

Evaluating the impact of price elasticity on revenue management and strategic business decision-making

Md Nazmul Huda Murad *

Sorrell College of Business, Troy University, 600 University Ave, Troy, AL-36082, USA.

World Journal of Advanced Research and Reviews, 2026, 30(03), 1716-1723

Publication history: Received on 12 May 2026; revised on 21 June 2026; accepted on 23 June 2026

Article DOI: <https://doi.org/10.30574/wjarr.2026.30.3.1750>

Abstract

Objective: This study evaluates how price elasticity of demand shapes revenue management outcomes and strategic business decision-making.

Methodology: An integrative review of economics, marketing, operations research and hospitality revenue-management literature was combined with a deterministic constant-elasticity scenario analysis. The scenario model estimated the revenue effects of price changes from -20% to +20% across elasticity values from -0.5 to -3.0 using a reproducible baseline price, quantity and revenue.

Results: The review shows that elasticity converts pricing from a cost-plus or competitor-following activity into a decision system for segmentation, inventory allocation, promotion design, capacity control and governance of algorithmic pricing. Scenario results confirm the unit-elastic boundary: a 10% price increase raised revenue by 4.9% when elasticity was -0.5, had no revenue effect at -1.0 and reduced revenue by 9.1% when elasticity was -2.0. Conversely, price reductions created revenue gains only when demand was sufficiently elastic. Conclusion: Elasticity is not a static statistic but a dynamic managerial capability. Its practical value depends on credible demand estimation, controlled price experimentation, cross-functional integration and safeguards for fairness and transparency. Firms that embed elasticity into revenue management can improve revenue quality and strategic agility, whereas firms that ignore elasticity risk margin erosion, customer backlash and misallocation of scarce capacity.

Keywords: Price Elasticity; Revenue Management; Dynamic Pricing; Demand Estimation; Strategic Pricing; Business Decision-Making

1. Introduction

Price elasticity of demand expresses the percentage change in quantity demanded associated with a one-percent change in price and remains one of the core concepts linking microeconomic theory to managerial pricing practice [1]. Although the construct is mathematically concise, its managerial implications are extensive. A product with inelastic demand may tolerate price increases without proportionate loss of volume, whereas a product with elastic demand may generate more revenue from carefully designed discounts, bundles or capacity allocation rules. In both cases, elasticity influences not only the immediate revenue effect of a price change but also longer-term decisions about customer segmentation, channel strategy, promotional timing, capacity utilization and competitive positioning.

Empirical research confirms that price response is rarely uniform across products, customers or time. Tellis synthesized 367 elasticity estimates across brands and markets, showing that selective demand is generally price sensitive and that elasticity differs with model specification and market context [2]. Later meta-analysis by Bijmolt, van Heerde and Pieters

* Corresponding author: Md Nazmul Huda Murad

expanded the evidence base to 1,851 elasticities and reported that average sales elasticities had increased in magnitude over time, suggesting that modern consumers often operate in more transparent and substitutable markets [3]. These findings are strategically important because revenue management decisions depend on the ability to anticipate heterogeneous demand response rather than on an average price-response assumption.

Revenue management (RM) provides the operational discipline through which elasticity information is translated into pricing and allocation actions. Talluri and van Ryzin describe RM as a field concerned with selling the right product to the right customer at the right time and price, using both quantity-based controls and price-based optimization [4]. Phillips similarly frames pricing and revenue optimization as a systematic approach to estimating price-response functions and using them to guide repeated price decisions under constraints [5]. The foundational dynamic-pricing model of Gallego and van Ryzin demonstrated how finite inventory, stochastic demand and time can be integrated into optimal price paths [6], while later reviews emphasized the growing practical relevance of dynamic pricing as firms gained richer demand data, faster price-change capabilities and decision-support systems [7,8].

However, elasticity-based RM is not only a technical optimization problem. It is also a strategic business decision-making problem. Demand learning literature shows that firms often adjust prices while simultaneously learning the underlying demand function [9]. Hospitality and service research illustrates that dynamic price variability can increase revenue when implemented with inventory controls, demand disaggregation and customer-value considerations [10-13]. At the same time, behavioral and policy research warns that customers may perceive differential or personalized prices as unfair, which can reduce demand, trust and long-term profitability [14-20]. Thus, managers face a dual challenge: they must use elasticity to improve revenue performance while governing price changes in ways that preserve customer relationships, competitive legitimacy and regulatory resilience.

This paper evaluates the impact of price elasticity on RM and strategic decision-making through an integrative review and a reproducible scenario-based analysis. The specific objectives are to: (i) synthesize how elasticity informs revenue, margin and allocation decisions; (ii) quantify how revenue changes under alternative elasticity and price-change scenarios; (iii) identify strategic decisions that are most sensitive to elasticity estimates; and (iv) propose a managerial framework for embedding elasticity into pricing governance.

2. Materials and Methods

This study used a mixed conceptual and analytical design suitable for a research article in business and management. The first component was an integrative literature review covering economics, marketing, operations research, revenue management, hospitality and algorithmic-pricing governance. The second component was a deterministic scenario analysis designed to make the revenue implications of elasticity transparent and reproducible.

The literature review was conducted purposively rather than as a formal systematic review. To improve transparency and reproducibility, the literature component was bounded by iterative searches of Google Scholar, publisher databases and discipline-specific sources represented in the final reference set across economics, marketing, operations research, revenue management, hospitality and pricing-governance literature. Search terms included price elasticity of demand, price elasticity meta-analysis, revenue management, dynamic pricing, pricing and learning, hotel revenue management, personalized pricing fairness, algorithmic pricing regulation and related Boolean combinations. No date restriction was imposed for foundational economic and revenue-management theory; recent empirical and governance studies were prioritized when they reflected data-rich, algorithmic or personalized pricing practice. Sources were selected when they met at least one of four criteria: (i) they defined or estimated price elasticity; (ii) they connected price response to RM, dynamic pricing or inventory/capacity control; (iii) they provided empirical evidence from service, hospitality or digital-pricing settings; or (iv) they addressed behavioral, fairness or regulatory risks that influence the strategic implementation of elasticity-based pricing. Foundational works and high-citation reviews were included to establish theoretical consistency, while recent studies were included to reflect the current shift toward data-rich, algorithmic and personalized pricing.

The scenario analysis used a constant-elasticity demand function, a common managerial approximation because it keeps elasticity stable over the relevant decision range and produces directly interpretable revenue ratios. Let P_0 denote the baseline price, Q_0 the baseline quantity, ϵ the own-price elasticity of demand and g the proposed percentage price change. The post-change price is $P_1 = P_0(1 + g)$, quantity is $Q_1 = Q_0(1 + g)^{-\epsilon}$ and revenue is $R_1 = P_1Q_1$. The revenue ratio is therefore $R_1/R_0 = (1 + g)^{1 - \epsilon}$. A baseline of $P_0 = 100$ monetary units and $Q_0 = 10,000$ units was used, giving baseline revenue $R_0 = 1,000,000$ monetary units. Elasticity values of -0.5, -1.0, -1.5, -2.0 and -3.0 were analyzed across price changes of -20%, -10%, -5%, +5%, +10% and +20%.

This approach is intentionally simple and reproducible. It does not claim to estimate elasticity for a specific firm; rather, it isolates the logic that managers must understand before applying more advanced econometric, machine-learning or reinforcement-learning pricing models. The limitation of the constant-elasticity model is that real demand can exhibit reference-price effects, stockouts, competitor reactions, customer learning, channel substitution and fairness responses. These limitations are discussed as strategic implementation issues rather than ignored.

3. Results and Discussion

The review indicates that price elasticity affects revenue management through four linked mechanisms: demand sensitivity, segmentation, constrained-resource allocation and organizational governance. Figure 1 summarizes the proposed framework. Elasticity measurement provides the empirical input; demand and segment response translate that input into expected volume; RM levers such as fare classes, markdowns, booking limits, promotions and dynamic prices convert expected response into action; and strategic decisions allocate resources, define customer propositions and govern acceptable price variation. The feedback loop is essential because realized demand, competitive moves and customer reactions can invalidate prior elasticity estimates.

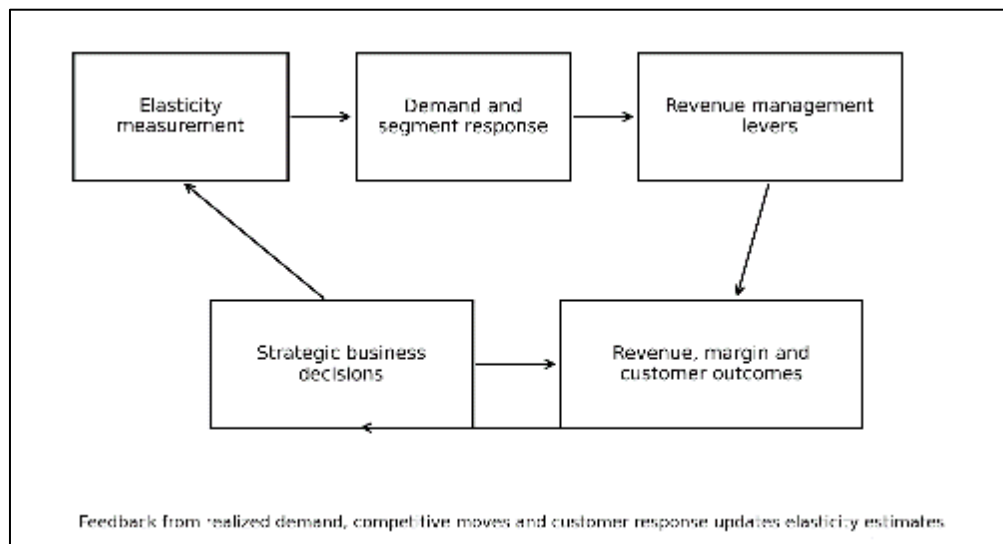


Figure 1 Conceptual framework linking price elasticity to revenue management and strategic business decision-making. The feedback loop emphasizes that elasticity estimates must be updated after realized demand and customer response are observed

The first implication is that elasticity changes the sign and magnitude of the revenue effect of price changes. Under constant elasticity, revenue increases after a price rise only when demand is inelastic in absolute value, remains unchanged at unit elasticity and falls when demand is elastic. Table 1 presents the modeled revenue changes. The pattern is symmetrical in managerial meaning but not exactly symmetrical in percentage arithmetic: when $\epsilon = -2.0$, a 10% price increase reduces revenue by 9.1%, whereas a 10% price decrease increases revenue by 11.1%. The result is strategically important because a price cut in an elastic market can be revenue expanding, while the same cut in an inelastic market can unnecessarily destroy revenue.

Table 1 Modeled percentage change in total revenue under constant-elasticity demand. Baseline assumptions

Elasticity (epsilon)	-20% price	-10% price	-5% price	+5% price	+10% price	+20% price
-0.5	-10.6%	-5.1%	-2.5%	+2.5%	+4.9%	+9.5%
-1.0	+0.0%	+0.0%	+0.0%	+0.0%	+0.0%	+0.0%
-1.5	+11.8%	+5.4%	+2.6%	-2.4%	-4.7%	-8.7%
-2.0	+25.0%	+11.1%	+5.3%	-4.8%	-9.1%	-16.7%
-3.0	+56.2%	+23.5%	+10.8%	-9.3%	-17.4%	-30.6%

$P_0 = 100$, $Q_0 = 10,000$ and $R_0 = 1,000,000$ monetary units. Values show percentage change in revenue relative to baseline.

Figure 2 visualizes the same relationship across a continuous elasticity range. The vertical marker at $\epsilon = -1.0$ is the unit-elastic boundary. To the right of this boundary, demand is relatively inelastic and price increases tend to raise total revenue. To the left, demand is relatively elastic and price increases tend to reduce total revenue. This finding supports a core RM principle: price levels and price fences should be based on estimated demand response by segment, product, channel and time rather than on a single organization-wide markup rule.

A second implication is that elasticity affects the trade-off between revenue maximization and contribution-margin maximization. Revenue is a useful top-line metric, but the profit-maximizing price also depends on marginal cost, capacity scarcity and opportunity cost. In a low-marginal-cost digital product, a lower price may be attractive when demand is elastic because incremental volume contributes strongly to profit. In a capacity-constrained hotel, airline or event venue, the same discount may displace higher-paying demand and reduce total contribution. For this reason, elasticity estimates should be combined with marginal cost and displacement cost, not treated as stand-alone price recommendations.

A third implication is that elasticity supports segmentation. High-willingness-to-pay or low-substitution customers often exhibit lower price sensitivity, while leisure, discretionary or deal-seeking customers may exhibit higher price sensitivity. RM systems use this heterogeneity through fare restrictions, advance-purchase rules, loyalty offers, channel-specific promotions and product versioning. The purpose is not simply to charge more; it is to align prices with demand response and capacity opportunity costs. If segments are poorly defined or price fences are easy to arbitrage, demand may migrate to lower-priced options and erode revenue quality.

A fourth implication concerns timing. Elasticity is dynamic across the product life cycle, season, booking horizon and macroeconomic conditions. Early in a sales horizon, firms may experiment with prices to learn demand; later, they may shift toward exploitation as inventory or capacity becomes scarce. Demand-learning models show why purely greedy pricing can underperform when it fails to generate informative price variation [21-25]. The managerial lesson is that price experimentation is not a side activity but a structured investment in future decision quality. However, experimentation must be designed with guardrails so that customers do not experience arbitrary or unfair price differences.

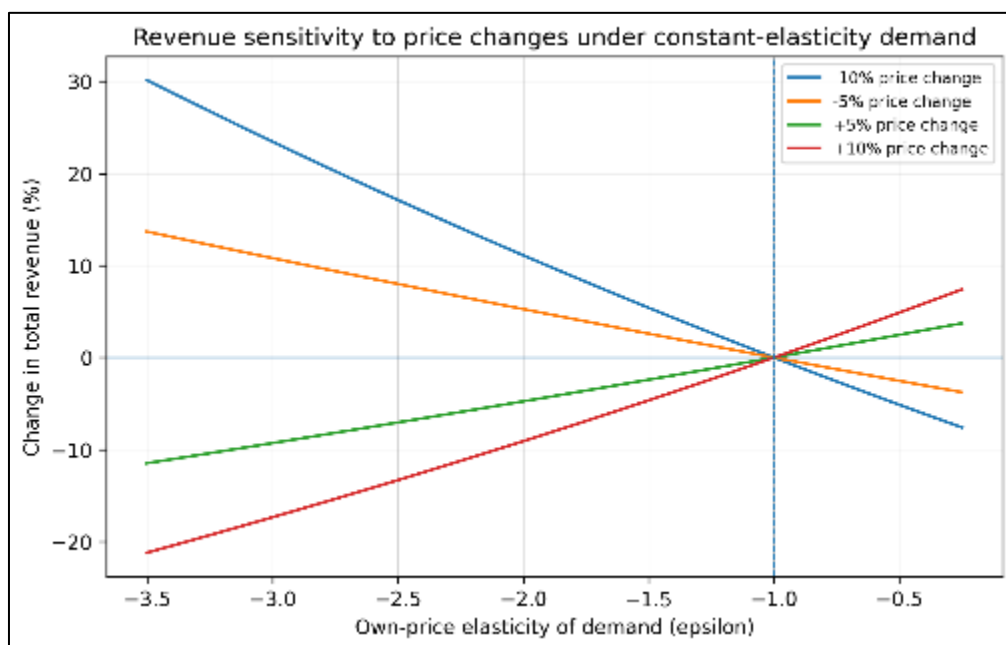


Figure 2 Revenue response curves for selected price changes. The dashed vertical line marks unit elasticity, the threshold at which price changes have no first-order revenue effect under the constant-elasticity model

The strategic impact of elasticity can be organized into four decision domains: price architecture, capacity and inventory allocation, market positioning and governance. Table 2 summarizes the managerial interpretation. In price architecture, elasticity determines whether managers should prioritize price increases, discounts, bundles, subscriptions or freemium structures. In capacity allocation, elasticity guides which demand to accept now and which demand to protect for future higher-value customers. In market positioning, elasticity informs whether the firm competes on premium

differentiation, convenience, service quality or low price. In governance, elasticity helps define when price changes are economically justified and when they may create fairness or reputational risk.

The paper's findings are consistent with the broader revenue-management literature. RM emerged in capacity-constrained industries such as airlines and hotels, where the marginal value of capacity changes over time and unsold capacity expires [4,10,26]. Dynamic pricing extends this logic to retail, e-commerce, energy, transportation and digital platforms, where firms can frequently observe demand signals and update prices [7-9]. The scenario analysis adds managerial clarity by showing that even basic elasticity arithmetic can reverse the expected direction of revenue after a price change. This reinforces the importance of demand estimation before pricing action. Strategic pricing texts likewise emphasize that elasticity estimates should be interpreted with customer value, margin discipline and implementation constraints rather than treated as mechanical pricing rules [27,28].

In practical implementation, firms should treat elasticity estimation as an iterative capability. Useful data include transaction prices, posted prices, promotion depth, stock availability, competitor prices, search traffic, conversion rates, customer attributes and timing variables. However, naïve regression of quantity on price can be biased because prices are often changed in response to expected demand. For example, high prices may coincide with high-demand periods, making demand appear less elastic than it truly is. Controlled experiments, randomized price tests, instrumental variables, panel models and machine-learning methods can reduce bias when designed carefully. Recent demand-learning research further shows that covariates can improve pricing policies when they capture relevant demand conditions [25].

Strategic decision-making also requires elasticity at the correct level of granularity. Category-level elasticity may be too broad for promotion decisions, while individual-level elasticity may be too narrow or risky for governance. Managers often need nested estimates: product-level elasticity for assortment and margin planning; segment-level elasticity for RM and offer design; channel-level elasticity for distribution strategy; and time-specific elasticity for markdowns or surge pricing. Cross-price elasticity is also necessary when products substitute for or complement one another. A single-product price increase may increase revenue on that product but shift demand to a substitute with lower margin or weaker customer retention.

The behavioral literature cautions that economically optimal prices may be strategically inferior when they violate customer fairness expectations. Anderson and Simester found that premium pricing for larger apparel sizes reduced demand and gross profits, consistent with perceived unfairness [14]. Personalized dynamic pricing studies similarly show that consumers can view individualized prices as less fair than segment-based prices, especially when based on sensitive or opaque data [15,16]. Diao and colleagues demonstrate that fairness concerns can alter optimal dynamic-pricing strategies and profits [17]. Therefore, RM should include fairness constraints, disclosure rules and escalation procedures rather than leaving algorithmic price changes unmanaged.

Algorithmic pricing amplifies both the opportunity and the risk. Advanced systems can update prices rapidly, learn from high-dimensional demand signals and personalize offers. Yet the same speed and opacity can intensify consumer distrust, increase regulatory scrutiny and create competitive concerns [18,19]. Fairness-aware pricing research suggests that revenue, welfare and equity objectives can be formalized, but their trade-offs must be explicit [20]. For executives, this means that elasticity-based pricing should be governed as a strategic capability involving finance, marketing, operations, legal, data science and ethics rather than as a purely technical model owned by analysts.

The scenario analysis has several limitations. First, constant elasticity is an approximation; actual demand curves can be nonlinear, kinked or discontinuous. Second, the analysis focuses on total revenue and does not optimize contribution profit or customer lifetime value. Third, it excludes competitive reaction, stockout constraints, customer learning and reference-price effects. Fourth, the review was integrative rather than systematic, so it synthesizes influential and relevant literature rather than exhaustively coding all studies. These limitations do not weaken the central conclusion; instead, they show why elasticity should be embedded in a broader RM decision system.

The resulting decision matrix is shown in Table 2. It provides a practical bridge between elasticity measurement and executive action.

Table 2 Elasticity-informed decision matrix for revenue management and strategic business decision-making

Elasticity condition	Revenue-management implication	Strategic decision emphasis	Risk if ignored
Relatively inelastic (epsilon > -1)	Price increases can raise revenue; discounts usually dilute revenue unless needed for capacity or acquisition.	Protect premium pricing, strengthen differentiation, use targeted discounts sparingly.	Unnecessary discounting, margin leakage and weak price discipline.
Unit elastic (epsilon = -1)	Small price changes have limited revenue effect; margin, capacity and retention become decisive.	Optimize contribution margin, customer lifetime value and operational constraints.	Overemphasis on revenue while profit or loyalty deteriorates.
Relatively elastic (epsilon < -1)	Price reductions can raise revenue if capacity and margin permit; price increases can reduce revenue sharply.	Use promotions, bundles, value tiers and channel offers to stimulate demand.	Volume loss, market-share erosion and misreading of competitive sensitivity.
Heterogeneous elasticity across segments	Different segments justify different restrictions, offers or timing rules.	Design price fences, loyalty offers, advance-purchase rules and product versions.	Customer migration to lower price fences or perceived unfairness.
Uncertain or changing elasticity	Learning value is high; controlled experimentation is needed before broad rollout.	Build experimentation, monitoring and governance into pricing operations.	Biased estimates, unstable algorithms and strategic overreaction.

4. Conclusion

Price elasticity materially affects revenue management and strategic business decision-making because it determines whether price changes expand or contract revenue, how capacity should be protected, which customer segments should receive differentiated offers and when pricing actions create fairness or reputational risk. The review shows that elasticity connects economic theory with operational RM tools, while the scenario analysis demonstrates that the unit-elastic boundary is a decisive managerial threshold. A 10% price increase can raise, preserve or reduce revenue depending entirely on the elasticity of demand.

The major finding is that elasticity should be treated as a dynamic capability rather than a static estimate. Firms gain strategic advantage when they measure elasticity at useful levels of granularity, combine it with marginal cost and capacity opportunity cost, update estimates through disciplined experimentation and govern dynamic prices with transparency and fairness safeguards. The significance of the study lies in its integration of quantitative pricing logic with broader strategic decision-making. Organizations that operationalize elasticity can improve revenue quality, reduce pricing errors and make more coherent decisions about segmentation, inventory, promotions, product design and market positioning.

Compliance with ethical standards

Acknowledgments

The author received no external funding for this manuscript.

Disclosure of conflict of interest

The author declares that there are no financial or non-financial conflicts of interest related to this manuscript.

Statement of ethical approval

This study used published literature and a deterministic scenario model only. It did not involve human participants, animals, clinical data or confidential organizational data. Ethical approval and informed consent were therefore not applicable.

References

- [1] Marshall A. Principles of economics. 8th ed. London: Macmillan; 1920.
- [2] Tellis GJ. The price elasticity of selective demand: A meta-analysis of econometric models of sales. *J Mark Res.* 1988;25(4):331-341. doi:10.1177/002224378802500401.
- [3] Bijmolt THA, Van Heerde HJ, Pieters RGM. New empirical generalizations on the determinants of price elasticity. *J Mark Res.* 2005;42(2):141-156. doi:10.1509/jmkr.42.2.141.62296.
- [4] Talluri KT, Van Ryzin GJ. The theory and practice of revenue management. New York: Springer; 2004.
- [5] Phillips RL. Pricing and revenue optimization. 2nd ed. Stanford: Stanford University Press; 2021.
- [6] Gallego G, Van Ryzin G. Optimal dynamic pricing of inventories with stochastic demand over finite horizons. *Manag Sci.* 1994;40(8):999-1020. doi:10.1287/mnsc.40.8.999.
- [7] Elmaghraby W, Keskinocak P. Dynamic pricing in the presence of inventory considerations: Research overview, current practices, and future directions. *Manag Sci.* 2003;49(10):1287-1309. doi:10.1287/mnsc.49.10.1287.17315.
- [8] Bitran G, Caldentey R. An overview of pricing models for revenue management. *Manuf Serv Oper Manag.* 2003;5(3):203-229. doi:10.1287/msom.5.3.203.16031.
- [9] Den Boer AV. Dynamic pricing and learning: Historical origins, current research, and new directions. *Surv Oper Res Manag Sci.* 2015;20(1):1-18. doi:10.1016/j.sorms.2015.03.001.
- [10] Kimes SE. The future of hotel revenue management. *J Revenue Pricing Manag.* 2011;10(1):62-72. doi:10.1057/rpm.2010.47.
- [11] Abrate G, Nicolau JL, Viglia G. The impact of dynamic price variability on revenue maximization. *Tour Manag.* 2019;74:224-233. doi:10.1016/j.tourman.2019.03.013.
- [12] Bandalouski AM, Kovalyov MY, Tarim SA. Dynamic pricing with demand disaggregation for hotel revenue management. *J Heuristics.* 2021;27(5):869-885. doi:10.1007/s10732-021-09480-2.
- [13] Zhu F, Xiao W, Yu Y, Wang Z, Chen Z, Lu Q, et al. Modeling price elasticity for occupancy prediction in hotel dynamic pricing. In: *Proceedings of the 31st ACM International Conference on Information and Knowledge Management*. New York: ACM; 2022. p. 4742-4746. doi:10.1145/3511808.3557646.
- [14] Anderson ET, Simester DI. Does demand fall when customers perceive that prices are unfair? The case of premium pricing for large sizes. *Mark Sci.* 2008;27(3):492-500. doi:10.1287/mksc.1070.0323.
- [15] Priester A, Robbert T, Roth S. A special price just for you: Effects of personalized dynamic pricing on consumer fairness perceptions. *J Revenue Pricing Manag.* 2020;19(2):99-112. doi:10.1057/s41272-019-00224-3.
- [16] Richards TJ, Liaukonyte J, Streletskaya NA. Personalized pricing and price fairness. *Int J Ind Organ.* 2016;44:138-153. doi:10.1016/j.ijindorg.2015.11.004.
- [17] Diao W, Harutyunyan M, Jiang B. Consumer fairness concerns and dynamic pricing in a channel. *Mark Sci.* 2023;42(3):569-588. doi:10.1287/mksc.2022.1395.
- [18] MacKay AJ, Weinstein SN. Dynamic pricing algorithms, consumer harm, and regulatory response. *Wash Univ Law Rev.* 2022;100(1):111-169.
- [19] Spann M, Bertini M, Koenigsberg O, Zeithammer R, Aparicio D, Chen Y, et al. Algorithmic pricing: Implications for marketing strategy and regulation. Cambridge (MA): National Bureau of Economic Research; 2024. Working Paper No. 32540. doi:10.3386/w32540.
- [20] Kallus N, Zhou A. Fairness, welfare, and equity in personalized pricing. In: *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*. New York: ACM; 2021. p. 296-314. doi:10.1145/3442188.3445895.
- [21] Besbes O, Zeevi A. Dynamic pricing without knowing the demand function: Risk bounds and near-optimal algorithms. *Oper Res.* 2009;57(6):1407-1420. doi:10.1287/opre.1080.0640.
- [22] Keskin NB, Zeevi A. Dynamic pricing with an unknown demand model: Asymptotically optimal semi-myopic policies. *Oper Res.* 2014;62(5):1142-1167. doi:10.1287/opre.2014.1294.

- [23] Den Boer AV, Zwart B. Simultaneously learning and optimizing using controlled variance pricing. *Manag Sci.* 2014;60(3):770-783. doi:10.1287/mnsc.2013.1788.
- [24] Qiang S, Bayati M. Dynamic pricing with demand covariates. *SSRN Electronic Journal.* 2016. doi:10.2139/ssrn.2765257.
- [25] van de Geer R, den Boer AV, Bayliss C, Currie CSM, Ellina A, Esders M, et al. Dynamic pricing and learning with competition: Insights from the Dynamic Pricing Challenge at the 2017 INFORMS RM and Pricing Conference. *J Revenue Pricing Manag.* 2019;18(3):185-203. doi:10.1057/s41272-018-00164-4.
- [26] Van Ryzin GJ, Talluri KT. An introduction to revenue management. *Tutorials Oper Res.* 2005;142-194. doi:10.1287/educ.1053.0019.
- [27] Nagle TT, Müller G. *The strategy and tactics of pricing: A guide to growing more profitably.* 6th ed. New York: Routledge; 2017.
- [28] Simon H, Fassnacht M. *Price management: Strategy, analysis, decision, implementation.* Cham: Springer; 2019.