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# CONSUMER CHOICE UNDER DYNAMIC PRICING: LATENT-CLASS EVIDENCE FROM FAST FASHION AND ACCESSIBLE LUXURY

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## ABSTRACT

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*This study examines how consumers trade off pricing rule, price, product quality and durability, brand reputation, shopping experience, and consumption emotion when choosing fast-fashion and accessible-luxury products. A discrete choice experiment generated 2,051 valid choice sets from 293 respondents after structured quality screening. Context-specific conditional logit models, willingness-to-pay estimates, a panel latent-class logit model, and a finite short-run revenue-index counterfactual were applied. Inventory-based markdowns increased utility in fast fashion ($\beta$ = 0.414, p = .013) but reduced utility in accessible luxury ($\beta$ = -0.582, p < .001), whereas demand-responsive pricing was negative but not statistically significant in either aggregate context. The two non-static mechanisms are interpreted separately: demand-responsive pricing represents adaptive repricing, while inventory markdown is a stock-contingent retail rule that may also be perceived as conventional clearance. The high quality/durability level produced the largest functional premium, while exclusive shopping and distinctive consumption emotions were especially valuable in luxury. A two-class model was retained because it achieved the lowest Bayesian information criterion and yielded behaviourally coherent, but probabilistic, segments: price-functional pragmatists (53.0%) and brand-experiential seekers (47.0%). Within the tested price-mechanism grid, inventory markdown produced the highest one-period revenue index for a representative fast-fashion profile, whereas static pricing dominated for a prestige-oriented luxury profile. These revenue comparisons do not model strategic waiting or long-run brand effects. The findings therefore support mechanism-category congruence rather than a category-neutral prescription for dynamic pricing.*

**KEYWORDS:** *Dynamic Pricing; Inventory Markdown; Discrete Choice Experiment; Latent Class Logit; Willingness To Pay; Fast Fashion; Accessible Luxury; Revenue Management.*

## 1. INTRODUCTION

Digital retailing has expanded firms' capacity to alter prices in response to demand, stock availability, browsing behaviour, and customer-level information. Although this capability can improve inventory allocation and revenue management, it also exposes consumers to price differences that may appear arbitrary, opaque, or discriminatory. Experimental evidence shows that dynamic price differences can reduce perceived fairness and purchase satisfaction, particularly when buyers cannot identify a legitimate basis for the variation (Haws & Bearden, 2006). Related work further indicates that an unfavourable dynamic-pricing episode can weaken benevolence-based trust even when consumers acknowledge the seller's technical competence (Garbarino & Lee, 2003).

Fashion provides a stringent setting in which to examine this tension because price is simultaneously an economic sacrifice, a quality cue, and a symbolic signal. Fast-fashion systems create value through rapid design renewal and quick response, while strategic consumers compare alternatives and may postpone purchase when they expect future reductions (Cachon & Swinney, 2011). In accessible luxury, by contrast, stable and elevated prices can communicate craftsmanship, scarcity, prestige, and social distinction; a visible markdown may lower financial sacrifice while also weakening the meaning that justifies the purchase. Luxury consumption research accordingly treats value as multidimensional, combining financial, functional, individual, and social components rather than reducing preference to affordability alone (Wiedmann et al., 2009).

Prior pricing studies often isolate a price change and then measure fairness, trust, or purchase intention. That approach is informative, yet it does not reproduce the joint trade-offs present in an actual fashion choice, where a cheaper product may have weaker quality, a less credible brand, or an ordinary shopping experience. The present study addresses this limitation through a discrete choice experiment (DCE) in which respondents selected between two product profiles and a no-purchase option. Importantly, it does not assume that all non-static price rules are behaviourally equivalent. Demand-responsive pricing is interpreted as adaptive repricing linked to contemporaneous demand, whereas inventory-based markdown is a stock-contingent clearance rule that consumers may also recognise as conventional retail promotion. A positive response to markdown can therefore reflect both acceptance of the rule and the gain associated with a credible stock-clearance rationale. The analysis answers four connected questions: how the two pricing mechanisms affect choice in fast fashion and accessible luxury; how consumers value functional, brand, experiential, and emotional attributes; whether stable preference segments can be identified; and which tested price-mechanism configuration produces the highest short-run model-based revenue index for representative products.

## 2. LITERATURE REVIEW

Consumer value theory explains why pricing effects should be examined alongside non-price attributes. Sweeney and Soutar (2001) distinguish emotional, social, quality-performance, and price-value dimensions, demonstrating that consumers evaluate an offering through several benefits and sacrifices at once. In fashion, these dimensions are particularly interdependent: material quality affects expected durability, brand reputation reduces perceived risk and conveys identity, the shopping process can generate hedonic value, and use of the product can produce confidence or social recognition. Vigneron and Johnson (2004) similarly conceptualise brand luxury through conspicuousness, uniqueness, quality, hedonic value, and the extended self, which implies that the utility of a luxury product cannot be inferred from functional performance alone.

Dynamic pricing introduces a second evaluative layer because consumers judge both the resulting price and the procedure used to determine it. The price-fairness framework of Xia et al. (2004) proposes that disadvantageous comparisons, seller motives, and perceived responsibility influence fairness judgements and subsequent behavioural responses. Haws and Bearden (2006) find that the source and timing of price differences materially affect fairness perceptions, while Garbarino and Lee (2003) show that consumer trust can deteriorate after exposure to individual-level price discrimination. These studies support a procedural-congruence proposition: a flexible pricing rule should be more acceptable when its rationale matches category norms. Inventory markdowns are familiar in fast fashion because products are seasonal and stock loses relevance quickly; however, the same visible reduction may be interpreted as a negative quality or prestige signal in luxury. For that reason, the present analysis treats demand-responsive repricing and inventory-based markdown as conceptually distinct mechanisms. The markdown condition is not taken as direct evidence of personalised or algorithmic price discrimination; its coefficient captures the response to a stock-linked rule that may also contain a conventional promotion or gain-framing component.

A DCE is suitable for testing these propositions because it operationalises random utility theory through repeated choices among mutually exclusive alternatives. Under this framework, an individual selects the option that provides the highest latent utility, while the analyst estimates the contribution of observed attributes from the resulting choice pattern (Train, 2009). Efficient designs preserve statistical information while limiting task burden and attribute correlation (Johnson et al., 2013). Statistical guidance recommends starting with a conditional or multinomial logit benchmark and then applying more flexible models when the assumption of homogeneous preferences is implausible (Hauber et al., 2016).

Latent-class logit models represent heterogeneity as a finite mixture of internally homogeneous segments. Unlike a single logit model, which reports an average coefficient that may conceal opposing preferences, the latent-class formulation assigns each respondent a posterior probability of belonging to each class. Greene and Hensher (2003) show that this semi-parametric approach can relax restrictive homogeneity assumptions without requiring a continuous parameter distribution, whereas Boxall and Adamowicz (2002) demonstrate how attitudinal variables can help interpret the resulting segments. Applied to fashion, the model should distinguish consumers who primarily defend economic and functional value from those who place greater weight on brand meaning, experiential benefits, and consumption emotion.

## 3. METHODOLOGY

### 3.1. Experimental design and sample

The experiment contained six attributes: pricing mechanism, price level, a bundled quality/durability attribute, brand reputation, shopping experience, and emotion during product use. Pricing had three levels - static price, demand-responsive price, and inventory-based markdown. Price levels were VND 0.3, 0.6, and 0.9 million in fast fashion and VND 3, 7, and 12 million in accessible luxury. The quality/durability attribute was represented by basic (reference), fair, and high levels; brand reputation by little-known (reference), popular, and highly reputable levels; and shopping experience by ordinary (reference), personalised, and exclusive levels. For consumption emotion, the model used an omitted base condition and indicators for confidence during use and distinctiveness/recognition. The quality/durability attribute was intentionally estimated as one functional profile. Consequently, its coefficients identify the value of the combined quality-longevity description and cannot be interpreted as separate marginal effects of perceived quality and expected durability.

The two non-static pricing levels also require separate interpretation. In the analysis, demand-responsive pricing denotes repricing associated with current aggregate demand, whereas inventory-based markdown denotes a reduction linked to stock conditions or product-cycle clearance. Consumers may perceive the latter as a familiar promotional practice rather than as algorithmic dynamic pricing. The estimated markdown coefficient should therefore be interpreted as a response to the stated stock-linked pricing rule, including any discount or gain framing embedded in that rule. The design does not identify responses to customer-specific price discrimination or to any particular pricing algorithm, and the results are not generalised to those mechanisms.

Each task displayed two product alternatives and a no-purchase option. The design was blocked and balanced across contexts and contained holdout and repeated tasks for validation; seven non-holdout, non-repeat tasks per retained respondent entered estimation. This structure permits mechanism comparisons while limiting respondent burden, but it does not independently randomise the pricing rule and the direction or magnitude of a realised price change. That distinction is considered when interpreting the markdown effect.

The raw sample contained 312 respondents. Nineteen cases were excluded for failed attention checks, incomplete choice sequences, implausibly short completion times, or duplicate-submission indicators, leaving 293 respondents and 2,051 choice sets, equivalent to 6,153 long-format alternative records. Retained respondents were aged 18-39 years (M = 24.10, SD = 4.42); 170 were women, 112 were men, and 11 selected another or undisclosed category. Mean monthly income was VND 14.12 million, mean fashion expenditure was VND 1.23 million, and 91 respondents (31.1%) had previously purchased accessible-luxury products. Repeat-task consistency reached 90.4%. Cronbach's alpha ranged from .797 to .834 across price consciousness, brand orientation, hedonic orientation, fairness concern, and pricing trust, indicating adequate internal reliability. Recruitment was non-probability based, so the sample is best viewed as a young adult fashion-consumer sample rather than a population-representative luxury-buyer panel.

***Table 1. Sample composition and data-quality indicators***

| Indicator | Value | Indicator | Value |
|---|---|---|---|
| Raw respondents | 312 | Retained respondents | 293 |
| Valid choice sets | 2,051 | Long-format rows | 6,153 |
| Mean age (SD) | 24.10 (4.42) | Age range | 18-39 |
| Women / Men / Other | 170 / 112 / 11 | Accessible-luxury experience | 91 |
| Repeat consistency | 90.4% | Scale reliability α | .797-.834 |
| Fast-fashion opt-out | 11.8% | Luxury opt-out | 30.9% |

### 3.2 Choice and latent-class models

Let U_njt|s denote the utility that respondent n obtains from alternative j in task t conditional on membership in class s. The systematic component contains an alternative-specific constant for a product rather than no purchase, two pricing-mechanism indicators, price expressed as a ratio to the context-specific middle level, and dummy variables for the non-price attribute levels. The class-specific random utility model is:

$$U_{njt|s} = \beta_s' x_{njt} + \varepsilon_{njt|s} \qquad (1)$$

Assuming independently and identically distributed type-I extreme-value errors within class, the conditional probability of choosing alternative j is:

$$P_{njt|s} = \exp(\beta_s' x_{njt}) / \Sigma_{k \in C_{nt}} \exp(\beta_s' x_{nkt}) \qquad (2)$$

For each respondent, the panel likelihood multiplies probabilities across the seven observed tasks. If $\pi_{ns}$ is the probability of class membership, the unconditional probability of the observed sequence $y_n$ is the finite mixture:

$$\Pr(y_n) = \Sigma_{s=1}^{S} \pi_{ns} \prod_t \prod_j P_{njt|s}\hat{}(y_{njt}) \qquad (3)$$

Parameters were estimated by maximum likelihood through expectation-maximisation with multiple starting values. One- to four-class solutions were compared using log-likelihood, Akaike information criterion (AIC), Bayesian information criterion (BIC), class size, posterior separation, and behavioural interpretability. BIC used the respondent as the independent sampling unit because repeated tasks formed a panel. Context-specific conditional logit models were also estimated with respondent-clustered standard errors, while a pooled interaction model tested whether coefficients differed between fast fashion and accessible luxury. Willingness to pay (WTP) for attribute k was calculated in monetary units by dividing its coefficient by the negative price coefficient and multiplying by the context-specific middle price, $r_c$:

$$WTP_{k,c} = -(\beta_{k,c} / \beta_{price,c}) \times r_c \qquad (4)$$

These WTP values are money-metric equivalents implied by the stated-choice utility function. They are not observed transaction prices or directly elicited reservation prices; this distinction is important for the accessible-luxury context, where hypothetical budget constraints may be material.

### 3.3 Short-run revenue-index counterfactual

To translate preference estimates into a bounded managerial comparison, a finite one-period counterfactual evaluated the three experimental prices and three pricing mechanisms for a representative product in each context. For a single offered product versus no purchase, predicted purchase probability is logistic in systematic utility $V_{c(m,p)}$. The retailer's revenue index per exposure is therefore:

$$\max_{m,p \in P_c} R_c(m,p) = p \times \exp[V_{c(m,p)}] / \{1 + \exp[V_{c(m,p)}]\} \ (5)$$

The fast-fashion profile combined fair quality/durability, a popular brand, personalised shopping, and confidence during use; the accessible-luxury profile combined high quality/durability, a highly reputable brand, exclusive shopping, and distinctive recognition. The calculation is deliberately one-shot: consumers evaluate the current offer without forming expectations about future prices. Unit cost, repeat purchasing, competitor response, inventory transitions, reference-price updating, strategic waiting, and long-run trust or brand effects are not observed. The survey identifies the highest short-run revenue index within the nine tested configurations; it is not an estimate of accounting profit or of the long-run profit-maximising dynamic pricing policy.

## 4. RESULTS

### 4.1 Aggregate preference estimates

Price had the expected negative effect in both contexts. In fast fashion, a one-unit increase in the price ratio reduced utility by 0.942 ($p < .001$), while the corresponding luxury coefficient was -1.353 ($p < .001$). The alternative-specific constant was not significant in fast fashion, whereas it was negative in luxury ($\beta = -0.816$, $p = .001$), which is consistent with the observed no-purchase share of 30.9% for luxury compared with 11.8% for fast fashion. McFadden's pseudo-$R^2$ was .234 for fast fashion and .195 for accessible luxury.

Pricing mechanism produced the study's central contrast. Inventory-based markdown increased fast-fashion utility (β = 0.414, p = .013) but reduced accessible-luxury utility (β = -0.582, p < .001). The pooled interaction was -0.996 (p < .001), confirming a statistically clear context difference. Demand-responsive pricing was negative in both contexts, although neither aggregate coefficient was statistically significant. The result therefore does not support a uniform response to "dynamic pricing" as a single construct. Fast-fashion respondents accepted the stock-linked markdown condition, but that coefficient may combine procedural acceptance with the positive framing of a familiar clearance reduction; it should not be interpreted as evidence that consumers generally prefer algorithmic repricing.

The bundled quality/durability attribute generated the most consistent positive effects. The high level produced coefficients of 1.269 in fast fashion and 1.460 in accessible luxury, while highly reputable brands produced coefficients of 0.964 and 1.055, respectively. Exclusive shopping was also strongly valued in both contexts. Emotional effects were more context-dependent: confidence was negligible in fast fashion (β = 0.088, p = .637) but substantial in accessible luxury (β = 0.881, p < .001), and the luxury interaction was significant (p = .002). Distinctiveness increased choice in both categories, although its luxury premium was significantly larger (interaction p = .037). Because quality and durability were bundled in the design, these coefficients should not be decomposed into separate quality and longevity effects.

***Table 2. Context-specific conditional logit estimates***

| Attribute | Fast fashion β | Accessible luxury β |
|---|---|---|
| Product ASC | 0.266 | -0.816*** |
| Demand-responsive pricing | -0.184 | -0.214 |
| Inventory markdown | 0.414* | -0.582*** |
| Price ratio | -0.942*** | -1.353*** |
| Fair quality/durability | 0.613*** | 0.804*** |
| High quality/durability | 1.269*** | 1.460*** |
| Popular brand | 0.632*** | 0.411* |
| Highly reputable brand | 0.964*** | 1.055*** |
| Personalised shopping | 0.714*** | 0.723** |
| Exclusive shopping | 1.128*** | 0.903*** |
| Confidence during use | 0.088 | 0.881*** |
| Distinctive/recognised | 0.594*** | 1.039*** |

**4.2 Willingness to pay**

WTP estimates clarify the money-metric magnitude of the stated preference trade-offs. In fast fashion, respondents were willing to trade approximately VND 0.81 million for the high rather than basic quality/durability profile, VND 0.72 million for exclusive rather than ordinary shopping, and VND 0.61 million for a highly reputable rather than little-known brand. The inventory-markdown mechanism carried a positive equivalent of VND 0.26 million, although this should not be interpreted as a recommendation to charge more for a markdown label: it is the price-equivalent utility of the stock-linked scenario relative to static pricing. Confidence did not have a reliable monetary value in this context.

In accessible luxury, the implied equivalents were larger because the price scale was higher: VND 7.55 million for the high quality/durability profile, VND 5.46 million for a highly reputable brand, VND 5.38 million for distinctiveness, and VND 4.67 million for an exclusive shopping experience. Inventory markdown generated a negative WTP of VND 3.01 million, with a 95% confidence interval from -4.66 to -1.36 million. This indicates the price compensation implied by the stated-choice model for accepting a stock-linked mechanism that conflicts with expected price stability. Given the age, income, and purchase-experience profile of the sample, these figures should be read as utility-equivalent trade-offs rather than market reservation prices for the wider accessible-luxury population.

***Table 3. Selected willingness-to-pay estimates (VND million)***

| Attribute | Fast fashion | Accessible luxury |
|---|---|---|
| Inventory markdown | 0.264 [0.032, 0.496] | -3.010 [-4.659, -1.362] |
| High quality/durability | 0.808 [0.521, 1.095] | 7.552 [4.808, 10.295] |
| Highly reputable brand | 0.614 [0.274, 0.954] | 5.458 [3.989, 6.926] |
| Exclusive shopping | 0.718 [0.400, 1.037] | 4.671 [3.166, 6.175] |
| Distinctive/recognised | 0.378 [0.170, 0.587] | 5.375 [3.582, 7.168] |

**4.3 Latent classes and model selection**

The homogeneous one-class model produced BIC = 3,784.2. Adding a second class reduced BIC to 3,641.0, whereas the three- and four-class models produced BIC values of 3,658.6 and 3,698.0. Although AIC continued to decline with additional classes, those solutions introduced smaller segments and weaker parsimony; therefore, the two-class model was retained. Its entropy-based separation index was .677, indicating moderate rather than deterministic classification certainty. The reported class shares are estimated proportions within this sample and should not be interpreted as externally calibrated market-segment prevalence.

Class 1, representing 53.0% of the sample, was labelled price-functional pragmatists. Its price coefficient was -1.510, more than three times the magnitude observed in Class 2, and high quality was its strongest positive attribute (β = 1.555). Brand, shopping, and emotional coefficients were comparatively modest. Class 2, representing 47.0%, was labelled brand-experiential seekers. This group placed high utility on brand reputation (β = 1.491), exclusive shopping (β = 1.640), and distinctiveness (β = 1.230), while remaining less sensitive to price (β = -0.471). However, it reacted more negatively to demand-responsive pricing (β = -0.698), suggesting that lower price sensitivity does not imply tolerance for opaque or unstable pricing.

Posterior-weighted profiling supported these labels. Class 1 had lower mean income (VND 12.51 million), higher price consciousness (4.16/7), and lower brand orientation (3.85/7). Class 2 had mean income of VND 15.94 million, lower price consciousness (3.77), and higher brand orientation (4.34). The classes were similar in age and prior accessible-luxury experience, indicating that attitudinal orientation was more informative than simple demographics.

***Table 4. Two-class latent-class logit results***

| Attribute / profile | Class 1: Price-functional | Class 2: Brand-experiential |
|---|---|---|
| Class share | 53.0% | 47.0% |
| Price ratio | -1.510 | -0.471 |
| Demand-responsive pricing | -0.377 | -0.698 |
| Inventory markdown | -0.134 | -0.081 |
| High quality/durability | 1.555 | 0.864 |
| Highly reputable brand | 0.413 | 1.491 |
| Exclusive shopping | 0.462 | 1.640 |
| Distinctive/recognised | 0.122 | 1.230 |
| Mean income (VND million) | 12.51 | 15.94 |
| Price consciousness (1-7) | 4.16 | 3.77 |
| Brand orientation (1-7) | 3.85 | 4.34 |

### 4.4 Short-run revenue-index counterfactual

For the representative fast-fashion profile, the highest one-period revenue index among the nine tested configurations occurred at VND 0.9 million under inventory-based markdown. Predicted purchase probability was .788 and revenue per exposure was VND 0.709 million, compared with VND 0.640 million under static pricing at the same price, an increase of approximately 10.9%. Demand-responsive pricing generated a lower index of VND 0.605 million. For the prestige-oriented accessible-luxury profile, static pricing at VND 12 million produced the highest tested index, with a predicted purchase probability of .789 and revenue per exposure of VND 9.474 million. Demand-responsive and inventory-markdown mechanisms reduced the index by approximately 4.8% and 14.2%, respectively. These rankings are conditional on a one-shot choice in which future markdowns are not anticipated. They indicate short-run mechanism-category fit, not an unrestricted or intertemporal pricing optimum.

## 5. DISCUSSION

The findings provide a coherent explanation of how healing tourism demand and psychological outcomes are formed among urban residents. Urban Psychological Pressure performs a dual function in the model. It positively influences Expectation and Travel Intention, indicating that stressed consumers actively seek restorative travel experiences. However, it retains a negative effect on Mental Well-being even after experience quality, perceived value and emotional response are considered. Healing tourism should therefore be interpreted as a compensatory mechanism that may alleviate urban stress, but cannot fully replace broader mental health support or improvements in urban living conditions.

Social Media Exposure has its strongest effect on Expectation, confirming that digital content plays a central role in constructing anticipated healing benefits. Visual representations of natural landscapes, meditation, wellness rituals and quiet retreats create an imagined emotional outcome before travel. Nevertheless, its direct influence on Travel Intention is weaker than those of Perceived Value and Emotional Response. Social media can therefore generate awareness and initial interest, but sustained behavioural intention depends more strongly on whether the actual experience delivers credible value and emotional benefits.

Communication Style is the strongest predictor of Perceived Authenticity. This finding demonstrates that consumers assess not only the content of promotional messages, but also their tone, credibility and consistency with service delivery. Healing tourism providers should consequently avoid exaggerated claims regarding transformation, detoxification or psychological recovery. More effective communication should emphasise realistic outcomes, including relaxation, mindfulness, reconnection with nature and emotional restoration.

Healing Tourism Experience Quality emerges as the principal operational driver because it significantly affects authenticity, value, emotional response and mental well-being. This confirms that healing tourism cannot be developed through branding alone. Natural environments, service professionalism, safety, programme design and restorative atmosphere must be integrated into a coherent customer journey. Perceived Value subsequently connects experience quality and authenticity with behavioural and psychological outcomes. In this context, value extends beyond price and facilities to include emotional relief, mental clarity, meaningful time use and a renewed sense of balance.

Emotional Response is the strongest predictor of Mental Well-being and a major determinant of Travel Intention. This supports the view that healing tourism operates primarily through affective mechanisms. Experiences that generate calmness, relief, positivity and inner balance are more likely to improve well-being and stimulate revisit or recommendation intentions. Emotional design should therefore be treated as a strategic capability, involving sensory atmosphere, staff interaction, activity pacing, silence, natural sound and reflective practices.

For Vietnam, the results imply that competitive healing tourism requires greater professionalisation, credible communication and measurable customer outcomes. Future research should validate the model using verified field data, longitudinal measurements and comparisons across different healing tourism formats.

## 6. CONCLUSION

This study provides choice-based evidence that the value of flexible pricing depends on the congruence between the pricing rule, the product category, and the targeted consumer segment. After quality screening, 293 respondents completed 2,051 estimable choices across fast-fashion and accessible-luxury contexts. Inventory-based markdown increased stated utility in fast fashion and produced the highest short-run revenue index for the representative fast-fashion profile, but it generated a substantial negative price-equivalent effect and weaker revenue performance in accessible luxury. This stock-linked markdown result should not be conflated with a general preference for algorithmic dynamic pricing. Demand-responsive repricing was not significant in the aggregate models and was particularly unattractive to the brand-experiential class. The high quality/durability profile, brand reputation, exclusivity, and distinctive emotion generated positive utility, although their money-metric importance differed sharply by context. The preferred two-class model further showed that price-functional pragmatists and brand-experiential seekers evaluate the same offer through different value structures, while its moderate classification certainty cautions against treating segment membership as deterministic. For accessible luxury, the young, non-probability sample and the high price-to-income ratio require additional caution because stated preferences may not reproduce choices under actual budget constraints. Retailers should therefore treat the revenue calculations as one-period counterfactual evidence, not as a long-run pricing optimum. In fast fashion, transparent stock-linked reductions may support inventory management when consumers do not systematically wait for them; in accessible luxury, stable pricing and non-price benefits are more consistent with preserving brand value. The practical implication is disciplined, mechanism-specific pricing rather than maximal price variation.

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