Number of Relevant Antitrust Markets. As Terrell McSweeny and Brian O'Dea pointed out,[8] sophisticated pricing algorithms can potentially segment a market into a massive number of customer groups with different willingness-to-pay by leveraging detailed customer data. In a merger investigation, granular customer segmentation can lead to narrower relevant antitrust markets defined by targeted "vulnerable" customers, and this could lead to a higher likelihood of finding a set of customers who may be harmed by the transaction.

The stylized car-buying example presented by McSweeny and O'Dea illustrates this point.[9] Suppose that an online retailer could use algorithms to predict whether a customer has a car. The pricing algorithm could then use that prediction and the customer location to identify the sellers that the customer will likely consider. Everything else the same, customers who have cars can get to brick-and-mortar retailers more easily than customers who do not. Thus, if there are five retailers, of which three are brick-and-mortar stores at a reasonable driving distance from the customers and two are online retailers, then customers who have cars will likely consider buying from any of the five retailers. But unless the brick-and-mortar stores are within walking distance or easily accessible by public transit, customers who do not have cars are more likely to consider only the online retailers.

If the online retailers cannot price discriminate, a merger between the two online retailers would be considered a five-to-four merger. But if the online retailers can and do price discriminate based on customers' car ownership status, the relevant antitrust market for customers without a car might include only the two online retailers. So, if the two online retailers merge, customers without a car would face a merger to monopoly.

The number of relevant "customer-based" antitrust markets can grow quickly if the online retailer's pricing algorithm determines *personalized* prices using multiple customer characteristics.[10] For example, in addition to car ownership, say, the algorithm also considers income, purchase history, and whether the customer is a student (assuming such information is available). Even if each of these four attributes has only two possible values, there would be $2^4 = 16$ unique combinations of customer attributes, leading to potentially 16 relevant antitrust markets. If each of these four attributes has three possible values, then the number of potential antitrust markets would be $3^4 = 81$. Of course, what determines the number of relevant antitrust markets is not necessarily the number of unique combinations of customer attributes, but rather the amount of variation in willingness-to-pay explained by these attributes and the extent to which the pricing algorithms can leverage this heterogeneity to effectively price discriminate.[11]

In the example above with eighty-one combinations of customer attributes, it is possible that customer willingness-to-pay is similar for several, or even most of the combinations of customer attributes, which limits the firms' incentive to price discriminate. An extreme example is when customers' willingness-to-pay does not vary with those attributes and all customers consider purchasing from the same competitors. In this case, the firm would find it optimal to charge the same price to all customers. In a less extreme example, the eighty-one combinations of customer attributes might yield a handful of customer groups, say three, with meaningfully different willingness-to-pay (e.g., "high", "medium", and "low" willingness-to-pay).[12] In this case, the firms will find it optimal to segment the market into *at most* three customer groups, reducing the potential number of relevant markets from eighty-one to three.

It is also important to recognize that even with a large number of potential relevant antitrust markets, the antitrust agencies and the parties do not need to separately analyze every market. For example, consider the case of two separate geographic markets for car-buying customers, Market A and Market B. Suppose that Market A and Market B have the same two brick-and-mortar retailers and the same two online retailers, but Market B has an additional brick-and-mortar retailer. Assuming the two markets are otherwise identical, then if there are no antitrust issues in Market A (the less competitive market), there should be no antitrust issues in Market B (the more competitive market).[13] As part of a merger review, it would be useful to identify such "nested" cases and rank them from less to more competitive to prioritize areas of concern. In any case, dealing with several antitrust markets is not new for enforcement agencies, as they often review deals that involve several geographies and customer segments. For example, in the investigation of Waste Management's acquisition of Advanced Disposal Services, the U.S. Department of Justice considered over 50 relevant antitrust markets, which were based on geography and product offered.[14]

Identifying Antitrust Markets and Targeted Customers When Prices Are Set By a "Black Box"

Generally, a firm can use pricing algorithms to segment the market through a combination of the two mechanisms:

1. **"Black-box" segmentation:** The algorithm is given full autonomy to set prices and learn the optimal customer segmentation. In this case, the algorithm receives no human input as to how to segment the customer base and a "black box" determines the customer segments, if the algorithm deems doing so profitable.

2. **AI-assisted segmentation:** The algorithm sets optimal prices for each customer segment, but humans decide whether and if so, how to segment the customer base. In this case, customer segmentation is more transparent because humans determine the customer segmentation and hence to which set of consumers the algorithm can charge different prices.

Regardless of how firms use pricing algorithms to segment the customer base, information on customer segmentation is likely available in ordinary-course business documents. In fact, even if pricing and customer segmentation are determined by a "black box," firms will observe different prices set by the algorithms. Thus, it is possible that firms can and will use their data to study their customer base, including the characteristics that define each customer segment, the profitability of each segment, and the competition for each segment.

In addition to ordinary-course documents, interviews with the companies' pricing teams can be particularly helpful to understand how the firms define customer segments. If a firm's pricing algorithms are developed by its in-house pricing team, the data scientists and economists on the team are expected to understand the different building blocks of the algorithm. They should be able to identify the data sources and the parts of the algorithm that determine the different customer segments.

Even if such information is not already documented, data analysis can be used to infer the customer segments. Companies will likely have the input data (that were fed to the algorithms) and the prices offered to each customer.[15] With these data, economists can conduct statistical analyses to study the relationship between prices and customers' characteristics and behavior. Firms can use a variety of analytical methods to infer what variables drive price differences across customers and what variables are probably irrelevant. It may also be possible to understand the algorithmic decision process that leads to price discrimination through Explainable AI (XAI), an active field of AI research that aims to make an algorithm's decision-making process understandable to humans.[16]

Unilateral Effects

Standard tools for evaluating mergers are still valid for evaluating the likely competitive effects of mergers when prices are set by algorithms. For example, ordinary-course business documents will continue to help antitrust enforcers and practitioners understand the nature of competition and industry dynamics, and economic analysis of the companies' data, such as the analysis of the companies' win-loss data and natural experiments (e.g., entry of a new competitor), among others, will continue to help enforcers understand the competitive constraints that the merging parties face.

However, in addition to the standard tools for assessing the competitive effects of mergers, algorithmic competition brings the possibility of using the companies' pricing algorithms to simulate merger effects.

Using Pricing Algorithms to Conduct Merger Simulations. Merger simulations that consist of specifying an economic model and solving for the pre- and post-merger equilibrium prices are often criticized for relying on unrealistic assumptions. However, by using the merging parties' pricing algorithms, it might be possible to simulate more reliable merger effects (even if additional assumptions are still required). If at least one of the merging parties uses a pricing algorithm that considers the other merging party's behavior to determine prices, economists could use the algorithm to predict the post-merger prices or to estimate the efficiencies required to offset a predicted price increase and compare that to the expected, merger-specific efficiencies.

Using the parties' pricing algorithms to simulate unilateral effects may be particularly convincing when the algorithm is trained with data that exhibits substantial variation in competition and supply and demand conditions. For example, the training data could display such variation when the parties use algorithms to set prices in several (antitrust) markets that differ in the number and identity of competitors, particularly with respect to the presence of the other merging party. With rich variation on competition, supply, and demand, a merger simulation using the firms' pricing algorithms might be able to make useful predictions of what would happen to post-merger prices.

To conduct a full-blown merger simulation using one of the merging parties' pricing algorithms, it is likely necessary to modify the algorithm's objective to maximize the joint post-merger payoff (e.g., joint post-merger profit). How difficult (or feasible) it is to modify the objective will, of course, depends on the specifics of the case. If the algorithm accounts for competition in its pricing, a potential alternative that might not require modifying the algorithm is conducting an analysis that evaluates the effect of removing the merging partner as a competitor in each antitrust market. If the algorithm prescribes a meaningful price increase when the merging partner is removed from a relevant market, after taking into account other demand and supply factors, it might indicate that the merging partner is constraining the firm's prices.

As noted above, firms may opt not to grant pricing algorithms full autonomy to set prices and segment customers. But even if their primary role is to assist humans in making pricing decisions, pricing algorithms can provide valuable information about a transaction's potential competitive effects. For example, company documents and past experiences might indicate the extent to which and the circumstances under which prices can deviate from the ones by its algorithms. Examining the empirical relationship between actual prices and the algorithmic pricing recommendations can also shed light on the usefulness of firms' pricing algorithms in a merger simulation. One could investigate whether human decision makers have typically accepted algorithmic recommendations for price decreases when a competitor entered a market. In fact, one can think of this type of analysis as a partial validation of the usefulness of the pricing algorithm in predicting post-merger price changes. If algorithmic prices are seldom implemented post-entry, then one should be careful in making post-merger price predictions based on such an algorithm.

In this type of exercise, the merging parties have a distinct advantage because they are the most familiar with the inner workings of their pricing algorithms. Firms may individually use their own algorithm to assess merger effects to understand profitability and firm valuation. Conducting such studies internally, if feasible, even prior to the HSR filing, also enables the merging parties to understand the potential antitrust risks and to address antitrust authorities' inquiries and concerns.

Additional Considerations. When economists use premerger algorithms and data to simulate merger effects, they will also need to analyze whether the combined firm will have a unilateral incentive to change important features of their pricing algorithms and consequently the customer segmentation post-merger.

Consider a case where the merging parties are in the same relevant market but have complementary data and, as a result, integrating their data and/or their pricing algorithms leads to more finely segmented market. In this case, the effect on consumer welfare is ambiguous.[17] The integrated algorithm might enable identification of a new group of customers with low (high) willingness-to-pay and find it profitable to offer a lower (higher) price to those customers following the merger. And if a competitor views these customers differently from the combined firm (i.e., the high willingness-to-pay customers for the combined firm are low willingness-to-pay customers for the competitor), the additional customer segmentation could lead to increased competition and lower prices for these customers.[18]

In addition to updating the customer segments, the combined firm might change certain features of their pricing algorithms post-merger. Brown and MacKay (2021) show that, under certain theoretical conditions, if firms can choose their pricing frequency, then each firm has a unilateral profit incentive to choose a frequency different from those of their competitors and that could lead to higher prices. [19] In their model, a firm with a lower pricing frequency offers higher prices.[20] Now suppose that the two merging parties use different technologies and that one can adjust prices more often than the other. Would it be profitable for the merged firm to abandon the higher pricing frequency and instead price at the lower frequency (or vice versa)? Would this result in higher prices to consumers? While more research is needed to shed light on this question, this unilateral incentive is plausible.[21]

Coordinated Effects

Algorithmic collusion is a hot topic in the global antitrust community. For recent discussions on the subject, see Deng (2018, 2020), Schwalbe (2018), Van Uytsel (2018), and Gautier et al. (2020), among others.[22] Here, we focus on the implications of algorithms in the merger context.

Unlike unilateral effects, coordinated effects analysis in a merger does not lend itself to a common quantitative procedure because the theory of collusion does not offer a unique prediction about the market outcomes. Instead, coordinated effects analysis typically involves looking at a variety of structural characteristics of the markets in question that are conducive to collusion and then asking whether the merger could strengthen these characteristics and as a result make (tacit) collusion easier.[23] Along this line of inquiry, one can ask what impact firms' use of algorithms have on these market characteristics. Previous studies and agency reports have addressed this question in general terms.[24] We focus on two structural characteristics on which the impact of algorithms tend to be less obvious in a merger context.

One such structural factor is symmetry. Although the previous literature focuses on cost symmetry and the reasons it tends to facilitate collusion, the use of algorithms adds another dimension to the consideration of post-merger (a)symmetry. One pertinent question is whether for firms using algorithms the merger would homogenize the input data or even the pricing algorithms, leading to more symmetry with the effect of softening competition.[25] It may also be possible that one of the merging parties is the only firm in a market that is not using a third-party algorithm. A merger could then lead to the use of the same third-party algorithm market wide. In fact, Competition Markets Authority in the United Kingdom has expressed concern about the antitrust risk when "competitors decide . . . that it is more effective to delegate their pricing decisions to a common intermediary which provides algorithmic pricing services" and stated that "[i]f a sufficiently large proportion of an industry uses a single algorithm to set prices, this could result in . . . the ability and incentive to increase prices."[26] While the CMA's hypothesis appears to be plausible, Harrington shows that, under certain conditions, adopting a common pricing algorithm developed by a third party "does *not* reduce competition but does make prices more sensitive to the demand variation."[27] As Harrington's study is the first formal investigation of this important question, more research is needed before we fully understand the impact of pricing algorithm homogeneity on post-merger competition and its welfare implications. Of course, a merger may also potentially exacerbate the existing algorithmic asymmetry if one of the merging parties is the only firm using algorithmic pricing.

Transparency about market demand and supply conditions (e.g., costs, prices, and other offer terms) is another structural factor that may facilitate tacit collusion and which algorithms could enhance.[28] But as Deng (2020) emphasized, recent academic literature has shown that under certain conditions, market transparency, especially transparency about demand, can make collusion more difficult to sustain. Motivated by empirical evidence showing that firms in some cartels took pains to limit information exchange, Sugaya and Wolitzky (2018) provided an economic theory to explain why privacy (less transparency) can be beneficial to a cartel. The key intuition is that market transparency may, in some instances, increase firms' incentive to "cheat." As Miklos-Thal and Tucker (2019) explained in their study on the implications of algorithm-enhanced market demand prediction, while "better forecasting allows colluding firms to better tailor prices to demand conditions, it also increases each firm's temptation to deviate to a lower price in time periods of high predicted demand."[29] Therefore, the authors concluded that "despite concerns expressed by policy makers, better forecasting and algorithms can lead to lower prices and higher consumer surplus."[30] Overall, these studies call for a careful and nuanced approach to algorithm-enhanced market transparency in a coordinated effects analysis.

Divestitures and Remedies

The goal of divestitures is to preserve the level of premerger competition. When considering divestitures of the merging parties' pricing algorithms, antitrust enforcers should evaluate data compatibility issues and the risk of collusion. The considerations involved are complex. We highlight two in this section.

First, consider a situation where both merging parties (Firm A and Firm B) use pricing algorithms and the enforcement agency determined that preserving competition requires divesting a set of overlapping products from Firm B and the pricing algorithm for those products. Suppose further that instead of using the algorithm as is, the divestiture buyer "re-trains" the divested algorithm using its own data, which do not cover Firm B's products that were not divested. In such a case, it is not clear what effect re-training the algorithm would have on the prices of the divested products. The answers would be case-specific. This consideration is, of course, not new. Unanticipated changes in firm behavior post-merger, like post-merger product repositioning, are always a possibility.

Typically, a divestiture involves an entire business unit which would include not only physical assets but also the personnel. If a divestiture also involves the personnel who has intimate knowledge about the inner workings of the divested pricing algorithms (say, to mitigate the risk of tacit collusion), one complication that the antitrust agencies and the merging parties would need to resolve is what happens if some of these personnel are key to achieving efficiencies.

Conclusion

In this article, we discussed the implications of pricing algorithms on merger reviews. We touched on a wide range of issues related to market definition, unilateral and coordinated effects, and remedies. While our discussion is not all-encompassing, it illustrates some of the issues that both the antitrust agencies and the merging parties should carefully evaluate when pricing algorithms are involved in a merger review.

The answers to many important questions we identified in this article are necessarily case-specific. At the same time, the use of pricing algorithms also presents opportunities to better predict post-merger competitive effects. As AI technologies continue to advance, more companies will adopt and develop their own algorithms. The discussions in this article provide a conceptual framework and a starting point to evaluate mergers with a significant algorithmic component. ■

1 For a user-friend introduction to ML and AI and the differences between these two concepts, see Ai Deng, *Algorithmic Collusion and Compliance: Risks and Opportunities*, GAI Report on Digital Economy, 2020, https://gaidigitalreport.com/2020/10/04/algorithmic-collusion-theory-and-evidence/.

2 On the topic of algorithmic collusion, *see*, for example, Deng (2020), *supra* note 1. On the topic of algorithmic price discrimination, see CMA, *Algorithms: How They Can Reduce Competition And Harm Consumers*, https://www.gov.uk/government/publications/algorithms-how-they-can-reduce-competition-and-harm-consumers/algorithms-how-they-can-reduce-competition-and-harm-consumers].

3 Even in absence of customer segmentation, pricing algorithms may also shed light on candidate product and geographic markets to the extent that the algorithms explicitly take into account competitive responses in setting prices.

4 Emilio Calvano, Giacomo Calzolari, Vincenzo Denicolò, and Sergio Pastorello, *Artificial Intelligence, Algorithmic Pricing and Collusion*, 110(10), American Economic Review 3267, (2020).

5 Ai Deng, *An Antitrust Lawyer's Guide to Machine Learning,* 33 Antitrust 82, (2018).

6 See https://competera.net/resources/articles/dynamic-pricing-algorithm.

7 In 2000, Amazon apologized after receiving several customer complaints when the company conducted pricing experiments on 68 DVD titles. Amazon refunded an average of $3.10 to 6,896 customers who bought the DVDs at a higher price than other customers. https://www.computerworld.com/article/2588337/amazon-apologizes-for-price-testing-program-that-angered-customers.html. Other "fail-safe" mechanisms include limiting price variation or keep prices within pre-specified bounds and not allowing the algorithm autonomously updating its pricing mechanism with new data as in standard reinforcement learning.

8 Terrell McSweeny and Brian O'Dea, *The Implications of Algorithmic Pricing for Coordinated Effects Analysis and Price Discrimination Markets in Antitrust Enforcement*, Antitrust, Vol. 32, No. 1, Fall 2017

9 *Id*, at 77.

10 Note that personalized pricing is different from dynamic pricing which does not always lead to finer defined antitrust markets. As FTC/DOJ pointed out in their submission to Roundtable on Price Discrimination, "personalized pricing should be distinguished from dynamic pricing where prices vary with market conditions. For example, ride-sharing apps, airlines, hotels, and event venues engage in yield management strategies that result in prices changing based on supply and demand conditions." [hence, these are examples of dynamic pricing.] (¶ 6) https://www.ftc.gov/system/files/attachments/us-submissions-oecd-2010-present-other-international-competition-fora/personalized_pricing_note_by_the_united_states.pdf.

11 In addition to being able to distinguish among different types of consumers, an effective price discrimination strategy requires that "targeted customers must not be able to defeat the price increase of concern by arbitrage, e.g., by purchasing indirectly from or through other customers." See U.S. Dep't of Justice & Federal Trade Comm'n, Horizontal Merger Guidelines (2010), at 6, http://ftc.gov/os/2010/08/100819hmg.pdf..

12 The Horizontal Merger Guidelines indicate that the Agencies define markets for groups of targeted customers. "If prices are negotiated individually with customers, the hypothetical monopolist test may suggest relevant markets that are as narrow as individual customers . . . Nonetheless, the

Agencies often define markets for groups of targeted customers, i.e., by type of customer, rather than by individual customer." See U.S. Dep't of Justice & Federal Trade Comm'n, Horizontal Merger Guidelines (2010), at 13, http://ftc.gov/os/2010/08/100819hmg.pdf.

[13] This example assumes that the relative market shares are the same in Market A and Market B for the firms that are present in both markets.

[14] "Divestiture Will Preserve Competition in Markets for Small Container Commercial Waste Collection and Municipal Solid Waste Disposal in Over 50 Local Markets in 10 States." See https://www.justice.gov/opa/pr/justice-department-requires-waste-management-divest-assets-order-proceed-advanced-disposal

[15] "[. . .] No matter how complicated and incomprehensible the computerized decision process is, the outcome is always observable and can be interpreted by human decision-makers." See Ai Deng, *4 Reasons Why We May Not See Colluding Robots Anytime Soon*, Law360 (Oct 3, 2017).

[16] For a discussion on XAI's potential in antitrust compliance, see Ai Deng, "*Algorithmic Collusion and Algorithmic Compliance: Risks and Opportunities*," The Global Antitrust Institute Report on the Digital Economy (2020).

[17] See Patrick Coen and Natalie Timan, "*The Economics of Online Personalised Pricing*," Office of Fair Trading (2013).

[18] This is related to the concept of best-response asymmetry. See Mark Armstrong (2006), "*Recent Developments in the Economics of Price Discrimination,*" Advances in Economics and Econometrics: Theory and Applications: Ninth World Congress: volume II. (pp. 97-141). Cambridge University Press: Cambridge, UK.

[19] Zach Brown and Alexander MacKay, *Competition in Pricing Algorithms,* American Economic Journal: Microeconomics, forthcoming.

[20] The basic intuition of their finding is that "a superior-technology firm commits to best respond to whatever price is offered by its rivals, and its investments in frequency or automation makes this commitment credible.… Firms with inferior technology choose to compete less aggressively." *Id* at 4 and 35. Obviously, this result is true under their assumptions regardless whether the price is set by algorithms or humans. But the authors argue that the use of pricing algorithms makes firms' commitment to respond at given frequencies credible.

[21] Another interesting consideration is related to the "learning about demand" (LAD) hypothesis in a merger retrospective analysis. The LAD hypothesis postulates that the post-merger price increase, if any, is due to the merged firm's better ability to estimate the willingness to pay (i.e., the demand for) their products or services, rather than an exercise of market power due to reduced competition. Balan and Garmon discussed and criticized the LAD argument in the context of FTC's retrospective challenge in 2014 of the 2000 acquisition of the Highland Park Hospital by the two-hospital system comprising Evanston Hospital and Glenbrook Hospital on empirical and factual ground. In the case of big data and algorithmic pricing, the case for LAD in a retrospective study might be stronger if the merging parties can convincingly demonstrate that higher post-merger price is a result of (1) their under-estimation of the willingness to pay pre-merger and (2) their enhanced analytical capability and improved algorithm alone allowing them to better estimate it post-merger. David J. Balan and Christopher Garmon, *A Critique of the "Learning about Demand" Defense in Retrospective Merger Cases*, 8 Econ. Comm. Newsl. 5 (2008).

[22] Ai Deng, *What Do We Know About Algorithmic Tacit Collusion,* 33 Antitrust 88 (2018); Deng (2020), *supra* note 1; Ulrich Schwalbe, *Algorithms, Machine Learning, and Collusion*, 14 J. Competition L. & Econ. 568 (2018); Steven Van Uytsel, *Artificial Intelligence and Collusion: A Literature Overview*, in Robotics, AI and the Future of Law, (M. Corrales et al., 2018); Axel Gautier, Ashwin Ittoo & Pieter Van Cleynenbreugel, *AI Algorithms, Price Discrimination and Collusion: A Technical, Economic and Legal Perspective*, 50 Eur. J. L. Econ., 405 July 14, 2020.

[23] U.S. Dep't of Justice & Federal Trade Comm'n, Horizontal Merger Guidelines (2010), §7.2, http://ftc.gov/os/2010/08/100819hmg.pdf.

[24] See, for example, OECD Directorate for Financial and Enterprise Affairs, Competition Cmte., *Algorithms and Collusion* 76, No. DAF/COMP(2017)4 (June 2017), https://one.oecd.org/document/DAF/COMP(2017)4/en/pdf and Deng (2020), *supra* note 1.

[25] Michal Gal has argued that firms making "conscious use of similar data on relevant market conditions even when better data sources exist" is a red flag for potential collusive agreement. Michal Gal, *Algorithms as Illegal Agreements*, Berkley Tech L J 34:67 (2019), at 113.

[26] CMA, *Pricing algorithms: Economic working paper n the use of algorithms to facilitate collusion and personalised pricing*, 5.19 (2018), https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/746353/Algorithms_econ_report.pdf.

[27] Harrington Jr, Joseph E., *The Effect of Outsourcing Pricing Algorithms on Market Competition*, Management Sci, forthcoming.

[28] For example, see Bundeskartellamt & Autorité de la Concurrence, Competition Law and Data 14 (2016), https://www.bundeskartellamt.de/SharedDocs/Publikation/DE/Berichte/Big%20Data%20Papier.html (". . . market transparency . . . gains new relevance due to technical developments such as sophisticated computer algorithms. For example, by processing all available information and thus monitoring and analysing or anticipating their competitors' responses to current and future prices, competitors may easier be able to find a sustainable supra-competitive price equilibrium which they can agree on." See also Bundeskartellamt & Autorité de la Concurrence, Algorithms and Competition ii 18 (Nov. 2019), https://www.bundeskartellamt.de/SharedDocs/Publikation/EN/Berichte/Algorithms_and_Competition_Working-Paper.pdf?__blob=publicationFile&v=5 ("[m]arket transparency for companies facilitates the detection of deviations and thus can increase the stability of collusion. By allowing a greater gathering and processing of information, monitoring algorithms collecting these data could thus foster collusion.")

[29] Jeanine Miklós-Thal and Catherine Tucker, *Collusion by Algorithm: Does Better Demand Prediction Facilitate Coordination Between Sellers?* Management Sci. 65, 4:1552–1561, 2019.

[30] *See supra* note 29, at 1552. Interested readers are also referred to Deng (2020) for an extensive discussion of this recent literature. Under a different economic model, O'Connor and Wilson (2021) reached the same conclusion that greater transparency and clarity about the demand has ambiguous effects on consumer welfare and firm profits. These authors therefore call for a cautious antitrust policy toward the use of AI algorithms. Jason O'Connor & Nathan E. Wilson, *Reduced Demand Uncertainty and the Sustainability of Collusion: How AI Could Affect Competition*, Info. Econ. & Pol'y 54, March 2021.