International Center for Law & Economics

Comments of the International Center for Law & Economics

Canadian Competition Bureau Discussion Paper on Algorithmic Pricing and Competition

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Introduction

We thank the Government of Canada and the Canadian Competition Bureau for the opportunity to comment on the discussion paper "Algorithmic Pricing and Competition."[1] The International Center for Law & Economics (ICLE) is a nonprofit, nonpartisan global research and policy centre founded with the goal of building the intellectual foundations for sensible, economically grounded policy. ICLE promotes the use of law & economics methodologies to inform public policy debates and has longstanding expertise in the evaluation of competition law and policy. ICLE's interest is to ensure that competition law remains grounded in clear rules, established precedent, a record of evidence, and sound economic analysis.

In its ongoing efforts to ensure that competition law remains tethered to sound principles of economics, law, and due process, ICLE has engaged extensively with algorithmic-pricing issues across jurisdictions. We have filed *amicus* briefs in leading U.S. cases, including *Gibson v. Cendyn*[2] and *Cornish-Adebiyi v. Caesars*,[3] arguing against overly broad theories of algorithmic collusion.

The consultation's focus on algorithmic pricing raises important questions about how competition policy should adapt to technological change. In our view, the fundamental challenge is not the technology itself but ensuring that enforcement remains grounded in economic effects, rather than formalistic assumptions about how pricing algorithms operate. As former aptly noted by Maureen Ohlhausen, former chair of the U.S. Federal Trade Commission (FTC), we should evaluate automated business practices by asking whether they would be legal if performed manually. Ohlhausen's "guy named Bob" test provides a useful heuristic that Canadian authorities should embrace.[4]

Our comments focus primarily on the following aspects of algorithmic pricing:

1. The economic effects of algorithmic pricing, including both efficiencies and potential harms;
2. The application of existing legal frameworks to concerns about algorithmic collusion;
3. The distinction between conscious parallelism and actual agreement in algorithm-mediated markets;
1. The role of market structure in determining competitive effects; and
4. The importance of preserving incentives for innovation while addressing legitimate competition concerns.

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[1] *Algorithmic Pricing and Competition: Discussion Paper,* COMPETITION BUREAU CANADA (Jun. 10, 2025), https://competition-bureau.canada.ca/en/how-we-foster-competition/education-and-outreach/publications/algorithmic-pricing-and-competition-discussion-paper.

[2] Brief of the International Center for Law & Economics as *Amicus Curiae* in Support of Defendants, *Cornish-Adebiyi v. Caesars Ent., Inc.*, No. 24-3006 (3d Cir. Mar. 31, 2025)

[3] Brief of the International Center for Law & Economics as *Amicus Curiae* in Support of Defendants' Motion to Dismiss, *Gibson v. Cendyn Grp., LLC*, No. 1:23-cv-02536 (D.N.J. Mar. 1, 2024)

[4] Maureen K. Ohlhausen, Acting Chairman, *Should We Fear the Things That Go Beep in the Night? Some Initial Thoughts on the Intersection of Antitrust Laws and Algorithmic Pricing*, FED. TRADE COMM'N (May 23, 2017), at 10, *available at* https://www.ftc.gov/system/files/documents/public_statements/122 0893/ohlhausen_-_concurrences_5-23-17.pdf.

The competitive effects of algorithmic pricing depend on three key factors: market structure, software design, and implementation methods. Algorithmic adoption can facilitate coordinated outcomes, but it also offers consumer benefits through improved capacity utilization and dynamic pricing. The same technology that intensifies price competition in some contexts can dampen it in others. These findings underscore that technology amplifies existing market characteristics, rather than fundamentally altering competitive dynamics. Those markets that are susceptible to tacit coordination with human decisionmakers remain problematic with algorithms; competitive markets remain competitive.

In addition to what we know from economic research, various legal cases have brought forward other factors relevant to understanding algorithmic pricing. Crucially, the modern pricing algorithms examined usually operate within careful boundaries regarding information use. As we've pointed out, in actual cases, reputable vendors design their systems to avoid any inter-firm sharing of sensitive information.[5] Firms typically feed their own internal data (sales volumes, inventory levels, cost data) into algorithms that combine these with publicly available market data, such as competitors' posted prices. This one-way flow of processed market intelligence differs fundamentally from scenarios in which competitors exchange confidential strategic information. A hotel using pricing software sees market analyses (demand trends, average rates scraped from travel sites) but not rivals' proprietary booking data or recommendations based on such data.

These empirical and legal findings converge on a crucial insight: algorithms seem to amplify existing market characteristics rather than fundamentally transforming competitive dynamics. In concentrated markets with high barriers to entry and homogeneous products, algorithmic pricing may facilitate coordination. These same markets were, however, already susceptible to tacit collusion with human decisionmakers. Conversely, in competitive markets with differentiated products and low entry barriers, algorithms typically intensify competition by enabling faster price responses, better capacity management, and more targeted offerings. The technology serves as an accelerant, not a catalyst. It serves to make existing competitive or anticompetitive tendencies more pronounced, without creating entirely new market dynamics.

The key distinction lies not in the use of algorithms, *per se*, but in whether firms move beyond legitimate monitoring of public information to actual coordination of competitive decisions. Using common analytical tools or receiving similar market intelligence does not establish unlawful coordination. In short, algorithmic pricing should be seen as an evolution of older forms of pricing, and not some revolution that requires throwing out everything we know about competition policy.

I. Algorithmic Pricing in Modern Markets

Algorithmic pricing refers to the practice of using computer algorithms to set or recommend prices for goods or services. Rather than relying solely on manual pricing decisions or simple rules of

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[5] *See* ICLE Amicus Briefs, *supra* notes 2-3.

thumb, firms input data into software that can automatically recommend or determine prices based on predefined criteria or learned patterns. These tools range from relatively simple algorithms (*e.g.*, dynamic rules that raise prices as inventory drops) to advanced artificial-intelligence (AI) systems that continuously learn from market data.

The Competition Bureau notes that algorithmic pricing is "is gaining momentum across sectors and industries worldwide," employed in industries from hospitality to concert tickets to ridesharing.[6] Indeed, algorithmic pricing is, in many ways, an extension of techniques that have existed for decades. Airlines and hotels, for example, have long engaged in dynamic pricing and yield management by systematically adjusting fares or room rates according to demand fluctuations, the timing of bookings, and capacity constraints. And they have, for decades, employed software—algorithmic tools—to do so.

What has changed is the scale and sophistication made possible by modern computing and data availability. Today, even mid-sized and small firms can access cloud-based pricing software or revenue-management systems that analyze large datasets—including sales history, competitor prices, or consumer behaviour—to adjust prices.

Pricing algorithms may analyze data to monitor market conditions, predict optimal pricing, or both. Common inputs include a firm's own sales and inventory data, publicly available information (such as competitors' prices scraped from websites), and broader factors like seasonality or local events. Depending on the complexity, an algorithmic tool might use simple rules (*e.g.*, "if inventory < X, raise price by Y%") or more complex machine-learning models that recognize patterns (*e.g.*, an AI that learns demand elasticity at different price points). Some algorithms use dynamic rules that adjust prices continuously in response to real-time data, while others use personalized rules that tailor prices to individual customer segments, or even to specific individuals, based on their characteristics or past behaviour. Other algorithms can do both.

It is important to demystify how these algorithms function in practice. Most pricing algorithms do not set prices in a vacuum or in a conspiratorial manner; rather, they replicate and enhance traditional pricing tasks that human managers have always done. The software simply automates these tasks, often with the aid of computational resources: observe competitor prices, analyze market conditions, and make pricing recommendations. In other words, algorithms are tools that follow the instructions or goals set by their human programmers (*e.g.*, maximize occupancy, or achieve a target revenue per-product).

In some cases, such as the case of Rainmaker's pricing software used by hotels, the algorithm presents recommendations to a human decisionmaker, who can choose to accept or override the suggested price.[7] Even in fully automated settings like e-commerce platforms, the algorithms are tuned to

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[6] Competition Bureau Canada, *supra* note 1.

[7] ICLE Amicus Brief, *supra* note 2.

known business objectives, like clearing stock by a season's end or undercutting a competitor's price by a small margin. This operational reality is crucial to bear in mind: using an algorithm is not a magical means to collude or to exploit consumers, but a way to process information more efficiently.

A. Data Sources

The consultation inquires about the sources of algorithmic-pricing data and suggests that "pooling data among competitors may raise issues under the Competition Act."[8] This would only occur in the case of third-party software, not in the case of, *e.g.*, an airline using its own data to construct a pricing algorithm. In the case of external software, firms typically feed their own internal data (sales volumes, inventory levels, cost data) into the algorithm, often combined with publicly available market data, such as competitors' posted prices.

Modern pricing tools do not usually involve exchanging confidential data among competitors. In fact, reputable vendors design their systems to avoid any *inter-firm* sharing of sensitive information, precisely to steer clear of risk to competition.[9] For example, a hotel using a pricing algorithm will see analyses of its market (demand trends, average competitor rates scraped from online-travel sites), but it will not be given a direct feed of a rival hotel's proprietary booking data or recommendations based on such proprietary competitor data.

Competition law draws important distinctions between distinct types of information use. Monitoring publicly available competitor prices has always been legitimate competitive conduct, whether done manually by human analysts or automated through algorithms. The automation of this process does not transform lawful activity into unlawful coordination.

The Competition Bureau's own guidance provides helpful context for evaluating information sharing in algorithmic contexts. In its Competitor Collaboration Guidelines, the bureau analyzed a scenario in which trade-association members agreed to share aggregated sales and cost data through an independent third party.[10] The bureau recognizes that information exchanges among competitors can "impair competition by reducing uncertainties regarding competitors' strategies and diminishing each firm's commercial independence," but notes that most such exchanges "do not raise concerns under the Act because competitors generally avoid sharing information that is competitively sensitive."[11]

The bureau's analysis of when information sharing becomes problematic offers useful guidance by analogy. The bureau focuses on whether information is "competitively sensitive," with "publicly

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[8] Competition Bureau Canada, *supra* note 1.

[9] ICLE Amicus Brief, *supra* note 3 ("there is no allegation here that Rainmaker's pricing recommendations to one subscriber are based on the confidential information of another subscriber.")

[10] *Competitor Collaboration Guidelines,* COMPETITION BUREAU CANADA (May 6, 2021), https://competition-bureau.canada.ca/en/how-we-foster-competition/education-and-outreach/competitor-collaboration-guidelines#sec04-7.

[11] *Id.*

available information" generally not raising concerns.[12] The bureau also distinguishes between "information exchanged directly between competitors" (more concerning) and "information that is supplied to an independent third party" in aggregated form (less concerning).[13]

The key legal test focuses on whether firms have moved beyond information gathering to actual coordination of competitive decisions—*e.g.*, by sharing non-public, competitively sensitive information. Using common analytical tools or receiving similar market intelligence does not establish such coordination. Rather, enforcers must prove that competitors have agreed to act in concert, using shared information as a facilitating mechanism for price-fixing, rather than independent competitive decision-making.

Using one's own and public data to set prices has always been a legitimate business practice, as we will explain later. Doing it faster with an algorithm does not change that fundamental point. Indeed, competition law draws a line between public price monitoring (generally lawful) and sharing confidential pricing plans (potentially unlawful). Algorithms that stick to the former are tools that promote efficiency, not collusion.

B. Types of Algorithmic Pricing

Two key concepts highlighted in this consultation are dynamic pricing and personalized pricing (or algorithmic price discrimination). We briefly define each:

1. Personalized pricing

Personalized pricing refers to setting different prices for different customers (or segments or groups of customers) based on their individual characteristics or willingness to pay. This could mean offering targeted discounts or higher prices depending on a customer's profile, purchase history, location, or device. For instance, an e-commerce site might algorithmically offer a coupon to price-sensitive shoppers (those who haven't purchased in a while) while charging full price to frequent purchasers who have shown low price sensitivity. Personalized pricing is enabled by data analytics that can estimate a consumer's willingness to pay.

While the idea sometimes raises fairness questions, it is important to note that personalized pricing can be broadly procompetitive. It often means that more consumers can be served, as price-sensitive consumers get access to lower prices, rather than being priced out entirely under a one-price-for-all strategy. We discuss the consumer-welfare implications of personalized pricing below.[14]

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[12] *Id.*

[13] *Id.*

[14] *Infra* Section II.

The FTC recently introduced the term "surveillance pricing" to describe certain personalized-pricing practices.[15] But while this terminology comes from the academic literature, it has gained little traction. With no clear application or applicable research, it adds nothing to our understanding of the economic effects that are of interest in competition policy. The phrase appears designed more for rhetorical impact than analytical clarity; personalized or algorithmic price discrimination already captures the relevant economic phenomena without the pejorative connotations.[16] As a general rule, Canadian authorities should focus on the actual economic effects of these practices, rather than adopting loaded terminology that may prejudge outcomes.

2. *Dynamic pricing*

Dynamic pricing refers to adjusting prices over time in response to changing market conditions. The same phenomenon is also sometimes dubbed "surge pricing" or "real-time pricing." The strategy can involve temporal price discrimination: the price for the same item may be higher at times of peak demand and lower at times of slack demand.

There are, at least, four distinct types of dynamic pricing. While all involve updating prices over time, the underlying economics and policy implications of each could differ.

The first form is pure intertemporal price discrimination, where firms exploit predictable differences across consumer types. Examples include "early-bird" concert tickets that are offered at lower prices months in advance, or last-minute business-class airline fares that skyrocket even when plenty of seats remain. The price path is pre-programmed and does not respond to new demand information; it is instead designed to sort diverse types of consumers based on their planning horizons or willingness to pay. A busy executive who books a flight the night before travel reveals something about their time value that the airline can exploit. This pricing strategy uses time of purchase as an imperfect proxy for consumer type, and is a form of price discrimination.

But not all dynamic pricing is pure price discrimination. The second form responds to predictable demand cycles, rather than consumer heterogeneity. Electricity companies charge more during peak hours (4 to 9 p.m.), because that's when aggregate demand systematically spikes. Ski resorts charge less in April than February for the same reason. Here, the pricing algorithm does not try to discriminate among customer types. It is instead aligning prices with known fluctuations in market-wide demand to keep marginal revenue roughly equal to marginal cost.

The third form is real-time market balancing under flexible capacity constraints. This is where Uber's surge pricing really shines: when demand unexpectedly spikes (say, when a concert lets out), prices jump to ration limited driver capacity and signal additional drivers to enter the market. The key

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[15] *FTC Surveillance Pricing 6(b) Study: Research Summaries A Staff Perspective*, FED. TRADE COMM'N (Jan. 2025), *available at* https://www.ftc.gov/system/files?file=ftc_gov/pdf/p246202_surveillancepricing6bstudy_researchsummaries_redacted.pdf.

[16] Moreover, the term "surveillance" suggests that consumer behaviour and/or choices are observed in spaces with a reasonable expectation of privacy, not in the context of a consumer-provider relationship where the data collector is a party to the transaction.

feature here is that higher prices can serve to expand total supply; more drivers get on the road when surge multipliers kick in. Unlike the first two forms, the price path responds to real-time demand shocks, and the "capacity constraint" is soft, rather than hard. There is no doubt that consumers prefer lower prices, all else being equal. But consumers also prefer adequate supply (in the case of ridesharing, the ability to secure a ride), which is not likely to meet surges in demand in circumstances of constrained pricing.

The fourth form may be described as "capacity-based pricing," which is a practice of yield management under fixed capacity constraints. Airlines exemplify this mechanism: a plane has exactly 200 seats, and no price increase can create more. As the flight date approaches, the algorithm learns about demand by observing booking pace. If business travelers are snapping up seats faster than expected, prices on the remaining seats rise to maximize revenue from that fixed inventory. If bookings lag, prices might drop to avoid empty seats. Here, unlike in Uber's pricing model, supply cannot respond to price signals. The algorithm is purely optimizing allocation of a fixed (in the short run) capacity.

3. How common is algorithmic pricing?

While it is difficult to quantify with precision the prevalence of algorithmic pricing in Canada, surveys in other jurisdictions suggest that a significant minority of firms have adopted some form of automated pricing, especially in online markets. This may be illustrative of the adoption of such tools in Canada.

Survey evidence from multiple jurisdictions demonstrates that algorithmic pricing has moved from a niche practice to a mainstream business tool. In 2017, the European Commission found that 49% of European retailers tracked competitor prices, with 66.6% of those using price-monitoring software; that is, roughly one-third of all retailers employed some form of algorithmic price monitoring.[17] More tellingly, among those who use monitoring software, 78% actively changed prices in response to competitor moves, and 35% used specialized pricing algorithms for automatic adjustments.[18] Similar patterns have been observed across jurisdictions in the EU.[19]

The observed adoption patterns reveal important sectoral differences. Airlines and hotels have long been pioneers in dynamic pricing and yield management, extending decades-old practices with more sophisticated computational tools. Retail sectors—especially e-commerce—show high adoption rates,

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[17] *Final Report on the E-Commerce Sector Inquiry*, EUR. COMM'N (May. 10, 2017), at 17, 22, 24, 29-32, https://ec.europa.eu/commission/presscorner/detail/en/ip_17_1261

[18] *Id.*

[19] *See Algorithmic Competition, OECD Competition Policy Roundtable Background Note*, OECD (2023), at 12, *available at* www.oecd.org/daf/competition/algorithmic-competition-2023.pdf. In 2020, the Norwegian Competition Authority found that 55% of surveyed firms used monitoring algorithms, while 20% employed pricing algorithms. In Denmark, 17% of e-commerce companies used pricing algorithms, with varying degrees of automation—from simple information provision to full algorithmic control. The Netherlands Authority for Consumers and Markets reported that 36% of firms used competitor-pricing data, with 16% (6% of all firms) employing pricing algorithms.

with academic research identifying algorithmic pricing among at least 500 sellers (2.4% of roughly 30,000 sellers) on Amazon alone.[20]

Implementation approaches vary significantly across firms and sectors. A 2021 study by the Danish Competition and Consumer Authority (DCCA) found that, among firms using pricing algorithms, roughly 30% used them for information gathering, 60% for price recommendations with human oversight, and 35% for direct price control.[21] This spectrum—from human-assisted to fully automated pricing—reflects different levels of algorithmic sophistication and organizational comfort with automated decisionmaking.

Importantly, algorithmic pricing isn't confined to online markets. The Danish survey revealed that, while 80% of algorithmic pricing occurred in online sales, approximately 33% of firms also used algorithms to set prices in physical stores.[22] This convergence reflects the broader digitization of retail operations and the integration of online and offline pricing strategies. The UK Competition and Markets Authority (CMA) documented evidence of growing adoption of algorithmic pricing in traditionally offline sectors, including large supermarkets and retail gasoline stations.[23] This trend suggests that the competitive effects of algorithmic pricing will extend well beyond digital-native industries.

Despite concerns about algorithmic price discrimination, survey evidence suggests that personalized pricing remains relatively uncommon. The European Commission's mystery shopping exercise found that only 6% of tests recorded personalized pricing, with a median price difference of less than 1.6%.[24] Most price variations were found in the airline and hotel sectors, where price discrimination has long been standard practice. The limited adoption of personalized pricing may reflect both technical challenges and consumer resistance. As the Organisation for Economic Co-operation and Development (OECD) puts it:

> …firms may either refrain from adopting personalised pricing to protect their reputation or be less forthcoming and open when they do use personalised pricing. This may explain why there is not much evidence of firms using personalised pricing.[25]

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[20] Le Chen, Alan Mislove, & Christo Wilson, *An Empirical Analysis of Algorithmic Pricing on Amazon Marketplace*, *in* PROCEEDINGS OF THE 25TH INTERNATIONAL CONFERENCE ON WORLD WIDE WEB 1339-1349 (Apr. 2016), *available at* https://mislove.org/publications/Amazon-WWW.pdf.

[21] *Prisalgoritmer og Deres Betydning for Konkurrencen*, DANISH COMPETITION AND CONSUMER AUTHORITY (2021), *available at* https://kfst.dk/media/yecpmmxu/prisalgoritmer.pdf.

[22] *Id.*

[23] *Pricing Algorithms - Economic Working Paper on the Use of Algorithms to Facilitate Collusion and Personalised Pricing*, CMA (Oct.18, 2018), at 19, *available at* https://assets.publishing.service.gov.uk/media/5bbb2384ed915d238f9cc2e7/Algorithms_econ_report.pdf

[24] *Consumer Market Study on Online Market Segmentation Through Personalised Pricing/Offers in the European Union*, EUR. COMM'N (Jul. 19, 2018), at 171, 219-220, https://commission.europa.eu/publications/consumer-market-study-online-market-segmentation-through-personalised-pricingoffers-european-union_en.

[25] OECD, *supra* note 19.

A significant portion of algorithmic-pricing adoption occurs through third-party software providers, rather than in-house development. A 2020 survey by the Netherlands competition authority found that 80% of firms using pricing algorithms had developed them internally, while 20% worked with third-party providers.[26] But the availability of cloud-based pricing software has democratized access to sophisticated pricing tools, allowing smaller firms to compete with larger rivals' pricing capabilities.

This trend toward third-party solutions has important competitive implications. When multiple competitors use the same pricing software, it can create the conditions for coordinated pricing outcomes even without explicit agreements—a concern that has emerged in academic research on German gasoline markets[27] and in recent litigation involving hotel and rental-housing software.[28] We discuss both cases below.[29]

II. Economic Effects of Algorithmic Pricing

In this section, we focus on the competitive effects of algorithmic pricing, drawing on both economic theory and empirical studies. The bureau's consultation rightly notes that algorithmic pricing "could improve resource allocation and lower production costs,"[30] even as it also carries some risks. We strongly emphasize these economic efficiencies, as they often are overlooked in public debates. While demonstrable risks shouldn't be ignored, nor should they be overstated or overgeneralized. Sound competition policy depends on due consideration of economic efficiencies and other consumer benefits, not simply potential risks to competition.

In particular, we highlight how dynamic pricing can improve allocative efficiency and consumer welfare; how personalized pricing and price discrimination can benefit consumers by expanding market output; and how algorithmic tools generally tend to intensify competition (especially by empowering smaller firms and new entrants).

A. Personalized Pricing and Algorithmic Price Discrimination: Competitive Benefits

Personalized pricing—that is, charging different prices to different customers for the same product based on data-driven predictions of their willingness to pay—is among the more controversial aspects of algorithmic pricing. But it can be highly procompetitive, or at least neutral, in its competitive

[26] *Position Paper: Oversight of Algorithms*, ACM (2020), *available at* https://www.acm.nl/sites/default/files/documents/position-paper-oversight-of-algorithms.pdf.

[27] OECD, *supra* note 19.

[28] *Id.*

[29] *Infra* Section 4.C & III.1.

[30] Competition Bureau Canada, *supra* note 1.

effects. It is not generally considered an antitrust violation, absent some exclusionary or collusive purpose, and it often reflects healthy competition to win over different segments of customers.

The fundamental rationale for price discrimination is to expand output and serve more consumers. In a classic single-price scenario, a firm sets a price too high for those consumers who value the product below that price, but above cost. Those potential customers are left unserved, which is a deadweight loss. By offering a lower price (a discount) to price-sensitive consumers, while still charging higher prices to those willing to pay more, a firm can sell to both groups. That increases total sales, potentially making both the firm and the price-sensitive consumers better off.

Basic economic theory shows that, under many conditions, price discrimination can bring output closer to the socially efficient level (where each consumer who values the product at or above marginal cost gets to buy it). This is why airlines, for instance, use various differentiation tools (advance-purchase requirements, Saturday-night-stay rules, frequent-flyer segmentation) to effectively charge lower fares to leisure travelers and higher fares to business travelers.

But even when price discrimination does not increase output, it can still benefit consumers under competition where multiple firms have access to the requisite. data. Brian Albrecht offers a simple model to illustrate this effect.[31] He finds a stark result: unlike under monopoly, under competition, consumer prices are minimized when firms have complete information and can perfectly price discriminate. Firms can identify when consumers view their products as perfect substitutes, triggering the kind of intense competition that the French economist Joseph Bertrand demonstrated in the 19th century would drive prices toward marginal cost for those consumers.[32] The mechanism works by eliminating firms' ability to charge high prices to consumers who would switch to competitors; perfect information reveals exactly which consumers are price-sensitive, forcing aggressive competition for their business.

Recent empirical evidence from ride-hailing markets provides a more cautionary perspective on personalized pricing. Nicholas Buchholz *et al.* (2025) studied the European platform Liftago, which features a unique auction-based mechanism that allows consumers to choose among drivers offering different combinations of price and wait time.[33] Using this rich variation, the authors estimate individual-level preferences for time and money, and simulate several counterfactual pricing regimes.

They found that, if the platform were to move from its current fee-based model—in which prices are determined by competitive bidding and the platform takes a 10% cut—to a personalized-pricing scheme, consumer surplus would decline by 2.5%, platform profits would increase threefold, and

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[31] Brian C. Albrecht, *Price Competition and the Use of Consumer Data* (Aug. 11, 2020), *available at* https://briancalbrecht.github.io/albrecht_price_competition_consumer_data.pdf.

[32] Joseph Bertrand, *Book Review of Theorie Mathematique de la Richesse Sociale and of Recherches Sur les Principles Mathematiques de la Theorie des Richesses*, 67 JOURNAL DE SAVANTS 499–508 (1883).

[33] Nicholas Buchholz *et al.*, *Personalized Pricing and the Value of Time: Evidence from Auctioned Cab Rides*, 93 ECONOMETRICA 930, https://onlinelibrary.wiley.com/doi/epdf/10.3982/ECTA18838

20% fewer trips would be completed, due to higher prices.[34] Most consumers (62.5%), however, would actually benefit from personalized pricing, with losses concentrated among the least price-sensitive riders.[35]

Importantly, the study demonstrated that most of the reduction in consumer surplus arose not from personalization itself, but from the platform's ability to exercise market power by setting prices on both sides of the market. This suggests that the welfare consequences of personalized pricing depend critically on the underlying market structure and the degree of platform control, not merely on the use of consumer data.

B. Dynamic Pricing: Matching Prices to Demand for Greater Efficiency

Dynamic pricing may be the most common form of algorithmic pricing, and its procompetitive benefits are well-documented. By adjusting prices in line with real-time demand and supply conditions, dynamic pricing serves to allocate resources to their highest-valued uses and avoids the inefficiencies of static pricing.

In a static-pricing regime (where a firm sets one price for all times), the price is often too high during low-demand periods (resulting in unsold products and unsatisfied consumers—those who would have bought at a lower price) and too low during peak periods (resulting in shortages or long wait times when more consumers want more of the product than there are units available). Dynamic pricing corrects this inefficiency by lowering prices during off-peak times to encourage additional consumption and raising them in peak times to ration limited supply to those who value it most.

Consider a simplified example of Uber rides: if Uber charged the same flat price all week, many willing riders and drivers would fail to transact during weekday lulls (because the price floor of a flat rate is too high). Meanwhile, on a busy weekend night, a flat price would leave many riders stranded, because excess demand would overwhelm supply.[36] In contrast, surge pricing at busy times raises the fare to entice more drivers onto the road and to allocate rides to those who urgently need them, while off-peak price cuts get more people riding when cars are sitting idle. The net effect is more efficiently matching supply and demand across time.

The best research on dynamic pricing, due to the abundance of available data, is from the airline industry. An influential study by Kevin R. Williams estimated a structural model on U.S. monopoly routes and shows that allowing airlines to update fares in real time raises output by about 3%, boosts

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[34] *Id.* at 931.

[35] *Id.* at 932.

[36] *See* Cody Taylor, *The Case for Algorithmic Pricing: Consumer Welfare, Market Efficiency, and Policy Missteps*, MERCATUS CTR., GEO. MASON UNIV. (May 14, 2025), https://www.mercatus.org/research/policy-briefs/case-algorithmic-pricing-consumer-welfare-market-efficiency-and-policy.

revenues by 8%, and reallocates seats toward early-booking leisure passengers.[37] Because late-arriving business travelers pay much higher prices, aggregate consumer surplus falls by roughly 6%. But the revenue gain more than offsets this loss, such that total welfare rises by about 1% overall. Roughly two-thirds of the revenue improvement comes from third-degree intertemporal price discrimination, while the remaining third reflects capacity-based responses to demand shocks.

One unique feature of the Williams dataset is that it focuses exclusively on monopoly routes. By using novel flight-level seat-map data for markets served by a single carrier, the paper can abstract from strategic interaction and cleanly isolate the welfare effects of dynamic pricing itself.

The net effects on consumers will depend crucially on the level of competition, just like in the static case. For example, Nan Chen and Przemyslaw Jeziorski found that introducing dynamic pricing in a competitive airline network led to a Pareto improvement: both consumers and producers benefited overall.[38] The airlines could increase load factors and revenues through better yield management, while consumers benefited from more opportunities to find cheaper fares or available seats when they needed them. The study attributes this welfare gain to two aspects of dynamic pricing: intertemporal price discrimination (*e.g.*, charging different prices to leisure vs. business travelers) and capacity-based pricing (adjusting fares as seats fill up).

Interestingly, Chen and Jeziorski note that, while price discrimination can soften head-to-head competition (since airlines focus on their own customer segmentation), the capacity-responsive pricing aspect actually intensifies competition by making firms react more aggressively to fill remaining seats. On net, consumers saw increased surplus on average in dynamic-pricing regimes relative to static pricing.

Dynamic pricing in competitive settings can, however, also create new inefficiencies. Jose M. Betancourt *et al.* introduce a theoretical framework for studying dynamic price competition in perishable-goods markets and identify what they term the "Bertrand scarcity trap."[39] Using novel data from competing U.S. airlines, they show that intense algorithmic price competition can lead to inefficiently low prices early in the booking period, resulting in overprovision of seats far from departure and under-provision close to departure. Their empirical analysis of 50 routes reveals that, when airlines use pricing heuristics instead of fully competitive algorithmic pricing, revenues increase (by 4-5%) and consumer surplus improves (by 3%).

This finding suggests that, while algorithmic pricing can enhance efficiency in monopolistic settings, competitive dynamics may sometimes warrant more restrained pricing strategies. The study

[37] Kevin R. Williams, *The Welfare Effects of Dynamic Pricing: Evidence from Airline Markets*, 90 ECONOMETRICA 831 (2022).

[38] Nan Chen & Przemyslaw Jeziorski, *Consequences of Dynamic Pricing in Competitive Airline Markets* (Jan. 26, 2023), at 3, https://ssrn.com/abstract=4285718.

[39] Jose M. Betancourt *et al.*, *Dynamic Price Competition: Theory and Evidence from Airline Markets* NAT'L BUREAU ECON. RSCH., Working Paper No. 30347 (Aug. 2022; rev. Apr. 2023), https://doi.org/10.3386/w30347.

demonstrates that the welfare effects of algorithmic pricing depend critically on market structure and the degree of competitive interaction between pricing algorithms.

One common misconception is that, if dynamic pricing raises some prices (*e.g.*, during peak demand), it must harm consumers. This ignores the other side of the coin: dynamic pricing lowers prices during off-peak times, directly benefiting consumers who have flexible timing or lower willingness to pay. Moreover, even during peak times, dynamic pricing ensures that those who most urgently need the product can get it (albeit at a higher price), rather than finding it unavailable.

For example, airlines often charge much more for a ticket bought the day before departure than one bought months in advance. While the last-minute buyer pays more, the higher price also provides seat availability for travelers with urgent needs (business or emergency travelers) instead of the flight being fully booked weeks earlier by tourists paying a cheap fare. In a world of static pricing, that business traveler might simply have no seat available at any price, because the airline—not being able to raise the price—has no mechanism or incentive to hold inventory for high-value last-minute customers.

With dynamic pricing, the market is better segmented: high-value, time-pressed consumers can buy what they need (at a premium), while low-value consumers can enjoy lower prices if they buy early or when demand slackens. Overall consumer welfare can increase because more consumers get what they value most: the ones who highly value immediacy get the product and the ones who highly value low prices get discounts if they plan accordingly. Dynamic pricing moves the allocation of goods from a random or first-come-first-served basis (which can be inefficient) to allocating by willingness to pay, which tends to be more efficient and welfare-enhancing.

Importantly, even those who face higher prices at peak times are not necessarily worse off relative to static pricing, and not just because they might not obtain the product at all under a static-pricing policy. They might, for example, endure nonmonetary costs like waiting in line or rationing. Dynamic pricing often reduces nonmonetary costs (like wait times, stockouts, missed opportunities) by clearing markets. If you can reliably get a ride during a storm because the price rose to attract drivers, that might be preferable to not being able to find a ride at all at the old price. In economic terms, the higher price compensates drivers to supply more service, which can alleviate the shortage and lower the total cost to the consumer, when also considering time saved or utility gained. Meanwhile, consumers who are price-sensitive have the option to wait for lower prices at a later time or choose off-peak consumption. This dynamic adjustment is often more efficient than, say, leaving a marketplace chronically undersupplied at an artificially low price.

There is empirical work outside of airlines that finds this. Juan Camilo Castillo provides detailed insights into surge pricing's welfare effects using data from Houston's Uber market.[40] The study

[40] Juan Camilo Castillo, *Who Benefits from Surge Pricing*, ECONOMETRICA (forthcoming 2025), *available at* https://www.econometricsociety.org/publications/econometrica/0000/00/00/Who-Benefits-from-Surge-Pricing/file/19106-4.pdf.

finds that surge pricing increased total welfare by 2.15% of gross revenue relative to uniform pricing, but with asymmetric effects across market participants. Rider surplus increased by 3.57% of gross revenue, while driver surplus decreased by 0.98% of gross revenue.

The asymmetry in welfare effects arises from three key mechanisms: surge pricing saves time by mitigating supply-demand imbalances (benefiting riders more due to their higher value of time); allocates trips more efficiently to high willingness-to-pay riders when drivers are scarce; and results in lower average prices relative to uniform pricing. Importantly, the study finds that surge pricing benefits riders at all income levels, with low-income riders benefiting most from lower prices, shorter pickup times, and more reliable trips, while high-income riders also benefit, but would prefer even higher prices for further reduced wait times.

Far from always softening competition, dynamic pricing can intensify competitive rivalry under many circumstances. Because firms using algorithms monitor market conditions constantly, they are quick to react to competitors' price changes. If one firm tries to cut prices to gain market share, rivals' algorithms may detect the move and match or beat the price drop, nearly in real time. This rapid matching can lead to vigorous price competition that benefits consumers. Traditional static pricing might involve a slower, more tacit form of coordination (competitors adjusting prices infrequently and cautiously). In contrast, dynamic algorithms can create a fast-paced environment in which prices are always under pressure from current demand and competitor actions.[41]

Another vivid demonstration of dynamic pricing's intricate effects comes from the rental-housing sector. Sophie Calder-Wang and Gi Heung Kim compared property owners who used algorithmic-pricing software to set apartment rents, versus those who priced manually.[42] During the Great Recession (when demand plummeted), landlords using algorithms lowered rents more quickly and significantly. As a result, they achieved higher occupancy rates than those who kept rents steadier. In other words, tenants of algorithm-using landlords saw rent decreases that they might not have gotten otherwise, and more units stayed filled (fewer empty apartments). By contrast, during the post-recession expansion, algorithmic landlords raised rents more aggressively and tolerated lower occupancy, which helped sustain higher average market rents.

Most notably, Calder-Wang and Kim's structural model finds that algorithmic adopters priced as if they were maximizing joint profits, not individual profits. This led to rent increases of roughly $25 per-unit per-month on average, affecting millions of apartments. These findings underscore a key point: algorithmic pricing can improve efficiency in weak markets but may also facilitate coordinated outcomes in tight markets. The same mechanism that enables faster rent cuts when demand falls can also support supracompetitive pricing when demand recovers.

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[41] *See* George J. Stigler, *A Theory of Oligopoly,* 72 J. POL. ECON. 44 (1964). For a modern treatment, *see* Yuliy Sannikov & Andrzej Skrzypacz, *Impossibility of Collusion Under Imperfect Monitoring with Flexible Production*, 97 AM. ECON. REV. 1794 (2007).

[42] Sophie Calder-Wang & Gi Heung Kim, *Algorithmic Pricing in Multifamily Rentals: Efficiency Gains or Price Coordination?* (2024), *available at* https://doi.org/10.2139/ssrn.4403058.

The fundamental policy implication is that automated pricing is not, in and of itself, either procompetitive or anticompetitive. Rather, the specific type or function of algorithmic pricing needs to be assessed in the context of specific market conditions, lest competition enforcement be overly lax *or* overly stringent, to be detriment of both competition and Canadian consumers.

Even in industries like airlines or hotels, the fear that dynamic pricing leads to uniformly higher prices is not borne out when multiple firms compete. Instead, each firm's algorithm is trying to optimize its own performance, often by stealing demand from rivals when advantageous (*e.g.*, lowering a fare to fill seats if a competitor's flight is going empty). The Chen & Jeziorski study mentioned earlier explicitly found that one element of dynamic pricing (optimizing on remaining capacity) tends to intensify competition, as firms have strong incentives to undercut each other to avoid being the one left with unsold inventory.[43] This competitive dynamic again favours consumers through lower prices or more choices.

C. Algorithmic Price Competition

Zach Y. Brown and Alexander MacKay study algorithmic-pricing competition using high-frequency price data from online retailers.[44] They find that retailers using high-frequency pricing algorithms (updating prices within hours) systematically charge lower prices than competitors that rely on slower technology (daily or weekly price updates), even for identical products. They further document that consumer surplus declined 4.1% and firm profits increased 9.6% due to asymmetric algorithmic competition, translating to an estimated $300 million annual cost to online consumers in the personal-care category alone. Brown and MacKay's theoretical framework demonstrates that simple pricing algorithms can support supracompetitive prices, even in competitive equilibrium, without explicit collusion.

Stephanie Assad *et al.* (2024) provide empirical evidence from the retail-gasoline market in Germany, where algorithmic-pricing software became widely available in 2017.[45] They identify adopting stations through structural breaks in pricing behaviour (frequency of price changes, response times to competitors) and use brand-level adoption as an instrument. The study found that algorithmic adoption increases margins by roughly 9%, but the effects vary dramatically with market structure. In monopoly markets, adopting stations see no meaningful change in margins. But in duopoly markets where both stations adopt, margins increased by 38% relative to markets where neither adopts. Importantly, these margin increases emerged gradually over about a year, suggesting the algorithms learn to avoid price competition. The study documents that algorithmic adopters become more likely

[43] Chen & Jeziorski, *supra* note 38.

[44] Zach Y. Brown & Alexander MacKay, *Competition in Pricing Algorithms*, 15 AM. ECON. J. MICROECON. (May 2023), https://www.aeaweb.org/articles?id=10.1257/mic.20210158.

[45] Stephanie Assad *et al.*, *Algorithmic Pricing and Competition: Empirical Evidence from the German Retail Gasoline Market*, 132 J. POL. ECON. 763 (Mar. 2024), https://www.journals.uchicago.edu/doi/10.1086/726906.

to match competitors' price decreases but less likely to undercut rivals, consistent with learned coordination without explicit agreement.

D. Algorithmic Tools, Market Entry, and Small Firm Competitiveness

An often-underappreciated benefit of algorithmic pricing is that it can lower barriers to entry and improve small firms' ability to compete. While not part of the empirical studies described in the preceding paragraphs, this has important implications for dynamic competition and innovation in markets.

Historically, implementing sophisticated pricing strategies required substantial resources (data collection; analytics expertise, whether contracted or in-house; and continuous monitoring), which only large incumbents could afford. This gave larger firms an advantage in pricing acumen over smaller rivals. Today, however, third-party algorithmic-pricing services have become widely available, effectively outsourcing a data-analytics department to any firm that wants one. As a result, new entrants and smaller companies can quickly adopt state-of-the-art pricing techniques without developing them in-house.

This levels the competitive playing field. A startup can use the same revenue-management software that industry leaders use, ensuring that it does not leave money on the table or misprice its product out of ignorance. In economic terms, algorithms can reduce economies of scale in pricing, because even a small firm can get scale-like insights by pooling data via a vendor's platform. The OECD has explicitly recognized this benefit: algorithms can "reduce barriers to entry by allowing smaller entrants to gain market insights or develop new disruptive products at lower cost."[46]

Another dynamic procompetitive aspect is that algorithms can spur entry by new business models. Consider how Uber and other platform-based services have leveraged dynamic-pricing algorithms as an integral part of their model. Surge pricing allowed ride-hailing platforms to ensure supply met demand in real time, which was a key innovation over traditional taxis (which often faced shortages at peak times). This innovation created a whole new market for on-demand rides, clearly benefiting consumers who now find it easier to get a ride at nearly any time.

If surge pricing had been banned from the outset as "price gouging," the platform model might not have proven viable or attractive to drivers (who rely on earning more in peak times to make the service worthwhile). Algorithms also enable entirely new products like real-time price-comparison services, personalized shopping assistants, and dynamic-discounts apps—all of which increase competition by making markets more transparent and giving consumers more power to find deals. The competitive pressure that these innovations bring (often to the dismay of incumbents) should not be underestimated.

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[46] OECD, *supra* note 19.

Based on the literature review and economic analysis presented, several key takeaways emerge. Perhaps most importantly, algorithmic pricing represents an evolutionary step in established business practices, rather than a fundamental departure from traditional market dynamics. Airlines have engaged in yield management for decades; hotels have long adjusted rates based on occupancy and demand patterns; and retailers have always monitored competitor prices to inform their own pricing decisions. There is nothing inherently magical about algorithms that transforms legitimate pricing strategies into anticompetitive conduct. When a hotel manager manually checks competitor rates each morning and adjusts prices accordingly, this is recognized as normal competitive behaviour. When the same process is automated through an algorithm that monitors competitor websites and updates prices in real time, the fundamental economic activity remains unchanged—only the efficiency of pricing has improved.

The empirical evidence demonstrates that the competitive effects of algorithmic pricing depend heavily on market structure and competitive dynamics, rather than the technology itself. In competitive markets, algorithms can intensify price competition. In oligopolistic markets, on the other hand, they may facilitate coordination—although this requires careful case-by-case analysis to distinguish between conscious parallelism (which is generally legal) and actual agreement (which is not). Because the effects of algorithmic pricing are generally ambiguous, competition authorities should resist developing categorical rules for it. Instead, authorities should apply established legal principles and the best available evidence.

Enforcers should, among other things, focus on evidence of actual agreements to coordinate pricing, rather than the mere use of common algorithms or software platforms. Given the substantial efficiency benefits and competitive potential of algorithmic pricing, policymakers should be cautious about premature regulatory interventions, as these are likely to fit actual practices and their effects poorly. Instead, they should continue to monitor markets, technical developments, and the developing literature, while pursuing enforcement actions only where evidence of actual anticompetitive agreements and actual or likely harm to competition and consumers emerges.

To synthesize the empirical literature: algorithmic pricing can lead to higher prices in oligopolistic settings where firms use similar tools, supporting concerns about tacit collusion. At the same time, in competitive or dynamic settings, algorithms tend to improve efficiency and can benefit consumers (through lower prices for some, better allocation, and expanded output). The presence of both effects even within one market (as in housing) means regulators' inquiries should be case-specific. It would be misguided to be always skeptical of algorithmic pricing, let alone to ban algorithmic pricing outright (we would lose substantial efficiencies and innovation), or to ignore the potential need for enforcement when clear coordinated effects emerge.

The bureau should continue to gather data and monitor outcomes in algorithm-heavy markets (fuel retail, airlines, ridesharing, e-commerce, housing). If patterns of sustained unexplained price elevation coincide with the adoption of algorithms, it may warrant investigation (looking for facilitating practices or agreements). Conversely, evidence of consumer benefits should make the bureau cautious about intervening unless absolutely necessary.

III. Addressing Competition-Law Concerns

To this point, we have focused primarily on the economic effects of pricing algorithms. We turn now to the potential competition concerns associated with algorithmic pricing, as highlighted in the discussion paper. In particular, we discuss: (A) the legal framework for distinguishing legitimate parallel conduct from unlawful agreements in algorithmic contexts; (B) concerns about unilateral anticompetitive conduct by dominant firms; and (C) issues of deceptive or manipulative practices.

Throughout, we argue that existing competition-law principles (if properly applied) are capable of handling truly anticompetitive behaviour, but that we must be careful to distinguish such behaviour from superficially similar but benign conduct. A recurring theme is that parallel or similar pricing outcomes should not be presumed illegally collusive without evidence of an agreement, and that the automation of a practice does not change its legality. If a strategy is legal for a human, it is legal when done by or with an algorithm, and vice versa.

A. Algorithmic-Collusion Theories: Legal Framework and Evidentiary Standards

Perhaps the foremost concern in this area is that competitors could use pricing algorithms to facilitate collusion, either explicitly (through a common intermediary coordinating prices) or tacitly (if self-learning algorithms learn to avoid price competition). The bureau's paper warns that sharing algorithms "may facilitate coordinated behaviour, such as price-fixing."[47] They may, under certain facts and circumstances, but that does not mean that they are likely to do so as a general matter.

Moreover, and critically, algorithmic pricing introduces novel mechanisms for price setting, but it does not change the fundamental structure of competition law. Under Canadian law, competition enforcement remains grounded in clear statutory elements, most notably Section 45 of the Competition Act.[48] Section 45(1) prohibits conspiracies, agreements, or arrangements between competitors to fix prices, allocate markets, or restrict output.[49] It does not, however, render parallel conduct or shared practices unlawful absent a meeting of the minds. There is a straightforward rationale for the distinction: a range of factors—not just anticompetitive intent, much less likely anticompetitive effects—can lead to parallel conduct. Crucially, this provision requires proof beyond a reasonable doubt of an agreement or arrangement.

As clarified in Section 45(3), the court may infer such an agreement from circumstantial evidence, but there must still be sufficient facts to support the conclusion that competitors consciously

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[47] Competition Bureau Canada, *supra* note 1.

[48] Competition Act, R.S.C. 1985, c C-34.

[49] *Id.*, s 45(1).

coordinated their conduct.[50] While it does not require a smoking gun, it does require evidence of an agreement. The provision allows courts to infer conspiracy from circumstantial evidence, but it leaves the substantive elements of Section 45(1) untouched.

This statutory structure mirrors the analytical framework laid out in U.S. cases like *Cornish-Adebiyi v. Caesars* and *Gibson v. Cendyn*.[51] In those cases, plaintiffs alleged a "hub-and-spoke" conspiracy because hotels used the same pricing software. But as ICLE explained in *amicus* briefs, simply subscribing to the same vendor—without evidence of a "rim" (*i.e.*, a horizontal agreement among competitors)—does not suffice to establish an unlawful conspiracy under U.S. or Canadian law.[52]

The Competition Bureau's own guidance makes clear that conscious parallelism is not a crime: rivals may lawfully mimic each other's prices, even when they do so with full awareness of their interdependence, so long as each firm decides pricing for itself.[53] Thus, a price trajectory produced by identical algorithms used by competing firms does not, without more, establish a cartel. To convert lawful rivalry into a criminal conspiracy, the Crown must still point to plus factors—*e.g.*, evidence showing that competitors:

1. coordinated the adoption or parameter-setting of their software;
2. exchanged competitively sensitive information; or
3. agreed not to deviate from the algorithm's recommendations.

Absent such proof, identical or highly correlated prices remain the product of legitimate competition—not an unlawful "meeting of the minds." The evidentiary flexibility makes agreements easier to prove, but it does not render the agreement unnecessary as an element of the offense. Any enforcement action aimed at algorithmic pricing must respect that line. The provision was drafted to catch clandestine cartels, not to criminalize modern pricing tools or the parallel outcomes they can generate.

1. Hub-and-spoke theories in algorithmic pricing

Internationally, authorities are grappling with cases like the U.S. Justice Department's (DOJ) *RealPage* case, which alleges that landlords who used a common pricing software effectively formed a cartel, or similar class-action suits brought by private plaintiffs in the hospitality sector (*e.g.*, *Cornish-*

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[50] *Id.*, s 45(3).

[51] *See* ICLE Amicus Briefs, *supra* notes 2-3.

[52] *Id.*

[53] *Competitor Collaboration Guidelines*, COMPETITION BUREAU CANADA (May 6, 2021), https://competition-bureau.canada.ca/en/how-we-foster-competition/education-and-outreach/competitor-collaboration-guidelines. ("The Bureau does not consider that the mere act of independently adopting a course of conduct with awareness of the likely response of competitors or in response to the conduct of competitors, commonly referred to as "conscious parallelism", is sufficient to establish an agreement for the purpose of subsection 45(1). However, parallel conduct coupled with facilitating practices, such as sharing competitively sensitive information or activities that assist competitors in monitoring one another's prices, may be sufficient to prove that an agreement was concluded between the parties.")

Adebiyi v. Caesars and *Gibson v. Cendyn* in the United States) that have made hub-and-spoke conspiracy claims.

ICLE has been active in these discussions, filing *amicus* briefs that urged the courts to carefully apply collusion doctrine to the specific facts and circumstances presented by algorithmic-pricing cases. Our core argument is this: using the same pricing algorithm as one's competitors is not itself evidence of an unlawful agreement. There must be proof of a "meeting of minds," an agreement to fix prices or otherwise restrain competition, separate from the mere use of a common tool. Indeed, case-specific facts about the customization of pricing platforms have suggested it is misleading even to say that the software licensees all used *the same* data and algorithms.

In traditional hub-and-spoke cases, a central party (the "hub") coordinates anticompetitive conduct among multiple competitors (the "spokes"). Crucially, liability requires demonstration of a "rim": horizontal agreements that connect the spokes to one other. As the 3rd U.S. Circuit Court of Appeals explained in *Howard Hess Dental Labs v. Dentsply* (2010), "the rim of the wheel is the connecting agreements among the horizontal competitors (distributors) that form the spokes."[54] Without this rim, there would be merely a series of vertical relationships between the hub and each spoke, which typically does not violate competition law.

This distinction becomes critical when evaluating algorithmic-pricing platforms. When multiple hotels use Rainmaker software or multiple landlords use RealPage, each has a vertical relationship with the software provider. To transform these vertical relationships into a horizontal conspiracy requires evidence that the competitors agreed among themselves to coordinate through the platform. The mere fact that they all chose the same software vendor cannot establish this horizontal agreement.

Thus, even if an algorithmic platform enables competitors to be more aware of each other's pricing intentions (say, via aggregated market forecasts), that is not illegal unless it crosses into an actual concerted plan to fix prices. And it is not illegal, in no small part, because the forecasts might foster competition, rather than collusion.

The appropriate enforcement approach is thus to look for "plus factors" that indicate an agreement. Was there some communication or conduct ensuring that firms would not undercut each other beyond what the algorithm suggested? Did they agree not to override the algorithm or to follow certain rules collectively? In that regard, U.S. courts have mirrored Canada's statutory requirements, which permit circumstantial evidence of an agreement but nonetheless require an agreement as an element of the offense. That evidence need not comprise an express written (or otherwise recorded) agreement to fix prices. But in the absence of such evidence, parallel pricing facilitated by a common tool should be seen as "conscious parallelism," which competition law generally permits so long as each firm retains independent control.

[54] *Howard Hess Dental Labs., Inc. v. Dentsply Int'l, Inc.*, 602 F.3d 237 (3d Cir. 2010). ("The rim of the wheel is the connecting agreements among the horizontal competitors … that form the spokes.")

The economic reality of how these platforms operate further undermines hub-and-spoke theories. In the *Gibson v. Cendyn* litigation, evidence showed that hotels retained full discretion to accept or reject Rainmaker's pricing recommendations. As ICLE noted in its *amicus* brief, hotels "frequently override Rainmaker's pricing recommendations," with the software presenting recommendations to "a human decision-maker, who can choose to accept or override the suggested price."[55] This retention of independent pricing authority is fundamentally inconsistent with the horizontal agreement required for hub-and-spoke liability.

Furthermore, the timing and circumstances of adoption matter. In the casino hotel cases, defendants adopted the software over a span of 14 years, making it "quite implausible that they tacitly agreed to anything, much less to fix the prices of their hotel rooms."[56] Each firm's decision to adopt pricing software at various times, for different properties, and with different customizations suggests independent business judgment, rather than coordinated action.

The data flow in these systems also distinguishes them from traditional hub-and-spoke conspiracies. Modern pricing algorithms typically aggregate market data and provide market intelligence without facilitating direct competitor-to-competitor communication. A hotel using Rainmaker sees analyses of its market (demand trends, average competitor rates scraped from online-travel sites) but does not receive a direct feed of a rival hotel's proprietary booking data. This one-way flow of processed market intelligence differs qualitatively from scenarios where competitors use an intermediary to exchange confidential strategic information.

Again, we stress that the automation of pricing does not transform legal conduct into illegal conduct. Maureen Ohlhausen's "guy named Bob" test is instructive here: if it is legal for Bob the pricing manager to review competitors' public prices and adjust his company's prices accordingly (which it is, as a form of savvy competition), then Bob doing the same via a computer program is also legal.[57]

2. *Autonomous algorithmic coordination*

A more novel concern is that self-learning AI algorithms might independently reach tacitly collusive outcomes without any agreement or human facilitation. Essentially, the algorithms could learn that competing on price is counterproductive and settle into a supracompetitive pricing pattern. This theoretical possibility has been explored in models and simulations (*e.g.*, work by Emilio Calvano *et al.* showing Q-learning algorithms in a simple duopoly sometimes converged to high-price equilibria).[58] It is crucial to note, however, that there is no conclusive evidence that such autonomous tacit collusion is occurring in real markets or is currently a significant issue, much less that it is a necessary

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[55] ICLE Amicus Brief, *supra* note 3.

[56] *Id.*

[57] Ohlhausen, *supra* note 4.

[58] Emilio Calvano *et al.*, *Artificial Intelligence, Algorithmic Pricing, and Collusion*, 110 AM. ECON. REV. 3267–97 (Oct. 2020), *available at* https://www.jstor.org/stable/pdf/26966472.pdf.

result of automated-pricing software generally. The OECD's recent analysis in 2023 underscores this point, while advising vigilance as AI systems develop.[59]

This theoretical concern about autonomous algorithmic coordination differs importantly from, for example, the empirical findings in Assad *et al.*'s gasoline study.[60] While Assad and colleagues documented that algorithmic adoption led to higher margins and reduced price competition (with stations becoming more likely to match price decreases but less likely to undercut rivals), this represented a softening of competition, rather than explicit collusion. The gasoline algorithms learned to avoid aggressive price competition over time, but there was no evidence of an actual agreement among competitors to fix prices or coordinate conduct. Instead, the algorithms appeared to independently converge on less competitive behaviour as a profit-maximizing strategy.

This distinction is crucial for legal analysis: softened competition through parallel algorithmic learning, while potentially concerning from a welfare perspective, does not necessarily constitute the "agreement" required under Section 45 of the Competition Act.[61] The theoretical autonomous coordination concern, by contrast, envisions algorithms that might effectively replicate the outcomes of explicit price-fixing agreements without any human agreement or coordination—a scenario that would present novel challenges for competition law's focus on proving concerted action.

The economic literature reviewed above demonstrates that algorithmic-pricing effects are fundamentally dependent on context. The same technology that enables coordination intensifies competition. Dynamic pricing can enhance efficiency in competitive markets, while potentially softening competition in oligopolistic ones. This context dependence provides strong economic justification for maintaining high legal burdens of proof. Because parallel-pricing outcomes can emerge from either coordination or competition, and because the welfare effects vary dramatically with market structure and implementation, legal standards cannot presume harm from algorithmic adoption alone. The economic evidence shows that distinguishing beneficial competition from harmful coordination requires careful analysis of facts and circumstances: the pricing software at-issue, its application, specific market conditions, information flows, timing patterns, and competitive responses and effects.

Canadian authorities evaluating potential algorithmic coordination should therefore focus on evidence of horizontal agreements, rather than vertical adoption patterns. Key indicators would include: evidence that competitors communicated about their mutual adoption of the software; agreements among competitors not to deviate from algorithmic recommendations; coordinated customization of algorithms to achieve common pricing outcomes; or use of the platform to exchange competitively sensitive information beyond what is publicly available. Without such evidence, the

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[59] OECD, *supra* note 19 at 14.

[60] Assad *et al.*, *supra* note 45.

[61] Competition Act, *supra* note 48.

use of common pricing software remains a series of independent vertical relationships, regardless of how many competitors happen to use the same vendor.

In other words, while researchers have shown algorithms could collude under certain idealized conditions, competition authorities worldwide have yet to encounter a proven instance where an algorithm, on its own, created and sustained a collusive outcome that would not have happened with human operators. In Canada's context, one might imagine concern in oligopolistic industries (say, retail gasoline or airlines) that pricing AIs could make tacit coordination "easier." But even here, absent communication, it's worth remembering that tacit collusion is not illegal under the Competition Act. The law instead targets "conspiracies, agreements or arrangements" (Section 45), which implies a meeting of minds, not mere conscious parallelism or intelligent adaptation to market conditions.[62]

If algorithms simply mirror what rational oligopolists would do anyway (recognize their interdependence and avoid price wars), that may be frustrating for regulators, but it is not caught by the letter of the law. The focus should remain on detecting any evidence of agreement or explicit facilitating practices. If companies deliberately design algorithms to reach collusive outcomes and have an understanding that they will do so, regulators could treat that as an agreement by proxy. Short of that, agencies should be cautious about stretching theories of liability too far. Doing so could chill the development of procompetitive algorithms. As former Deputy Assistant U.S. Attorney General Roger Alford remarked:

> …in the absence of evidence of concerted action, we cannot presume the simple use of pricing algorithms is an antitrust violation. Any approach that bypasses proof of concerted action risks false prosecution of potentially pro-competitive pricing decisions. Misplaced enforcement efforts have the potential to discourage innovation and deter efficiency-enhancing pricing.[63]

B. Unilateral Anticompetitive Conduct

Pricing algorithms may also raise concerns about unilateral conduct, such as predatory pricing, tying, or self-preferencing. These concerns are valid in principle but must be assessed under the proper legal standards. In Canada, unilateral conduct by a dominant firm is governed by abuse-of-dominance provisions (Sections 78 & 79), which require that conduct have an exclusionary, predatory, or disciplinary negative effect on a competitor, or that it is likely to result in a substantial lessening or prevention of competition.

Algorithmic pricing can facilitate targeted price cuts, but this alone is not predatory. As the bureau recognizes, firms have long used targeted discounts to retain customers or respond to entry.[64]

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[62] *Id.*

[63] Roger Alford, Dep'y Asst. Att'y Gen., Antitrust Div., *The Role of Antitrust in Promoting Innovation*, U.S. DEP'T OF JUSTICE (Feb. 23, 2018), at 8.

[64] Competition Bureau Canada, *supra* note 1.

Algorithms simply make such responses more precise. It would be paradoxical to suggest that enforcers should, in the service of Canadian consumers, be generally suspicious of discounting or price cutting. Enforcement should focus on whether *below-cost* pricing is sustained long enough to eliminate rivals, and whether there is a realistic prospect of recoupment—standards that remain appropriate even in algorithmic contexts.

IV. Conclusion

Algorithmic pricing represents an evolutionary step in established business practices, rather than a fundamental transformation of competitive dynamics. The empirical evidence demonstrates that these tools can both intensify and soften competition, depending on market structure, implementation details, and competitive context. In concentrated markets with barriers to entry, algorithmic pricing may facilitate coordination, but the same markets were already susceptible to tacit collusion with human decisionmakers. Conversely, in competitive markets, algorithms typically enhance efficiency through improved capacity utilization, dynamic pricing, and more precise demand forecasting. The technology serves as an accelerant of existing market characteristics, not a catalyst for entirely new competitive dynamics.

Canadian competition authorities should resist the temptation to develop categorical rules for algorithmic pricing. The substantial efficiency benefits documented across airlines, ride-hailing, hospitality, and other sectors warrant protection, while legitimate competition concerns require careful case-by-case analysis grounded in established legal principles. Enforcement should focus on evidence of actual agreements to coordinate pricing, rather than the mere use of common algorithms or software platforms.

Ohlhausen's "guy named Bob" test provides a useful heuristic: automated business practices should be evaluated by asking whether they would be legal if performed manually.[65] Using algorithmic tools to monitor public competitor prices and adjust accordingly remains legitimate competitive conduct, just as it was when done by human analysts.

As algorithmic pricing continues to evolve, the Competition Bureau should maintain its commitment to evidence-based enforcement, while monitoring developments in algorithm-heavy markets. The bureau's existing analytical frameworks—particularly its guidance on information sharing and conscious parallelism—provide sufficient tools to address genuinely anticompetitive conduct without chilling innovation.[66] By focusing on economic effects rather than technological form, Canadian competition policy can preserve the substantial consumer benefits of algorithmic pricing while guarding against the genuine risks of coordination. The goal should be to ensure that competition law remains grounded in sound economic principles and clear legal standards, allowing Canadian

[65] Ohlhausen, *supra* note 4.

[66] Competition Bureau Canada, *supra* note 53.

businesses to harness the efficiency gains of modern pricing technology, while maintaining vigorous competitive markets.