Algorithmic Pricing, Anticompetitive Counterfactuals, and Antitrust Law

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I. Introduction

One of antitrust law's core contributions to social welfare is to prohibit explicit collusion between would-be competitors on price. Without a legal ability to collude, firms must rely on informal means to stabilize an understanding to set prices above marginal costs: they must be able to reach a mutual understanding on what prices to set without communicating and agreeing on price (which would be illegal); they must be able to detect deviations from that understanding; and they must be able to punish such cheating (Stigler 1964).

Stigler's conditions for sustaining uncompetitive outcomes are undoubtedly met in some contexts. But antitrust law for the most part accepts these unfortunate outcomes for two basic reasons. First, there is a sense that such coordination is possible, but difficult to achieve in many settings (Gal, 2023). Firms in relatively unconcentrated markets, for example, may find it difficult to reach an understanding on optimal prices. Markets in which demand and costs fluctuate make reaching such understandings more difficult, and moreover make it harder to detect cheating: was a drop in sales at a firm caused by cheating, or by a drop in demand? (Stigler, 1964; Green and Porter, 1984)

Second, even in markets where there is a high degree of confidence that a cooperative outcome is manifest, there is a formidable challenge of crafting an appropriate remedy (Turner, 1962). As Judge Breyer (as he then was) once wrote, "[I]t is close to impossible to devise a judicially enforceable remedy for 'interdependent' pricing. How does one order a firm to set its prices without regard to the likely reactions of its competitors?"[1] Given that reliance on competition to promote socially desirable outcomes rests on an assumption that firms will act in their own self-interest, and given that telling firms not to act in their self-interest is impracticable in any event, law cannot do much to remedy independent action that leads to cooperative outcomes.[2]

Given these two reasons, antitrust law typically eschews attempts to address tacit collusion directly and instead relies on mergers law to impede the emergence of concentrated markets that are conducive to tacit collusion.

Algorithmic pricing changes the prospects for tacit cooperation amongst firms, and therefore has implications for mergers law. The burgeoning literature[3] identifies several different kinds of algorithmic pricing, from manually generated pricing formulae, to artificial intelligence-driven algorithmic pricing ("AI pricing"). The literature also identifies different anticompetitive concerns about such pricing (Ezrachi and Stucke, 2016). Some of the concerns relate to algorithmic pricing supporting an illegal cartel.[4] Agreements between competitors to rely on a particular pricing algorithm are illegal under existing law, which makes sense in part because there is a straightforward remedy: do not agree with a competitor on pricing algorithms.

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[1] Clamp-All Corp. v. Cast Iron Soil Pipe Institute, 851 F.2d 478, 484 (1st Cir. 1988), cited in Harrington (2018).Gal (2023).

[2] There is a decades-old debate about this, with some suggesting financial penalties for supracompetitive pricing (e.g., Posner 1971, Kaplow 2014), and others agreeing with Judge Breyer that such an approach would do more harm than good (e.g., Posner 2013). I set this aside for the moment but return to it below.

[3] See, e.g., Ezrachi and Stucke (2016, 2017, 2020), Mehra (2016), Gal and Rubinfeld (2023), Gal (2023), Calvano, Calzolari, Denicolo and Pastorello (2020), Assad, Clark, Ershov and Xu (2024), Competition and Markets Authority (2021).

[4] Plea Agreement, United States v. David Topkins [30 April 2015] ; Information, United States v. David Topkins [6 April 2015]. See discussion in Mehra (2016).

The more difficult policy issues arise with AI pricing that does not support an otherwise illegal agreement. Independently adopted, and therefore legal, AI pricing technologies may support cooperative outcomes more effectively than human-driven pricing. There are several reasons for this identified in the literature (see, e.g., Harrington, 2018). As a base condition, data on pricing are increasingly available. In the future, AI will itself allow the gathering of even more data, either directly or through inference. For example, a sophisticated AI pricing package may be able to infer that a rival has lowered price from outcomes and data on costs and demand rather than observing price directly (Gal and Rubinfeld, 2023). Moreover, especially as AI becomes more sophisticated, one would expect highly intelligent pricing strategies that not only learn from past patterns of pricing and outcomes, but are also capable of making profit-maximizing decisions that turn on past patterns and anticipated reactions, and on raw data about demand and costs.[5] AI pricing will also be capable of responding immediately to rivals' changes in price, which implies smaller gains from cheating on a pricing understanding. In short, AI pricing may generate more profitable understandings that underlie cooperative outcomes, may be better able to detect cheating, and may be better able to mete out punishment for deviations by immediately updating the non-cheating firm's pricing to punish the cheater, all of which will stabilize monopolistic, cooperative pricing (Ezrachi and Stucke, 2016, Mehra 2017).

There are some sceptics about the importance of AI pricing for contemporary law. For example, Kühn and Tadelis (2018) observe that markets in the real world are complicated and reaching agreement may not be feasible even with AI pricing technology.[6] But there is evidence that AI pricing is already affecting markets. Experiments reveal that machine learning tends to

[5] With AI and ubiquitous data, the cost of prediction falls dramatically: Casey and Niblett (2017). It follows that AI pricing ought to be better able to predict the monopoly price in a market, and thus to coalesce around that price.
[6] See also, Schrepel (2020).

lead to anticompetitive outcomes in simulations (Calvano et al., 2020), and AI pricing resulted in supercompetitive prices in the German gasoline retail market (Assad et al., 2024). Whatever the status quo, recent remarkable progress in AI and massive growth in data suggests that AI pricing will become both more powerful, and less costly, which in turn will increase the probability in the future of monopoly pricing because of cooperative understandings between would-be competitors.

To be sure, AI pricing will not result in anticompetitive outcomes in all markets. Bidding on a massive, one-off project in a sealed bid auction, for example, may remain prone to uncoordinated outcomes given the short-run gains from cheating, and the lag that likely exists before a cheater could be punished. And it is possible that some markets are too complex, or entry is too easy, for anticompetitive outcomes to be sustained. But many markets that currently find it difficult or impossible to sustain cooperative pricing because of the complexity involved in doing so will become coordinated as data become more available and AI pricing becomes more powerful.

What can antitrust law do about this? As I elaborate below, the algorithmic pricing literature identifies two alternative paths, one conduct-based, the other structural. For example, with respect to conduct, antitrust law could address high prices directly, perhaps by banning certain kinds of AI pricing algorithms, analogously to what it presently does by banning explicit price-fixing agreements (Harrington 2018). To address structure, antitrust law could challenge more mergers to reduce the prevalence of concentrated markets that are susceptible to anticompetitive outcomes in the presence of AI pricing (Gal and Rubinfeld, 2023; Gal, 2023; McSweeny and O'Dea, 2017).

This article will focus largely on structural responses to AI pricing in antitrust, outlining the bulk of the argument in the context of mergers law but also considering abuse of dominance law and exclusionary conduct. Section II outlines the promise and shortcomings of relying on mergers law in antitrust to address AI pricing. It argues that the relationship between the strictness of the law and the sophistication of AI pricing is not straightforward. In the short run, a stricter approach to merger review might well make sense, but as AI pricing becomes more sophisticated, mergers policy ought to become *less* strict: if anticompetitive outcomes are inevitable with or without a merger because of highly sophisticated AI pricing, antitrust interventions to stop mergers will not affect pricing, and instead will create social losses by impeding efficient acquisitions. Section III considers the same questions in the context of abuse of dominance. Section IV concludes by observing that he rise of AI pricing will strengthen the case for antitrust law to shift its focus away from high prices, and static, allocative inefficiency, and toward innovation and dynamic efficiency.

II. AI Pricing and Mergers Policy

Gal and Rubinfeld (2023) and Gal (2023) consider various responses to the dangers of coordinated behavior resulting from AI pricing, including mergers law. Because AI pricing technology may result in stable supracompetitive pricing even in markets with many firms, mergers law in their view ought to be sensitive to AI pricing. In particular, they would have the law account for the risks of AI pricing by focusing on novel questions for merger review, and by lowering concentration standards in assessing markets prone to uncompetitive outcomes. The novel questions would concern whether a particular merger would enhance AI pricing in a market, in which case the authorities ought to be more willing to challenge the merger. For example, if a merger gives a firm access to a database that would help sustain cooperation through AI pricing going forward, then perhaps the merger ought to be stopped. Or if a firm has a particularly powerful AI pricing tool, then perhaps its acquisition might harm competition by spreading the impact of that tool.

The concentration argument is straightforward: since AI pricing may sustain cooperative outcomes even where markets are not especially concentrated, merger authorities ought to scrutinize mergers for the prospects of anticompetitive cooperative outcomes at lower levels of concentration that would not be problematic under human-driven pricing. Gal and Rubinfeld (2023) observe at pp. 18-19:

> Concentration parameters (such as the Herfindahl-Hirschman Index) are given substantial weight in determining intervention thresholds, based on a general assumption that oligopolistic coordination is likely to take place where the market is highly concentrated. The current level at which these parameters are set assumes that mergers in markets with four or more firms are not likely to lead to coordination. Algorithmic coordination challenges these assumptions. Accordingly, where the risk of algorithmic coordination is high, concentration parameters might need to be lowered. Furthermore, intervention thresholds should also be more sensitive to the accumulated knowledge regarding the market conditions that increase the probability of algorithmic coordination. For example, the speed and sophistication of reactions when algorithms are used to monitor, predict and set trade terms, should affect presumptions as to the maximal number of firms in a market needed to raise coordination concerns. [Footnotes omitted.]

These suggestions are sensible reactions to AI pricing at present. But they are less likely to be effective in the future. Currently, there are limitations both on the availability of data and AI pricing technology such that mergers could well be motivated by access to data, or by access to technology, and should therefore be scrutinized accordingly. But data are increasingly available through a variety of means (see, e.g., Aidid and Alarie, 2023; Casey and Niblett, 2017; Casey and Niblett, 2021; Gal and Rubinfeld, 2023). Moreover, AI pricing technology is in its relative infancy, and its costs will drop over time; its future ubiquity suggests that access to technology will not motivate many mergers going forward.

The idea of lowering concerning concentration thresholds to account for AI pricing also has force at present but will be less effective in the future. The problem is that as AI pricing becomes more sophisticated, what we would now consider to be significantly unconcentrated markets may be prone to cooperative outcomes because of sophisticated AI pricing. That is, as AI pricing improves, concentration levels will say less and less about the probability of cooperative outcomes on price.

This is not to say that all markets will always result in monopoly prices. For example, as noted above, markets with one-off, high value transactions and secret pricing (e.g., sealed bid auctions), may remain competitive on price even with AI pricing. Markets with firms with radically different cost structures may also not support cooperative pricing.[7] But while other factors may become more relevant, concentration levels, which merger law directly affects, may no longer affect anticompetitive pricing.

How should the law evolve as AI pricing evolves? It is superficially appealing to argue that if the first generation of AI pricing calls for stricter mergers enforcement, then as AI pricing becomes extremely powerful, mergers enforcement ought to become extremely strict. This would be wrong as a matter of policy, though perhaps consistent with current approaches to enforcement, as I will discuss.

If monopoly pricing is inevitable in a market, concerns about anticompetitive pricing that motivate mergers law at present become irrelevant: there will be anticompetitive pricing if the merger takes place and if the merger does not take place; stopping the merger has no impact on pricing. If anticompetitive pricing is inevitable, as a matter of logic mergers law concerned about anticompetitive pricing should become permissive because anticompetitive pricing is not

[7] For example, a low-cost firm may find it more profitable to capture the entire market by setting prices just below its rivals' cost.

motivating the merger. Even a radical change in concentration from a merger or series of mergers[8] would not affect the competitiveness, or lack thereof, of pricing.

The policy case for a permissive approach to mergers given the anticompetitive counterfactual from AI pricing sits uncomfortably with antitrust enforcement at present (outside of the failing firm defence[9]). Existing approaches to mergers enforcement tend not to treat anticompetitive counterfactuals as supporting non-intervention, but rather the opposite. The US Department of Justice and Federal Trade Commission Merger Guidelines (2023) provide a prominent example.[10] Section 2.3.A states in part:

> ***Prior Actual or Attempted Attempts to Coordinate.*** Evidence that firms representing a substantial share in the relevant market appear to have previously engaged in express or tacit coordination to lessen competition is highly informative as to the market's susceptibility to coordination. Evidence of failed attempts at coordination in the relevant market suggest that successful coordination was not so difficult as to deter attempts, and a merger reducing the number of rivals may tend to make success more likely.

The second sentence is straightforward to understand and plausible: a merger in the wake of failed attempts to cooperate seems more likely to have anticompetitive motivations and outcomes than a merger in a market without such failed attempts. On the other hand, it is less obvious why the Guidelines treat as a negative the fact that firms have engaged in explicit or tacit collusion in the past: if the purpose of the inquiry is to compare competition with and without the merger, then it might be reasonable to conclude that an anticompetitive outcome pre-merger would tend to *reduce* the negative competitive impact of the merger.[11]

[8] The Merger Guidelines (2023) emphasize the risks to competition from a series of mergers.
[9] Current merger law creates exceptions for anticompetitive mergers when one of the firms is failing, given that there will be a lessening of competition whether or not the merger takes place. This failing firm exception is, however, infrequently successful: see e.g., Ayal and Rotem (2020).
[10] The approach is common: see, e.g., Canadian *Merger Enforcement Guidelines* (2022), para. 6.34.
[11] Strictly speaking the Guidelines simply state that past coordination suggests that the market is prone to such coordination, but it is clear that this is a factor that the authorities would hold against the merger.

In the current state of the world, there are good reasons to treat a cooperative outcome amongst firms pre-merger as a negative for merger approval. First, there is the risk that the cooperative understanding will break down, perhaps because of conflict between the merging parties, while post-merger the understanding will be more stable – at the very least, the merger eliminates the risk of competitive conflict between the merging parties themselves.

Second, while cooperative outcomes pre-merger may not reflect competitive outcomes, they may not reflect monopoly outcomes either. There is a risk that a merger would aggravate the problem of supracompetitive pricing that exists pre-merger. For example, a duopoly may have a shared understanding to set prices above competitive levels but are not able to share an understanding to set monopoly prices. A merger of duopolists will increase prices to monopoly levels. This is significant for merger review not just because a merger may harm competition even when markets are not competitive pre-merger, but also because the harms of higher prices are disproportionately worse if prices rise from supracompetitive levels than if they rise from competitive levels. This is because the marginal consumers priced out of the market when prices rise from supracompetitive levels value the product more than consumers who are priced out of the market when prices rise from competitive levels; all things equal, the social losses are greater in the former than the latter context.

Thus, there are justifications for current enforcement approaches to treat pre-merger cooperation as a negative for a merger. Those justifications lose force, however, in the presence of AI pricing. As AI pricing becomes more sophisticated, pre-merger cooperative outcomes will be more stable, and are more likely to mimic monopoly. Sophisticated tools with access to vast amounts of data will recognize not just that cooperation is better than competition given instant responses to lower prices by competitors, but also that cooperation at monopoly levels is better than cooperation at high, but sub-monopoly-level prices. In such a case, there is considerably less reason to expect competition over price to be stronger without the merger either because of instability or sub-monopoly pricing. Comparing the merger to the anticompetitive counterfactual without the merger, it will become difficult to substantiate an allegation that the merger would harm competition because of higher prices.

If a merger is not motivated by the prospect of higher prices or a more stable cooperative outcome amongst firms, the justification for intervention weakens dramatically, and justifications for lax policy strengthen, because it is more likely that the merger is motivated by efficiency considerations than anticompetitive considerations. For example, Gal and Rubinfeld (2023) note that if higher prices are not motivating a merger, a concentrative merger motivated by economies of scale would have positive social impacts. It could also be, following Iacobucci and Triantis (2007), that capital structure is more efficient from a governance perspective with two firms' assets combined into one legal entity than in two legal entities. Whatever the specifics, the fact that the merger is motivated by something other than higher prices suggests that it is more likely to be motivated by efficiency gains, and ought to be permitted. (I will consider non-price anticompetitive motivations in the Conclusion.)

This new world of increasingly anticompetitive counterfactuals is not all bad. At present, with a more aggressive mergers regime and less effective coordination, it is more likely that markets will have competitive and thus efficient pricing, but less likely that firms will make efficient merger decisions. The latter is true because while combining assets may or may not be efficient from either a productive or capital structure perspective, combining assets increases the probability of supracompetitive pricing. While mergers review is intended to catch anticompetitive mergers, this review is inevitably imperfect. If the gains from anticompetitive mergers are great enough, then there is a bias to merge for anticompetitive reasons even if from a productive perspective it would be better if the firms stayed separate.

In the future with sophisticated AI pricing and a permissive mergers regime, there is more likely to be supracompetitive pricing, but decisions to merge will be more efficient. A merger that creates a suboptimal capital structure, or diseconomies of scale, in order to achieve supracompetitive pricing will not make sense given that supracompetitive pricing will occur regardless. Rather, would-be merging parties can set pricing considerations to the side and focus only on the efficiency of the combination.

Whatever productive efficiencies might accrue from a merger, a first best world would be one in which aggBeressive, competitive pricing results regardless of the merger. For this to arise, antitrust would have to shift tactics. At the moment, independent behaviour even if cooperative is legal, which creates space for independently-adopted AI pricing to result in monopoly pricing even in unconcentrated markets. Various commentators have proposed regulating the use of AI pricing tools to address this concern (e.g., Harrington 2018). I am sceptical, as are other commentators (e.g., Gal 2023), that interventions to address AI pricing tools directly will succeed. Attempts to require AI pricing tools to ignore competitive reactions would run into the same problems that the law confronts in the "old" world of human-set prices: the authorities would essentially require the firm not to act in its self-interest, which is fraught with unintended consequences given the foundational role that economic self-interest plays in markets.

Alternatively, authorities could punish anticompetitive pricing, a suggestion that Posner (1969) and others have made (e.g., Kaplow 2013). The debate over treating tacit collusion as problematic under antitrust law has long recognized that doing so would be tantamount to price regulation, given that the authorities would require knowledge of the competitive price in order to punish supracompetitive prices (see, e.g., Posner 2014). I am doubtful that the state would do an effective job of enforcing such a law at present, but in a future world of sophisticated AI pricing tools, such price regulation may be feasible (Beneke and Mackenrodt 2021). Just as AI pricing tools adopted by firms in the market could get access to data and vast computational power to converge on monopoly prices, the authorities could adopt AI tools that rely on extensive data and computing power to determine competitive price benchmarks. Posner's (1969) suggestion of fines for supracompetitive prices becomes practical in this context.

The conclusion that mergers law ought to become more permissive as AI pricing tools become more powerful holds, however, whether or not it becomes practical to regulate supracompetitive prices with AI regulatory tools. If it remains impractical to address supracompetitive pricing from AI pricing in a market, then mergers in many markets will not be motivated by the prospect of supracompetitive pricing because it will arise with or without the merger; given that the merger and the no-merger counterfactual are both equally anticompetitive, mergers policy should be permissive in this case. On the other hand, if there are rational and effective interventions that deter supracompetitive pricing, then mergers will not be motivated by the prospect of supracompetitive pricing because it will *not* arise with or without the merger; mergers policy should also be permissive in this case. While the world in which the law can effectively address supracompetitive pricing is the better one from a social welfare perspective, mergers policy to counter high prices will recede in importance in any event.

III. Monopolization

The rise of AI pricing has implications for more than just permissive mergers policy; it also ought to render monopolization law more permissive. Monopolization cases often concern efforts by a dominant firm to protect its position not by competing effectively, but by excluding competition. Outlawing such exclusionary behaviour rests on various justifications, including two that will lose force in the presence of AI pricing.

First, there is a concern that a monopolist may seek to prevent entry in order to preserve monopoly pricing. In a world of AI pricing (and no practical regulatory response[12]), however, it is predictable that monopoly pricing levels will exist regardless of entry in many markets. The monopolist would rather realize all monopoly profits for itself than share them with an entrant, but this is inherently neutral from a social welfare perspective: whether monopoly profits are realized by the monopoly or shared by duopolists is irrelevant. There is no justification for preventing exclusion out of concern for higher prices if they would occur with or without the conduct.

Second, there is a concern that a monopolist may exclude a more efficient competitor, which may occur, for example, because of collective action problems that distort buyer choices to accept exclusive contracts (Aghion and Bolton 1987, Segal and Whinston 2000).[13] In a world of AI pricing, this concern should also dissipate. Even with heterogenous costs, there will remain in many cases a joint profit-maximizing price that AI algorithms will be able to attain should there be entry. Because AI pricing would generate monopoly pricing whether or not there is entry, which implies that mergers are likely to be motivated by efficiency, mergers policy ought to be permissive, as discussed. Thus, even if a potential entrant decides to acquire an

[12] If there were a practical regulatory response, such as relying on sophisticated AI pricing tools to set fines for supracompetitive prices, then monopoly pricing ought not to be a concern regardless of dominant firm conduct.
[13] For a paradigmatic case, see *Canada (Director of Investigation and Research) v. D&B Companies of Canada Ltd.* (1996), 64 C.P.R. (3d) 216 (Comp. Trib.).

incumbent monopolist rather than enter and compete with it, mergers policy should adopt a permissive position. If a potential entrant has lower costs, it would be able, all things equal, to realize greater profits than the incumbent. It would make sense, therefore, for it to acquire the incumbent. There will remain a single firm and monopoly pricing in the market, but the more efficient firm will take over. There is no benefit to intervening with either mergers or monopolization law, and indeed an efficiency gain from not intervening and allowing the more efficient firm to become dominant.

There is a qualification: if the entrant is sufficiently efficient relative to the incumbent, it may be profitable for that entrant to set prices just below the rival's cost, thus capturing the market for itself. This too would result in a single firm serving the market, but at sub-monopoly prices, at least until the high-cost incumbent exits. Exclusion of such a radically more efficient competitor would be harmful. Just as some markets are not prone to supra-competitive prices even with AI pricing, there will be some contexts where conventional anticompetitive concerns will arise with respect to exclusion. But this domain will shrink over time.

IV. Conclusion: Dynamic vs Static Efficiency

Mergers policy and monopolization law designed to address concerns about high prices will become less important with the rise of AI pricing tools. If supracompetitive pricing, and attendant allocative efficiency losses, arise with or without a merger, or with or without exclusionary conduct, there is no pricing reason to stop mergers or exclusionary conduct. This does not imply that mergers and monopolization law concerned about price will cease to have all force in all settings. For example, there will be markets that are not susceptible to supracompetitive, AI-driven pricing, such as those with only occasional, high-value transactions and secret pricing. And heterogenous costs across firms may imply that monopolistic exclusion could be harmful.

Concerns over pricing reflect concerns over static allocative efficiency: buyers priced out of the market create social deadweight losses. Much of antitrust enforcement is presently motivated by concerns over these static efficiency losses. AI pricing will predictably shift competition law's focus away from such concerns, and towards questions that that existing law is currently inadequate and unsystematic in addressing: innovation and dynamic efficiency (OECD, 2023; Sidak and Teece, 2009).

Mergers and monopolization may diminish competition in static models, but also are likely to influence innovation. The rise of AI pricing and the growing irrelevance of static efficiency considerations in mergers and monopolization review ought to provide further impetus to antitrust enforcers now to shift their focus away from the familiar but potentially less important question of static efficiency towards building a systematic approach to antitrust law and innovation (OECD, 2023). Antitrust will remain important in the presence of ubiquitous and sophisticated AI pricing, but AI pricing will strengthen the case for shifting emphasis from static to dynamic concerns.

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