Adaptive Markets: AI, Competition, and the Future of Price Dynamics

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Last December, Consumer Reports, in collaboration with Groundwork Collaborative, released a report on an investigation into Instacart's use of AI-enabled price testing, finding that two customers with identical baskets, shopping at the same time, from the same retailer and location, could face price differences of up to 23% for some items for several major retailers (Albertsons, Costco, Kroger, Safeway, Sprouts Farmers Market, Target, etc.) while 75% of items tested showed price differences. These experiments were facilitated by Instacart's 2022 acquisition of Eversight, an AI-powered pricing and promotions platform designed to run continuous price experiments, effectively enabling individualized pricing at scale (Instacart, 2022). Although Instacart described this capability in corporate marketing and investor materials, the average Instacart consumer was not as aware of being involved in randomized pricing tests. Following the release of Consumer Report's findings and facing consumer backlash, Instacart announced that it would no longer allow retail partners to use Eversight-powered item price tests on its platform and committed that two customers at the same time, at the same location, shopping from the same store would see identical prices for the same goods (Instacart, 2025; Kravitz, 2025).

Instacart claimed that, similarly to how retailers are able to set and vary prices between their physical stores, they were also allowed to do so on the Instacart platform, effectively shifting responsibility for price setting onto retail partners rather than Instacart itself. At the same time, while Instacart denied that it was engaging in dynamic pricing based on market conditions or surveillance style pricing based on individual consumer data, characterizing the observed price differences as the result of random variation in tests, the combination of access to algorithmic pricing tools through Eversight and likely access to brokered personal data means that more granular, individualized pricing models are well within the firm's capabilities. Absent the Consumer Reports investigation and the ensuing public backlash that pushed Instacart to retire its price testing feature, it is likely that Instacart and its retail partners would have continued and expanded such practices to increase their marginal profits further, raising concerns about transparency, potential price discrimination, and consumer welfare (Instacart, 2025).

From Static to Adaptive: Understanding Algorithmic Pricing

Dynamic pricing refers to a strategy in which firms change prices in real time in response to current market conditions – such as expected demand, inventory levels, competitor pricing, time, and location – rather than keeping prices largely fixed over time. Traditional **static pricing** instead adjusts pricing only infrequently (e.g., on a monthly or seasonal basis), and is typically modeled as a single posted price per period. In modern markets, dynamic pricing is typically treated as a form of **algorithmic pricing**, where software and statistical models automate how observed market conditions and different price levels map to expected firm profits, instead of manual price setting by managers of firms (Aparicio et al., 2024). **Personalized pricing** is a closely related subset, where prices differ across groups of consumers or even individuals, and toward the limit, can approximate consumers' individual willingness to pay (WTP), approaching first-degree price discrimination. When such personalization relies on tracking and extensive personal data collection, it is often referred to as "**surveillance pricing**", reflecting growing concerns about privacy, fairness, and the potential exploitation of certain consumers (Akella et al., 2023; Gibson, 2024).

When Data Becomes a Price Signal

Before the age of the internet, prices were very slow-moving. Individuals needed to manually implement price changes (printing new catalogues, updating tags, or changing price boards), so price adjustments were, by necessity, infrequent. With digitization and increasing access to large amounts of data, early algorithmic pricing became feasible through simple if-then rules that took inputs such as inventory levels, competitors' prices, and time (time of day, day of week, season) to execute simple strategies (e.g., price matching with competitors or raising prices as inventory levels declined). Over time, as technology and pricing practices evolved, the frequency and specificity of price changes increased, but these systems still did not truly learn from data in a machine learning (ML) sense (den Boer, 2015).

Over the last decade, AI-based dynamic pricing systems have added machine learning models to these systems, using both historical and real-time data to estimate demand and WTP as functions of price and other relevant information, and then optimizing prices to maximize expected profits in almost real time. Under this new framework, AI integration means that imputed data is not only used to generate outputs (prices) or trigger actions (raising or lowering prices in response to changes in inputs), but also to update the underlying mapping from inputs to prices as new information becomes available. Firms use both historical and current data to predict demand at different price points, plug those forecasts into an optimization routine that finds the profit-maximizing price, and then retrain those models as new data filters in. Because these systems can handle far more data points than earlier rule-based systems, not only a wider variety of inputs, but also at a much greater scale, they can more readily create increasingly accurate predictions over time than traditional methods. In combination with the sheer volume of data available about individual consumers online, where firms can track and sell browsing behavior, purchase history, and other behavioral patterns, this process can become highly personalized, allowing AI pricing systems to more closely approximate WTP and adjust prices at a far finer level (if implemented), maximizing expected profits, enhancing competitiveness and optimizing inventory management for firms while cutting into consumer surplus (Aparicio et al., 2024; Sahota, 2024).

Digital Price Tags and Continuous Markets: Emerging Use Cases

Dynamic pricing has become increasingly integrated across industries – including air transportation, retail, rideshare, hospitality, and energy – and has reached new heights since the advent of sophisticated ML models.

In July of last year, Delta announced that it had been using AI to help set pricing on 1% of tickets and aimed to increase that to 20% by the end of 2025 to more effectively set prices and adapt to market conditions, through a partnership with Fetcherr, a generative AI pricing and inventory management company, with other clients including Azul, Virgin Atlantic, WestJet, and Aerobus. While Delta is not the first to use AI-powered pricing, it is one of the first major airline firms to be so public about its adoption (IATA, 2025; Keyes, 2025; McCarthy, 2025).

In ride-sharing, AI-powered dynamic pricing is typically utilized to help to balance supply and demand. During high demand times, such as late nights, ride-share companies raise prices, a strategy called surge pricing, to help to incentivize drivers to pick up more people than they would otherwise, which has resulted in a lot of pushback from consumers, especially in times of emergencies as demand for rides rises abruptly while the supply of drivers willing to move people could in some cases decrease due to potential situational risks. Even outside of emergencies, fare prices have been seen to be priced at six to eight times (or more) normal prices in times of demand spikes, prompting concerns about price gouging from the customer base (Kedmey, 2014).

In the retail sector, firms have moved to integrate dynamic pricing both online and in stores. Online, most major retailers utilize some form of AI dynamic pricing models, while third-party retailers on sites like Amazon may use far simpler algorithms (e.g., simply price-matching competitors). In stores, several retailers have started to use (e.g., Whole Foods, Amazon Fresh, and Kroger) or plan to integrate (e.g., Walmart) electronic shelf labels into their physical locations. Electronic shelf labels allow retailers to quickly adjust prices, increasing efficiency as employees no longer need to create and manually switch out price tags as prices change. For grocery retailers, this also means being able to better manage perishable inventories, quickly marking down prices as products near expiration. While most retailers have denied integrating dynamic pricing through new digital price systems, it does not mean that they could not eventually implement it in the future, especially now that centralized digital in-store pricing systems have made it far more feasible (Fishman, 2025; Shah, 2024).

A New Frontier: Implications for Consumers

As firms announce or are suspected of using dynamic pricing, consumer sentiment has typically been poor. The use of AI-enabled pricing in ride-share, Instacart, and Delta has repeatedly generated consumer backlash, amplified by the opacity of firm pricing models and the sense that prices are being modified without the general consumer's awareness of the changes. Airline fares have become visibly more volatile, with differences sometimes up to hundreds of dollars from one week to the next on the same route, leaving travelers to guess at the inputs driving the "black box" of AI pricing (e.g., weather, seasonality, demand, remaining inventory) (Wu et al., 2022). In newer applications, Instacart was pushed to roll back its use of algorithmic price tests after investigations documented large, otherwise unexplainable price differences for identical baskets. Major retailers faced scrutiny over whether electronic shelf label rollouts could allow for in-store dynamic or surveillance pricing, potentially driving up prices. Against this backdrop, a natural question emerges: how do AI-powered pricing systems affect consumers?

A persistent worry is that algorithmic pricing with elements of price discrimination, either by segment (third-degree price discrimination) or by individual consumers (first-degree price discrimination), will lead to higher overall prices by pushing them closer to consumers' WTP. In general, dynamic pricing, in contrast to personalized pricing, consumers are broken down into segments with observable traits (age, location, time of purchase, device type), and prices for each segment can be determined by models based on those groupings, with more frequent adjustments, attempting to determine prices by group. This concern is amplified as individual data can be used to more accurately determine individual WTP using big data (e.g, past purchases, location, device type, etc.) to tailor prices and "discounts" to individuals. In either case, prices would be expected to be higher per group to maximize firm profits while cutting down on consumer surpluses. This could be particularly concerning, however, for consumers with high need for certain goods, such as new parents buying formula, where pricing could be higher as pricing models see that they would still be willing to pay for formula at higher prices that could increase firm profits, bringing up the issue of both consumer privacy and use cases of dynamic pricing (Bar-Gill, n.d.; Dube & Misra, 2022). Additionally, surge pricing is also seen as a significant problem in general markets, with debates over its ethics, especially during emergencies, with firms claiming its necessity in incentivizing suppliers to meet heightened demand, while those who are subject to it may call it "unethical price gouging".

Another big concern is that AI-powered dynamic pricing models will "learn" to be less competitive when retaliation is near instantaneous. From a game theory perspective, this could be described as an infinite game (assuming firms stay in the market). As more firms use AI-powered dynamic pricing models which can respond in almost real time, this means that potential retaliation, or punishment, for lowering prices to undercut competitors could become effectively instantaneous, lowering the incentive to deviate. Because AI models, in contrast to less advanced pricing models, are able to learn over time, this effectively reduces competition pressures, leading to a situation of inadvertent collusion where firms keep prices higher for longer, referred to as "**algorithmic collusion**" (Brown & MacKay, 2022).

Designing Guardrails for Adaptive Markets: Regulatory Pathways

Amid a landscape of increasing use of opaque AI-powered pricing models among firms, regulatory response has been relatively tentative. Algorithmic pricing, in and of itself, is not considered illegal, only becoming an issue in the eyes of regulators when it facilitates anticompetitive, predictive or exploitative practices. Current proposals in both academia and government have mostly been centered around the issues of transparency, use of personnel data, limitations on surge pricing, and maintaining a competitive environment. For example, giving regulatory agencies the authority to audit pricing algorithms, restricting the use of personal or non-public competitor data, or capping surge pricing (FTC, 2025; Taylor, 2025). While regulatory responses have to this point been minimal, using more of a wait-and-see approach, it is clear that AI-powered pricing is by no means going away. With increased firm adoption, it is likely to eventually lead to more concrete responses from both consumers, legislators, and regulators going forward.

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Bruin Reserve Bank Macro Team

Terrence Yu Research Lead terrenceyu@g.ucla.edu

Sofia Sheremet Editorial Team

Nicole Pasternak Editorial Team

Ronojoy Borpujari Analyst ronojoyb19@gmail.com

Diego Perdomo Analyst diegoperdomo@g.ucla.edu

Nirvaan Singla Analyst nirvaan4871@g.ucla.edu

Madelyne Goforth Analyst madelynegoforth@g.ucla.edu

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