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Pricing Algorithms Aren't Colluding, Yet

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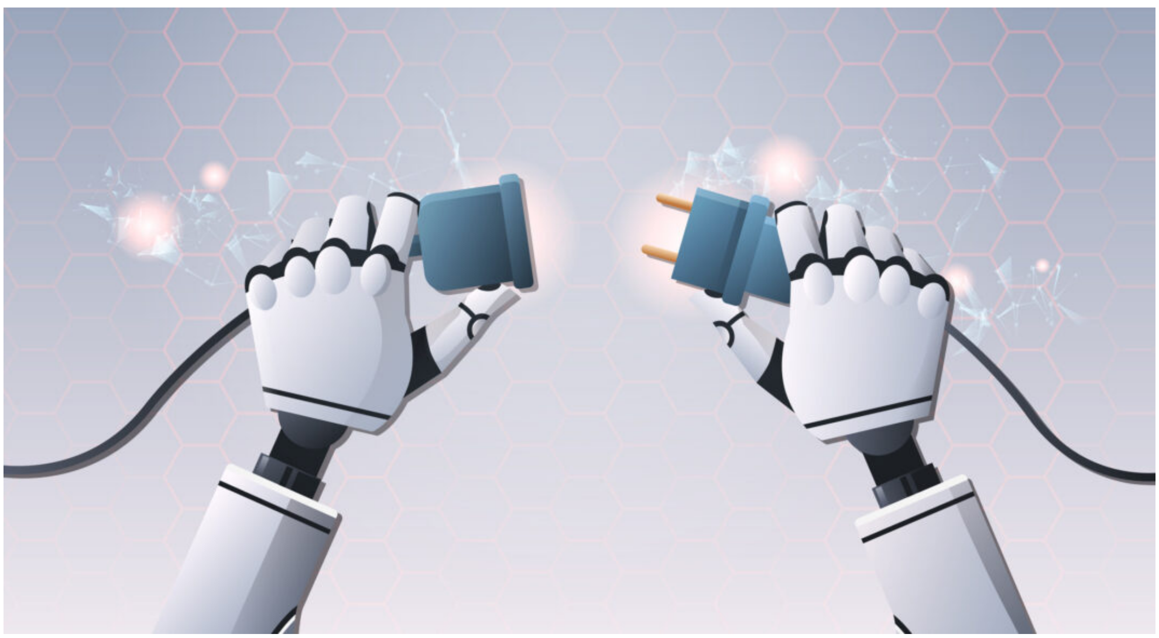

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Axel Gautier, Ashwin Ittoo, and Pieter van Cleynenbreugel write that the practice of pricing algorithms tacitly colluding remains theoretical for now, and technological obstacles render it very unlikely in the short term. However, regulators must still prepare for a future in which artificial intelligence achieves the necessary sophistication to collude.

Businesses increasingly use algorithms for pricing decisions, both in online channels, such as e-commerce platforms, and offline channels, such as in-store customer behavior.

The notion of algorithmic pricing covers all instances in which software determines the prices of products or services. Price-setting of that kind can take place either according to some pre-specified instructions/ objectives or via the use of machine learning methods that learn from past data, without requiring predefined instructions. One of the main advantages for businesses using algorithms is that they can rapidly collect and process a lot of information on, for example, rivals' prices, inventories, and demand, and use that information to adapt their own prices. Thanks to the speed with which software can react, such adaptations can take place almost instantaneously. Algorithms can therefore implement sophisticated pricing at a substantially lower cost.

However, algorithmic pricing may not only change the adjustment frequency and the sophistication of prices, but also the way in which firms are competing on the market. Questions therefore arise as to whether this increased reliance on algorithmic pricing creates increased risks for anticompetitive behavior taking the form of algorithmic collusion. Against that background, we:

1. Provide an overview of state-of-the-art pricing algorithms.
2. Analyze the economic implications of these algorithms, specifically, their ability to cause "customer harm" via collusion. We show that despite recent technological developments, there are still several longstanding issues to be resolved before algorithms learn how to collude.
3. Address algorithmic collusion from a legal perspective and posit that law should remain vigilant but not exaggerate its response to algorithmic collusion.

Pricing algorithms

Pricing algorithms learn how to set the price of products from past collected data. Commonly used data include those pertaining to customer demographic or behavioral variables, such as state, job category, employment type, past purchases, and online trail, including time spent scrolling web pages and clickstream. The advent of online platforms has rendered such data transparent and easily available, for e.g. via cookies, web scrapers, web beacons, and gaze analysis.

Different methods can be applied to these data to learn what characteristics (e.g. state, visits to competitors' websites, scrolling and gazing time) are most influential in customers' purchase decisions and the price that customers are willing to pay. Regression-based methods, such as LASSO and Logit, have been shown effective in estimating the price customers are willing to pay. Recent studies have investigated advanced supervised machine learning methods, including RandomForest, XG Boost and Gradient Boosting. Another research stream has focused on reinforcement learning, especially Q-Learning. Reinforcement learning methods require very little (if any) past training data. Instead, these methods learn how to set optimal prices by an explorative procedure. Recently, Deep Q-Learning, considered more robust and powerful (in terms of tasks that it can address) than Q-Learning, has also been investigated in pricing algorithms.

While pricing algorithms have shown much promise, they suffer from several limitations. First, data harvested via various means (e.g. cookies, scraping) need to be cleaned and preprocessed before being able to serve as input for supervised learning algorithms. However, data cleaning and pre-processing requires domain knowledge, and is an expensive manual procedure. Deep-learning methods address this issue to some extent. However, their implementation is much more complex. Concerning reinforcement-learning algorithms, their performance (and convergence) is influenced by a number of hyper-parameters, such as the discount-factor-learning rate and explore vs.

exploit rate, whose optimal values can be determined only after careful experimentation and fine-tuning. Furthermore, many of these algorithms overlook important economic factors, such as seasonality, product differentiation, the number of competitors, and the value customers attach to marketing and advertising. Integrating these factors into the algorithms is non-trivial. As a result, we posit that it is unlikely that these methods are deployed in practice. There is also the question as to whether such sophistication is warranted in practice. For most companies, simpler algorithms, based on traditional economic and econometric methods (e.g. regressions), coupled with human expertise, provide a sound basis for grounding pricing decisions. Furthermore, the lack of explainability of complex deep learning-based algorithms may constitute an obstacle to their deployment in practice, even more so when transparency is at the heart of the agenda of regulatory agencies.

Pricing algorithms as tools for algorithmic collusion?

The use of pricing algorithms may change the nature of market competition, and algorithmic pricing may lead to departures from a classical competitive benchmark, where each competitor chooses the best action given the choice of its competitors. There are two ways algorithms may depart from this benchmark. First, they may escape competition by colluding. Collusion is a cooperative outcome where firms choose supra-competitive prices in a repeated interaction environment. A key issue to support a collusive strategy is the ability to punish deviations from the collusive equilibrium. A credible punishment is the cornerstone of a collusive strategy. Without this threat of punishment, there is always a profitable deviation from the supra-competitive outcome and collusion cannot be sustained.

Following Ezrachi and Stucke, there is a fear that algorithms learn autonomously how to collude, a situation referred to as *algorithmic* *tacit collusion*. The ability to monitor the market and to react to changes may indeed be viewed as a factor facilitating collusion. Recent experiments have tried to test this conjecture. Calvano et al. have shown that Q-learning algorithms learn autonomously how to collude and charge supra-competitive prices. Furthermore, they document that the algorithms apparently punish deviations from the collusive outcome by charging temporarily lower prices after a breach of collusion has been observed. Klein observes a similar pattern. However, Abada and Lambin and den Boer et al. challenge this conclusion. For these authors, algorithms may indeed charge supra-competitive prices but not as a result of a sophisticated collusive strategy but rather by a failure to optimize. Q-Learning algorithms may lack the necessary sophistication to learn collusion.

Second, the use of pricing algorithms could mean that prices are set by software using pre-specified instructions or objectives to determine the price. Brown and MacKay show that the use of an algorithm is a short-term commitment device to a given pricing strategy. Instead of choosing prices, firms choose the instructions for pricing and this changes the nature of competition and may lead to supra-competitive prices.

The most recent research in economics shows that the use of algorithms for pricing may change the nature of competition and, possibly, make consumers worse off. While these discussions remain, at this stage, mostly theoretical or experimental, a recent paper by Assad et al. shows that the use of algorithm pricing in the German retail gasoline market increases the retail margin, especially in markets with few participants, suggesting that algorithms may learn *how not to compete.* Again, this is not evidence of collusion but rather a failure to compete.

Furthermore, economic research has mainly focused on Q-Learning algorithms. But, those algorithms are not scalable and their use is problematic as the number of firms grows. Also, there are no theoretical guarantees of the algorithms converging. If they do converge, it is unclear whether they will learn an optimal price. Deep Q-Learning algorithms might overcome these issues. However, as mentioned earlier, their performance is governed by a large set of hyper-parameters, which are challenging to determine, and for which there are no standard baselines. Incorporating relevant economic factors in these algorithms remains complex.

It follows from the foregoing overview that, despite existing economic incentives and possibilities to set prices at supracompetitive levels, technological advancements are not of such a nature as to make this practice happen in the real world in the short-term. The arrival of algorithms colluding in all markets and circumstances is therefore not to be expected immediately. However, its emergence should not be excluded in the near future.

Algorithmic collusion and the law: time for antitrust reforms?

Against the background of the technical and economic realities described above, questions may arise as to whether the law should be modified to prohibit or target more explicitly algorithmic collusion practices. Ezrachi and Stucke have argued that this should happen, which has given rise to lively debates among lawyers. Those debates call either for a modification of the law in the books and the development of remedies tailored to the realities of algorithmic collusion within the existing legal framework. However, technical and economic data show that disaster collusion scenarios are less likely to emerge than is sometimes assumed. As such, outright prohibiting algorithmic pricing practices would detract from the fact that algorithmic pricing also generates efficiencies for consumers. What is needed, however, is a constructive dialogue between regulators and firms, whereby the latter are given the space to develop and experiment with algorithmic pricing algorithms in a somewhat controlled environment. By doing so, firms would be able to explore the full potential of algorithmic pricing and regulators would retain the powers to take corrective actions, without outrightly prohibiting algorithmic pricing practices. The setup of regulatory sandboxes or real-world monitoring mechanisms as proposed in the EU's proposed AI Act therefore could serve as a useful starting point in the context of antitrust enforcement as well. Setting up such a regulatory regime would be the real reform antitrust needs in the context of algorithmic pricing.

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