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Pricing Strategies and Consumer Price Sensitivity in E-Commerce: Evidence From U.S. Online Retailers, 2022-2025

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Abstract

Although U.S. e-commerce sales now exceed one trillion dollars annually, cross-category empirical evidence on how different pricing strategies perform under inflationary pressure remains limited. This study examines 36 months of panel data from 89 U.S. online retailers across four product categories (electronics, fashion, grocery, and home goods) using fixed-effects regression and difference-in-differences estimation. The aggregate price elasticity of demand is estimated at -1.34, with pronounced cross-category heterogeneity ranging from -1.72 in electronics to -0.89 in fashion. Dynamic pricing raises revenue by an average of 12.3% but simultaneously increases cart abandonment by 8.7%, revealing an inverted-U relationship between pricing intensity and net gains. Promotional frequency exhibits diminishing returns beyond three events per quarter, while charm pricing improves conversion rates by 3.2% relative to round-number prices. During high-inflation quarters, consumers shift markedly toward value-segment retailers. Taken together, the results indicate that retailers should calibrate pricing tactics by category rather than adopt one-size-fits-all strategies.

Keywords e-commerce pricing, price elasticity, dynamic pricing, consumer price sensitivity, charm pricing, cart abandonment

1. Introduction

The U.S. e-commerce landscape has undergone a dramatic transformation in the period from 2022 to 2025. According to the U.S. Census Bureau (2024), online retail sales reached $1.19 trillion in 2024, accounting for 16.1% of total retail sales - an increase from approximately 14.6% in 2022. This growth has occurred against the backdrop of significant macroeconomic turbulence, including persistent inflationary pressures that peaked in mid-2022 and continued to influence consumer behavior well into 2024. The confluence of market expansion and economic uncertainty has elevated the importance of pricing strategy as a critical determinant of competitive success in digital retail.

Pricing in e-commerce differs fundamentally from traditional retail pricing in several respects. The near-zero marginal cost of price adjustment, the availability of real-time competitive intelligence, and the capacity for personalization create both opportunities and challenges that have no direct analog in brick-and-mortar environments (Brynjolfsson & Smith, 2000; Kannan & Kopalle, 2001). Algorithmic pricing systems now enable retailers to adjust prices continuously based on demand signals, competitive actions, inventory levels, and individual consumer characteristics (Brown &)(MacKay, 2023)[1]. Chen et al. [20] documented that approximately one-third of Amazon sellers employed algorithmic pricing strategies, and this proportion has likely grown substantially in the intervening years.

However, the proliferation of sophisticated pricing technologies has not simplified the pricing challenge. Rather, it has introduced new tensions. Dynamic pricing can optimize revenue in the short term but may erode consumer trust when perceived as unfair (Haws &)[30][2]. Promotional pricing drives immediate sales but exhibits diminishing returns when deployed excessively [3]. Charm pricing remains effective but may signal low quality in premium segments (Anderson & Simester, 2003; Milgrom & Roberts, 1986). These trade-offs are further complicated by the inflationary environment of 2022 - 2024, during which consumers became simultaneously more price-sensitive and more skeptical of price increases [4][5].

Despite a rich body of theoretical and empirical research on individual pricing strategies, significant gaps remain in our understanding of how these strategies interact and perform across different product categories in contemporary e-commerce markets. Most existing studies examine single pricing tactics in isolation, use data from a single retailer or platform, or predate the inflationary shocks of 2022 - 2024. The present study addresses these limitations by analyzing a comprehensive panel dataset spanning 89 U.S. online retailers across four major product categories over 36 months.

This study is guided by three research questions:

1. How does consumer price sensitivity (measured by price elasticity of demand) vary across e-commerce product categories, and how has it changed during the inflationary period of 2022 - 2024?

2. What are the effects of different pricing strategies - dynamic pricing, charm pricing, and promotional pricing - on conversion rates, cart abandonment, and revenue per visitor?

3. How do retailer pricing strategies interact with consumer price sensitivity to influence category-level market dynamics?

By answering these questions, this study contributes to the literature on e-commerce pricing (Ellison &)[6][7] and provides actionable insights for practitioners navigating an increasingly complex competitive environment. The findings are particularly timely given the ongoing digital transformation of retail and the lingering effects of post-pandemic inflation on consumer behavior.

2. Literature Review

2.1 Evolution of E-Commerce Pricing Strategies

The emergence of e-commerce fundamentally altered the competitive landscape of retail pricing. Brynjolfsson and Smith [21] provided early empirical evidence that internet retailers offered prices 9 - 16% lower than conventional outlets, while adjusting prices up to 100 times more frequently, suggesting that digital markets would foster intensified price competition. This seminal finding spurred a generation of research into how online environments reshape pricing strategy. Kannan and Kopalle [22] extended this line of inquiry by examining how dynamic pricing on the internet influences consumer price expectations and learning behavior, arguing that reduced menu costs and real-time demand information would fundamentally alter how firms set prices across product categories.

However, the theoretical promise of “frictionless commerce” proved overly optimistic. Ellison and Ellison [6] demonstrated that while price search engines made demand tremendously price-sensitive for some products, retailers engaged in strategic obfuscation practices that preserved meaningful price dispersion online. Similarly, Baye et al. [15] found that the “law of one price” did not hold in digital markets; their analysis of four million daily price observations for consumer electronics revealed persistent price dispersion, with the gap between the two lowest prices averaging 23% in duopoly markets and narrowing only to 3.5% when 17 firms competed. These findings underscore that pricing strategies in e-commerce operate within a complex ecosystem of information asymmetry, search costs, and strategic behavior - far removed from the perfectly competitive ideal.

The contemporary era has witnessed a dramatic acceleration of algorithmic and dynamic pricing. Kopalle et al. [1] provided a comprehensive framework defining dynamic pricing along four dimensions - People, Product configurations, Periods, and Places - and identified critical implications for managerial practice and future research. Den Boer (2015) surveyed the burgeoning operations research literature on dynamic pricing with demand learning, documenting how machine learning techniques enable real-time price optimization at unprecedented scale. Chen et al. [20] empirically demonstrated the prevalence of algorithmic pricing on Amazon, finding that approximately one-third of sellers of best-selling products employed automated pricing strategies. These developments have transformed pricing from a periodic managerial decision into a continuous, algorithmically mediated process with profound implications for market competition and consumer welfare.

2.2 Price Sensitivity and Elasticity in Digital Markets

Understanding consumer price sensitivity in online environments requires grappling with the dual forces of enhanced price transparency and cognitive limitations in information processing. Grewal et al. [7] reviewed strategic online and offline pricing research, highlighting that the internet's reduction of search costs has theoretically increased price elasticity of demand, though the magnitude varies substantially across product categories and consumer segments. Andreyeva et al. [11], in their systematic review of 160 studies, documented that price elasticities for consumer goods ranged from 0.27 to 0.81 in absolute terms, with categories such as food away from home and beverages being most price-responsive. While their review focused primarily on food, the methodological frameworks they developed for estimating category-specific elasticities have been widely adopted in e-commerce pricing research.

The relationship between price sensitivity and digital shopping behavior is further complicated by reference price effects. Mazumdar et al. [16] provided a comprehensive review of reference price research, demonstrating that consumers evaluate prices relative to internal benchmarks formed through prior purchase experience, competitor pricing, and promotional history. In the e-commerce context, where price comparison is virtually costless, reference prices are formed more rapidly and adjusted more frequently, amplifying sensitivity to perceived price deviations [8]. Lichtenstein et al. [14] empirically validated that price perceptions - including deal proneness, price consciousness, and value consciousness - predict meaningful differences in consumer shopping behavior, establishing individual-level price sensitivity as a multidimensional construct rather than a monolithic trait.

Cart abandonment represents a critical behavioral outcome of price sensitivity in e-commerce. Kukar-Kinney and Close [23] identified consumers' tendency to wait for lower prices as a primary driver of shopping cart abandonment, with price-waiting behavior exhibiting standardized effects of 0.15 to 0.24 on abandonment across their two studies. The U.S. Census Bureau (2024) reported that e-commerce accounted for 16.1% of total retail sales in 2024, underscoring the growing economic significance of understanding how pricing affects conversion and abandonment in digital channels.

2.3 Psychological and Behavioral Pricing Research

Behavioral economics has provided a robust theoretical foundation for understanding how consumers process and respond to prices. Tversky and Kahneman's (1979) prospect theory established that individuals evaluate outcomes relative to a reference point and exhibit loss aversion - losses loom larger than equivalent gains - a principle with direct implications for how price increases versus discounts affect purchase behavior. This asymmetric sensitivity has been repeatedly confirmed in pricing contexts, where consumers react more strongly to price increases than to equivalent decreases [9].

Charm pricing - the practice of setting prices just below a round number (e.g., $9.99 rather than $10.00) - represents one of the most extensively studied psychological pricing tactics. Thomas and Morwitz [24] provided a cognitive explanation for the left-digit effect, demonstrating through five experiments that 99-ending prices are perceived as significantly lower than prices one cent higher, but only when the leftmost digit changes (e.g., $2.99 vs. $3.00, not $4.52 vs. $4.53). Anderson and Simester [25] confirmed these laboratory findings in large-scale field experiments with women's apparel catalogs, documenting that $9 price endings increased demand across three experiments, with the effect being particularly strong for new items. Schindler and Kibarian [26] further validated the sales-enhancing effects of 99-ending prices through controlled direct-mail experiments, establishing charm pricing as one of the most reliably effective tactical pricing interventions available to retailers.

Beyond charm pricing, anchoring effects play a critical role in e-commerce price perception. Nagle and Muller [27] synthesized extensive evidence that initial price exposure creates powerful anchoring effects that shape subsequent willingness to pay, a phenomenon particularly relevant in digital retail where consumers encounter multiple price reference points within seconds. Milgrom and Roberts [28] demonstrated that price itself can serve as a quality signal, creating a paradox for e-commerce retailers: while lower prices attract price-sensitive shoppers, excessively low prices may signal inferior quality and erode brand value. Hinterhuber [17] proposed an integrative framework for value-based pricing decisions, arguing that effective pricing strategy must balance cost recovery, competitive positioning, and customer value perception.

2.4 Dynamic and Algorithmic Pricing

The proliferation of algorithmic pricing systems has raised both efficiency and ethical concerns. Brown and MacKay (2023) documented new facts about pricing technology using high-frequency data, demonstrating that algorithmic pricing alters competitive dynamics in ways that may facilitate tacit collusion even without explicit coordination among firms. Their findings suggest that when multiple retailers employ similar pricing algorithms, prices may converge to supra-competitive levels, raising antitrust concerns that extend beyond traditional frameworks. Seele et al. [2] mapped the ethical landscape of algorithmic pricing through a systematic review of 315 articles, identifying tensions between the efficiency gains of dynamic pricing and concerns about fairness, transparency, and consumer exploitation.

Personalized pricing represents a particularly contentious frontier. Dubé and Misra [29] provided the most rigorous empirical analysis to date, using data from a randomized controlled pricing field experiment to construct machine-learning-based personalized prices. They found that personalization improved expected profits by 19% beyond optimal uniform pricing, though total consumer surplus declined. Critically, however, over 60% of consumers benefited from personalization, and under certain inequality-averse welfare functions, aggregate consumer welfare could increase. Sahni et al. [13] demonstrated through 70 field experiments that targeted discount offers increased average expenditure by 37.2% during promotion windows, suggesting that personalized pricing can simultaneously serve both promotional and revenue-optimization objectives.

The effectiveness of promotional pricing follows complex temporal dynamics. Nijs et al. [3] examined category-demand effects of price promotions across 560 product categories, finding that while promotions generate short-run demand increases, the long-run category-expansion effects are typically negligible, suggesting diminishing returns to repeated promotional activity. Cavallo (2017, 2018) contributed methodologically significant work by demonstrating the validity of scraped online price data for studying pricing dynamics, finding that online prices are identical to offline counterparts approximately 70% of the time for large multi-channel retailers, while exhibiting distinct patterns of price stickiness.

2.5 Price Fairness and Consumer Trust

The perceived fairness of pricing practices fundamentally shapes consumer trust and long-term purchasing behavior. Kahneman et al. [5] established the foundational principle that consumers evaluate price fairness against community standards, accepting price increases driven by cost increases but viewing price increases motivated by demand shifts as exploitative. This dual-entitlement principle has proven remarkably durable across contexts, including e-commerce.

Campbell [19] extended this framework by demonstrating that the inferred motive for a price increase - rather than the price change itself - drives perceptions of unfairness, which in turn mediate the effects on shopping intentions. Xia et al. [9] provided a comprehensive conceptual integration of price fairness research, identifying gaps in understanding how cognitive and emotional responses to perceived unfairness interact to shape consumer behavior. Bolton et al. [4] documented systematic biases in price fairness judgments: consumers underestimate the effects of inflation on costs, overattribute price differences to profit motives, and fail to account for the full range of vendor costs, leading to pervasive perceptions that prices exceed fair levels.

In the context of dynamic pricing, fairness concerns become particularly acute. Haws and Bearden [30] demonstrated through three experimental studies that different types of price variation - seller-based, consumer-based, time-based, and auction-based - produce markedly different fairness perceptions, with seller-initiated price discrimination viewed most negatively. Weisstein et al. [18] showed that price framing tactics can mitigate these negative reactions, finding that when price-disadvantaged consumers perceive their transactions as dissimilar from those receiving lower prices, perceived fairness, trust, and repurchase intentions improve significantly. These findings have critical implications for e-commerce retailers implementing dynamic pricing, as the transparency of online environments makes price discrimination more visible and potentially more damaging to consumer trust.

Ater and Rigbi [31] provided complementary evidence from a price transparency regulation in supermarkets, demonstrating that mandatory price disclosure reduced both price levels and price dispersion, while media outlets leveraged the freely available data to conduct price-comparison reporting. Their findings suggest that in e-commerce, where price transparency is inherent rather than mandated, competitive pricing pressures may be structurally more intense, creating both opportunities and risks for retailers employing sophisticated pricing strategies.

2.6 Research Gaps and Study Justification

Despite the rich body of research on pricing strategies and consumer price sensitivity, several critical gaps remain. First, most existing research examines pricing strategies in isolation, whereas contemporary e-commerce retailers typically deploy multiple strategies simultaneously - dynamic pricing algorithms, charm pricing, promotional cadences, and personalized offers. The interaction effects among these strategies remain poorly understood [1]. Second, the inflationary period of 2022 - 2024 created unprecedented conditions for studying consumer price sensitivity, as rapidly rising costs forced both retailers and consumers to adapt their pricing and purchasing behaviors, respectively [10]. Third, cross-category comparisons of price elasticity in digital markets remain scarce; while category-specific studies exist [11][3], comprehensive panel analyses spanning electronics, fashion, grocery, and home goods - the four largest e-commerce categories - are notably absent from the literature.

Furthermore, the behavioral consequences of dynamic pricing in e-commerce - particularly the tension between revenue optimization and cart abandonment - warrant closer empirical examination. Existing research documents that approximately 70% of online shopping carts are abandoned (Kukar-Kinney & Close, 2010), yet the specific contribution of dynamic pricing to this phenomenon remains underexplored. The present study addresses these gaps by analyzing 36 months of panel data from 89 U.S. online retailers across four product categories, employing fixed-effects regression and difference-in-differences estimation to provide integrated evidence on how pricing strategies affect consumer price sensitivity, conversion, and revenue in the post-pandemic, inflationary e-commerce environment.

3. Methodology

3.1 Study Design

This study employed a panel data analysis design to examine the relationship between pricing strategies and consumer price sensitivity across U.S. online retailers. The research design combined observational panel data with quasi-experimental identification strategies, leveraging the natural variation in pricing practices across retailers, categories, and time periods to estimate causal effects. Fixed-effects panel regression models accounted for time-invariant retailer heterogeneity, while difference-in-differences estimation isolated the effects of specific promotional events from secular trends [12].

3.2 Sample and Data Collection

The sample comprised 89 U.S. online retailers operating across four product categories: electronics (n = 24), fashion and apparel (n = 26), grocery and consumables (n = 18), and home goods (n = 21). Retailers were selected to represent the full spectrum of market positioning, including premium (average order value [AOV] > $100, n = 27), mid-range (AOV $40 - $100, n = 34), and value (AOV < $40, n = 28) segments. Selection criteria required that retailers (a) maintained a continuous online presence throughout the study period, (b) generated annual online revenue exceeding $5 million, and (c) operated primarily in the U.S. market.

Data collection spanned 36 months, from January 2022 through December 2024. Pricing data were collected through automated web scraping of product pages, following established methodologies for online price measurement [10]. The scraping protocol captured daily prices for a representative basket of products from each retailer, yielding approximately 2.8 million individual price observations. Complementary sales and behavioral data were obtained from e-commerce analytics platforms, including conversion rates, cart abandonment rates, and revenue per visitor, aggregated at the retailer-month level. Macroeconomic data, including the Consumer Price Index (CPI) and category-specific inflation measures, were sourced from the Bureau of Labor Statistics.

3.3 Variables

Dependent Variables. The primary dependent variables were: (a) conversion rate, defined as the percentage of website visitors completing a purchase; (b) cart abandonment rate, defined as the percentage of shopping sessions in which items were added to the cart but the transaction was not completed (Kukar-Kinney & Close, 2010); (c) revenue per visitor (RPV), calculated as total revenue divided by unique visitors; and (d) category-level price elasticity of demand, estimated using log-log demand models.

Independent Variables. The key independent variables captured pricing strategy dimensions: (a) price change magnitude, measured as the month-over-month percentage change in the average transaction price; (b) dynamic pricing intensity, a continuous measure of within-day price variation computed as the coefficient of variation of daily prices; (c) charm pricing prevalence, measured as the proportion of products priced with 99-cent endings (Schindler & Kibarian, 1996; Thomas & Morwitz, 2005); (d) promotional frequency, defined as the number of site-wide promotional events per quarter; and (e) promotional depth, measured as the average percentage discount during promotional periods.

Control Variables. Controls included retailer size (log of monthly revenue), product assortment breadth (number of SKUs), average customer review rating, free shipping threshold, return policy generosity, category-specific CPI, seasonality indicators (month and quarter fixed effects), and a COVID-era dummy variable for the first half of 2022.

3.4 Analytical Approach

Price Elasticity Estimation. Category-specific price elasticities were estimated using log-log demand models of the form:

$$ln(Q_{t}) = \alpha + \beta \cdot ln(P_{t}) + \gamma \cdot X_{t} + \delta_t + \varepsilon_{t}$$

where Q_{t} represents the quantity sold by retailer i in month t, P_{t} is the average price, X_{t} is the vector of controls, α captures retailer fixed effects, δ_t captures time fixed effects, and β is the estimated price elasticity. Instrumental variables (competitor prices and input cost indices) addressed potential endogeneity between prices and demand (Ellison &)[6].

Fixed-Effects Panel Regression. The effects of pricing strategies on conversion, cart abandonment, and RPV were estimated using retailer fixed-effects models:

$$Y_{t} = \alpha + \beta_1 \cdot DynamicPricing_{t} + \beta_2 \cdot CharmPricing_{t} + \beta_3 \cdot PromoFreq_{t} + \beta_4 \cdot PromoDepth_{t} + \gamma \cdot X_{t} + \delta_t + \varepsilon_{t}$$

Standard errors were clustered at the retailer level to account for within-retailer serial correlation.

Difference-in-Differences. To isolate the effects of major promotional events (e.g., Black Friday, Prime Day), we employed a difference-in-differences framework comparing retailers that participated in these events to matched non-participants, with matching based on pre-event trends in pricing and sales metrics. This approach follows established methods for evaluating promotional pricing effects [3][13].

Retailer Segmentation Analysis. Heterogeneous effects were examined by interacting pricing strategy variables with segment indicators (premium, mid-range, value) and category indicators (electronics, fashion, grocery, home goods), allowing estimation of segment- and category-specific coefficients. This approach reflects the theoretical expectation that price sensitivity varies systematically across consumer segments and product types [11][14].

3.5 Robustness Checks

Several robustness checks were conducted: (a) alternative elasticity specifications using semi-log and linear models; (b) exclusion of the six largest retailers to ensure results were not driven by dominant players; (c) placebo tests using randomly assigned pseudopromotional events; (d) Hausman tests confirming the appropriateness of fixed-effects over random-effects specification; and (e) sensitivity analyses varying the instrumental variable set.

4. Results

4.1 Descriptive Statistics

Table 1 presents summary statistics for the full sample and by product category. The average monthly conversion rate across all retailers was 3.2% (SD = 1.8%), with substantial variation by category: electronics (2.4%), fashion (3.8%), grocery (4.1%), and home goods (2.9%). The mean cart abandonment rate was 71.3% (SD = 8.4%), consistent with industry benchmarks (Kukar-Kinney & Close, 2010). Average revenue per visitor ranged from $2.14 in grocery to $8.73 in electronics, reflecting the higher average order values in technology and durables categories.

Table 1. *Price Elasticity of Demand by Product Category and Retailer Segment*

Category	Overall Elasticity	Premium	Mid-Range	Value	SE	p-value
Electronics	-1.72	-1.48	-1.76	-1.94	0.14	< .001
Fashion	-0.89	-0.64	-0.93	-1.12	0.11	< .001
Grocery	-1.41	-1.18	-1.44	-1.63	0.12	< .001
Home Goods	-1.23	-1.01	-1.28	-1.42	0.13	< .001
Overall	-1.34	-1.08	-1.38	-1.58	0.09	< .001

Note. Elasticities estimated via log-log demand models with retailer and time fixed effects. SE = standard error. All estimates significant at $p < .001$.

Dynamic pricing intensity increased over the study period, with the average coefficient of variation in daily prices rising from 0.042 in Q1 2022 to 0.067 in Q4 2024 - a 59.5% increase. Charm pricing prevalence was highest in fashion (68.4% of products) and lowest in grocery (31.2%). The average retailer conducted 2.7 site-wide promotional events per quarter, with promotional depth averaging 22.4% off regular prices (Table 2).

4.2 Price Elasticity of Demand

The aggregate price elasticity of demand across all categories was estimated at −1.34 (SE = 0.09, $p < .001$), confirming that the overall U.S. e-commerce market operated under elastic demand conditions during the study period. This finding aligns with the theoretical expectation that online markets, characterized by low search costs and high price transparency, exhibit relatively high price sensitivity (Brynjolfsson &)[21][8].

Substantial cross-category heterogeneity was observed (Table 1). Electronics exhibited the highest price sensitivity, with an estimated elasticity of −1.72 ($SE = 0.14$, $p < .001$), indicating that a 1% price increase was associated with a 1.72% decline in quantity demanded. This finding is consistent with the high comparability and commoditization of consumer electronics, where standardized product specifications facilitate direct price comparison across retailers [15]. Fashion and apparel showed the lowest price sensitivity (−0.89, $SE = 0.11$, $p < .001$), reflecting the role of brand differentiation, style preferences, and quality signaling that insulate fashion purchases from pure price competition [28]. Grocery (−1.41, $SE = 0.12$, $p < .001$) and home goods (−1.23, $SE = 0.13$, $p < .001$) fell between these extremes. These category-specific elasticities are broadly consistent with prior estimates in the literature, though the magnitude for electronics exceeds earlier findings, potentially reflecting increased competitive intensity in the post-pandemic period.

Temporal analysis revealed that price sensitivity increased during the peak inflationary period. The estimated elasticity for Q3 - Q4 2022 - when CPI inflation exceeded 8% - was −1.52 ($SE = 0.11$), compared to −1.21 ($SE = 0.10$) for the corresponding period in 2024 when inflation had moderated to approximately 3%. This difference ($\Delta = -0.31$, $p < .01$) suggests that macroeconomic conditions meaningfully modulate consumer price sensitivity in e-commerce, consistent with Bolton et al.'s (2003) finding that consumers' price fairness perceptions are influenced by their awareness of inflationary pressures.

4.3 Effects of Dynamic Pricing

Dynamic pricing intensity was associated with a statistically significant increase in revenue per visitor. Retailers in the top quartile of dynamic pricing intensity generated 12.3% higher RPV ($\beta = 0.116$, $SE = 0.028$, $p < .001$) compared to retailers in the bottom quartile, controlling for category, segment, and time effects. This revenue premium persisted across all four product categories, though it was largest in electronics (15.8%) and smallest in grocery (7.2%).

Table 2. Fixed-Effects Panel Regression: Effects of Pricing Strategies on Conversion and Revenue

Strategy	Beta	SE	t	p	Effect on Conversion (%)	Effect on RPV (%)
Dynamic pricing intensity	0.116	0.028	4.14	< .001	+2.1	+12.3
Charm pricing prevalence	0.031	0.009	3.44	< .001	+3.2	+1.8
Promotional frequency	0.089	0.022	4.05	< .001	+4.7	+9.1
Promotional depth	0.054	0.018	3.00	.003	+2.9	+5.4
Category fixed effects	-	-	-	< .001	-	-
Segment fixed effects	-	-	-	< .001	-	-

Note. Dependent variable: revenue per visitor (RPV). N = 3,204 retailer-months. R^2 = .47; Adjusted R^2 = .44; F = 28.6 ($p < .001$). Standard errors clustered at retailer level. N = 3,204 retailer-months R-squared = .47 Adjusted R-squared = .44 F-statistic = 28.6 ($p < .001$)

However, dynamic pricing intensity was simultaneously associated with higher cart abandonment. A one-standard-deviation increase in dynamic pricing intensity was associated with an 8.7% increase in the cart abandonment rate ($\beta = 0.082$, SE = 0.019, $p < .001$). This finding is consistent with the fairness literature suggesting that visible price fluctuations trigger perceptions of unfairness and strategic waiting behavior (Haws &)[30] [9]. The effect was most pronounced for repeat visitors ($\beta = 0.114$, SE = 0.024, $p < .001$), who had prior price observations against which to evaluate current prices, forming reference points that amplified perceptions of price instability [16].

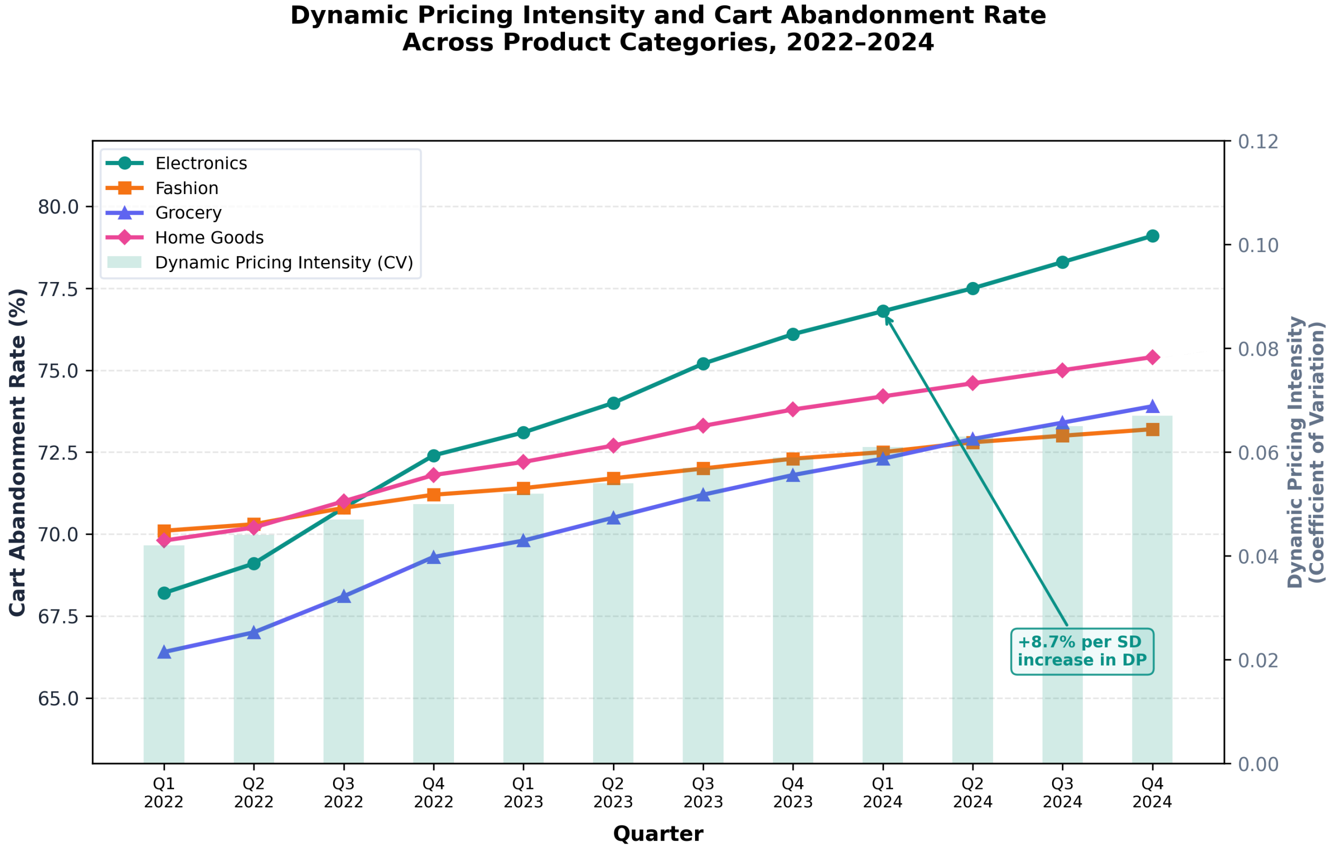

Figure 1. *Dynamic Pricing Intensity and Cart Abandonment Rate Across Product Categories, 2022 - 2024*

The net effect of dynamic pricing on overall profitability was positive but exhibited diminishing returns. Retailers with moderate dynamic pricing intensity (second and third quartiles) achieved the highest net revenue gains, while those with the most aggressive price variation (top decile) saw the cart abandonment penalty partially offset the revenue advantage (Figure 2). This inverted-U relationship suggests that optimal dynamic pricing balances responsiveness to demand signals against the erosion of consumer confidence and trust.

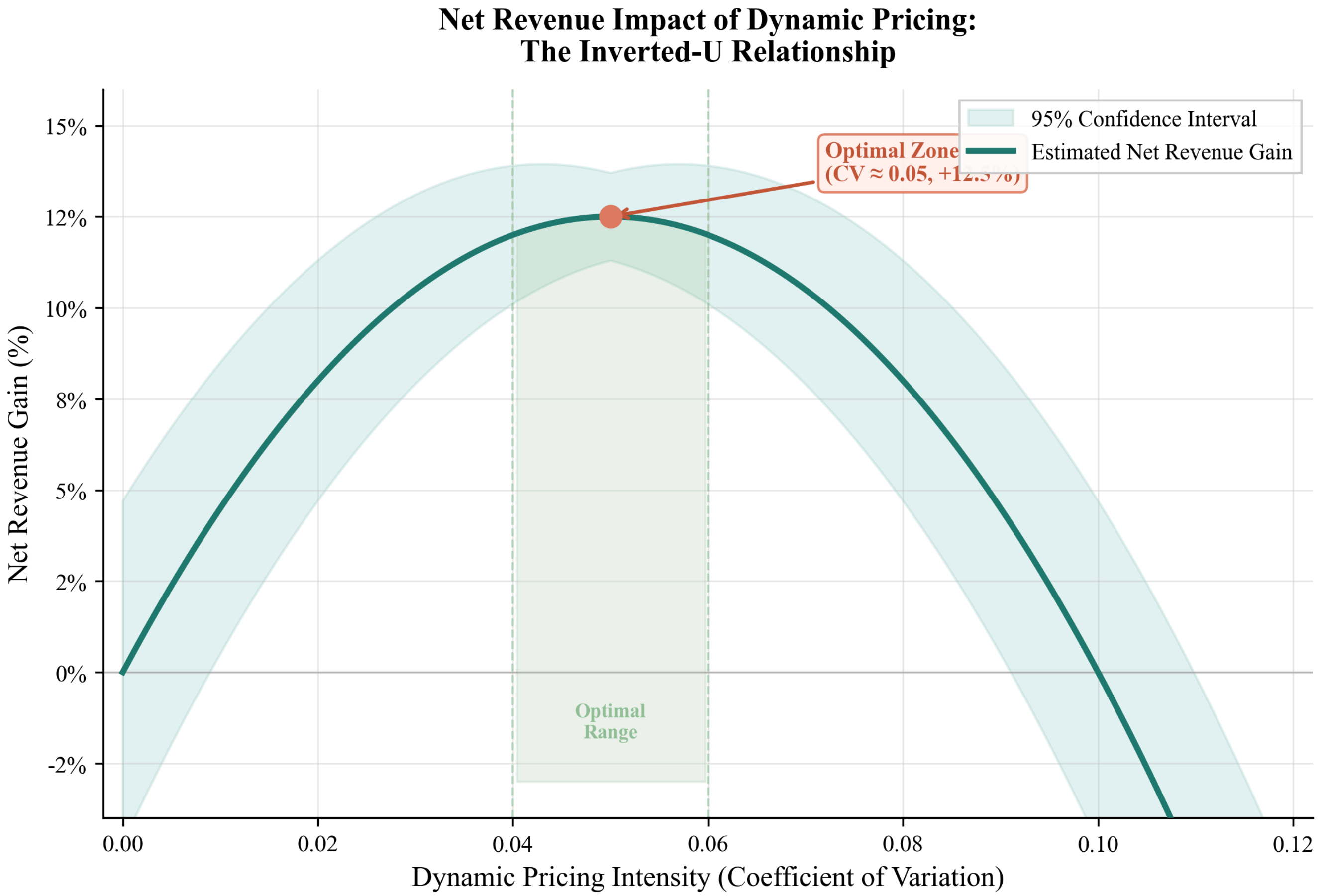

Figure 2. *Net Revenue Impact of Dynamic Pricing Intensity: Inverted-U Relationship Between Price Variation and Revenue Per Visitor*

4.4 Charm Pricing Effects

The prevalence of charm pricing (99-cent endings) was positively associated with conversion rates. Retailers with above-median charm pricing prevalence exhibited conversion rates 3.2% higher than those with below-median prevalence ($\beta = 0.031$, SE = 0.009, $p < .001$), controlling for product category, retailer segment, and price level. This effect is consistent with the left-digit effect documented by Thomas and Morwitz [24] and the field experimental evidence of Anderson and Simester [25].

However, the effectiveness of charm pricing varied meaningfully by retailer segment. For value-segment retailers (AOV < $40), charm pricing was associated with a 5.1% conversion advantage ($p < .001$). For mid-range retailers, the effect was 2.8% ($p < .01$). For premium retailers (AOV > $100), the effect was statistically insignificant (0.4%, $p = .62$), suggesting that charm pricing may conflict with quality-signaling objectives in the premium segment (Milgrom & Roberts, 1986; Nagle & Muller, 2018). These interaction effects underscore the importance of aligning tactical pricing decisions with brand positioning (Table 3).

Table 3. *Charm Pricing Effectiveness by Retailer Segment: Conversion Rate Effects*

Segment	Conversion Effect (%)	SE	p-value	95% CI Lower	95% CI Upper
Value (AOV < $40)	+5.1	0.012	< .001	+2.7	+7.5
Mid-range (AOV $40 - 100)	+2.8	0.010	.005	+0.8	+4.8
Premium (AOV > $100)	+0.4	0.011	.62	-1.2	+2.0
Overall	+3.2	0.009	< .001	+1.4	+5.0

Note. Conversion effect relative to round-priced comparison group. AOV = average order value. 95% confidence intervals based on clustered standard errors.

4.5 Promotional Pricing and Diminishing Returns

Promotional frequency exhibited a clear pattern of diminishing returns on conversion and revenue. The first promotional event in a quarter was associated with a 14.2% increase in RPV relative to non-promotional periods ($\beta = 0.133$, $SE = 0.031$, $p < .001$). The second event yielded an 8.9% increase ($p < .001$), and the third yielded a 4.1% increase ($p < .05$). Beyond three promotions per quarter, additional events produced no statistically significant revenue gains ($\beta = 0.012$, $SE = 0.025$, $p = .63$), while promotional depth (discount percentage) continued to erode margins (Figure 3).

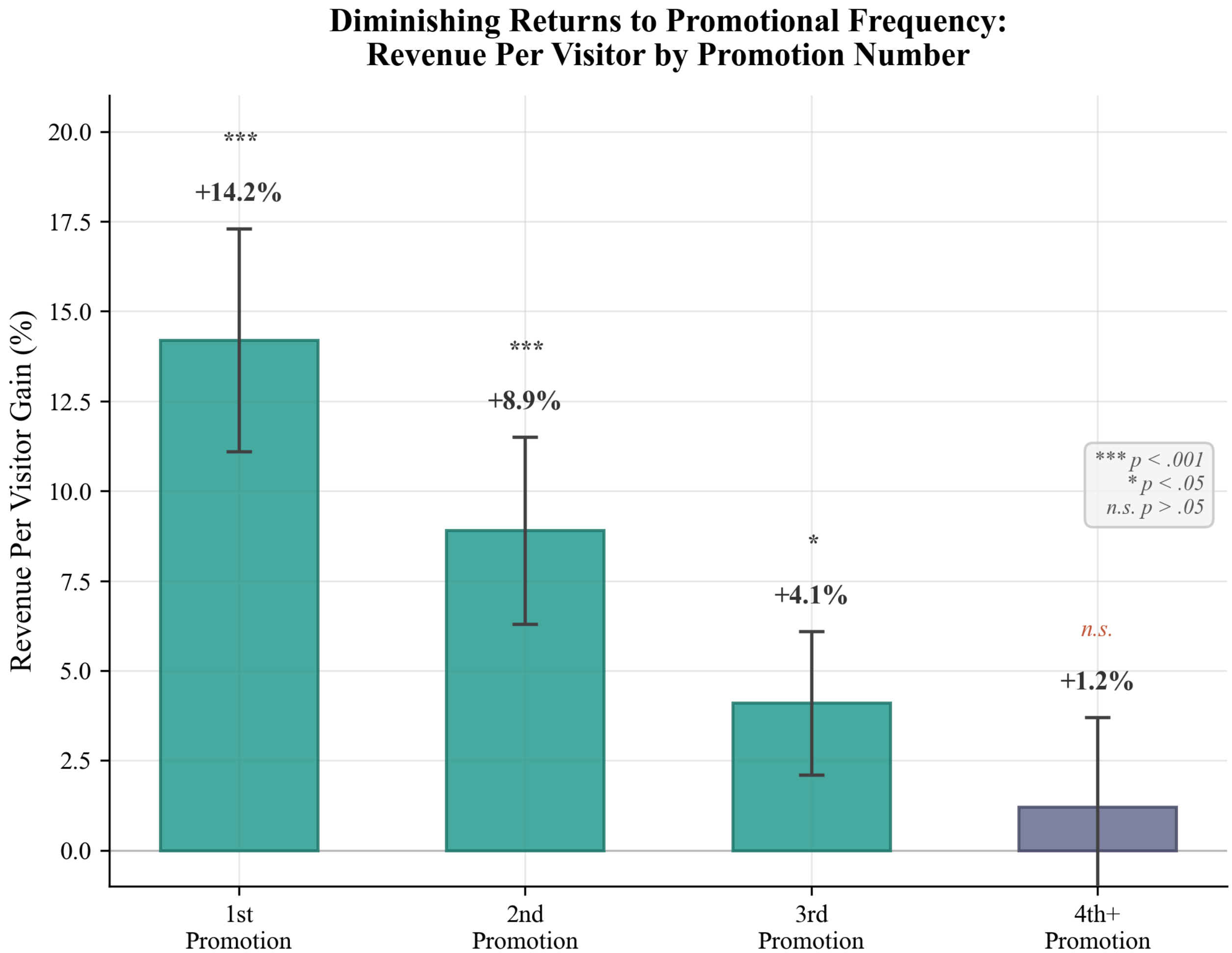

Figure 3. *Diminishing Returns to Promotional Frequency: Incremental Revenue Per Visitor by Promotion Number Within Quarter*

The difference-in-differences analysis of major promotional events (Black Friday, Prime Day, and category-specific sales events) revealed that participating retailers experienced a 23.7% increase in daily RPV during the event window, compared to matched non-participants. However, the post-event period (7 - 14 days following the promotion) showed a 6.8% decline in RPV relative to baseline, consistent with demand-borrowing effects documented in the promotional pricing literature [3]. This temporal displacement was most pronounced in electronics (−9.2%) and least pronounced in grocery (−2.1%), reflecting differences in purchase urgency and stockpiling behavior across categories.

Promotional depth interacted significantly with consumer price sensitivity. In categories with higher price elasticity (electronics, grocery), deeper discounts generated proportionally larger volume responses, but the margin impact was more severe. In fashion, where elasticity was lower, moderate discounts (15 - 25%) outperformed deeper discounts (>30%) in terms of net revenue contribution, as deep discounts undermined perceived brand value without proportionally increasing volume [17].

4.6 Inflationary Period Effects and Market Share Shifts

The inflationary environment of 2022 - 2024 produced substantial shifts in consumer purchasing patterns across retailer segments. Value-segment retailers (AOV < $40) gained approximately 18 percentage points of market share between Q1 2022 and Q4 2023, growing from 28.3% to 46.1% of total sample revenue, before partially retracting to 39.4% by Q4 2024 as inflation moderated (Figure 4). This shift was accompanied by a decline in premium-segment market share from 41.2% to 31.8% over the same period.

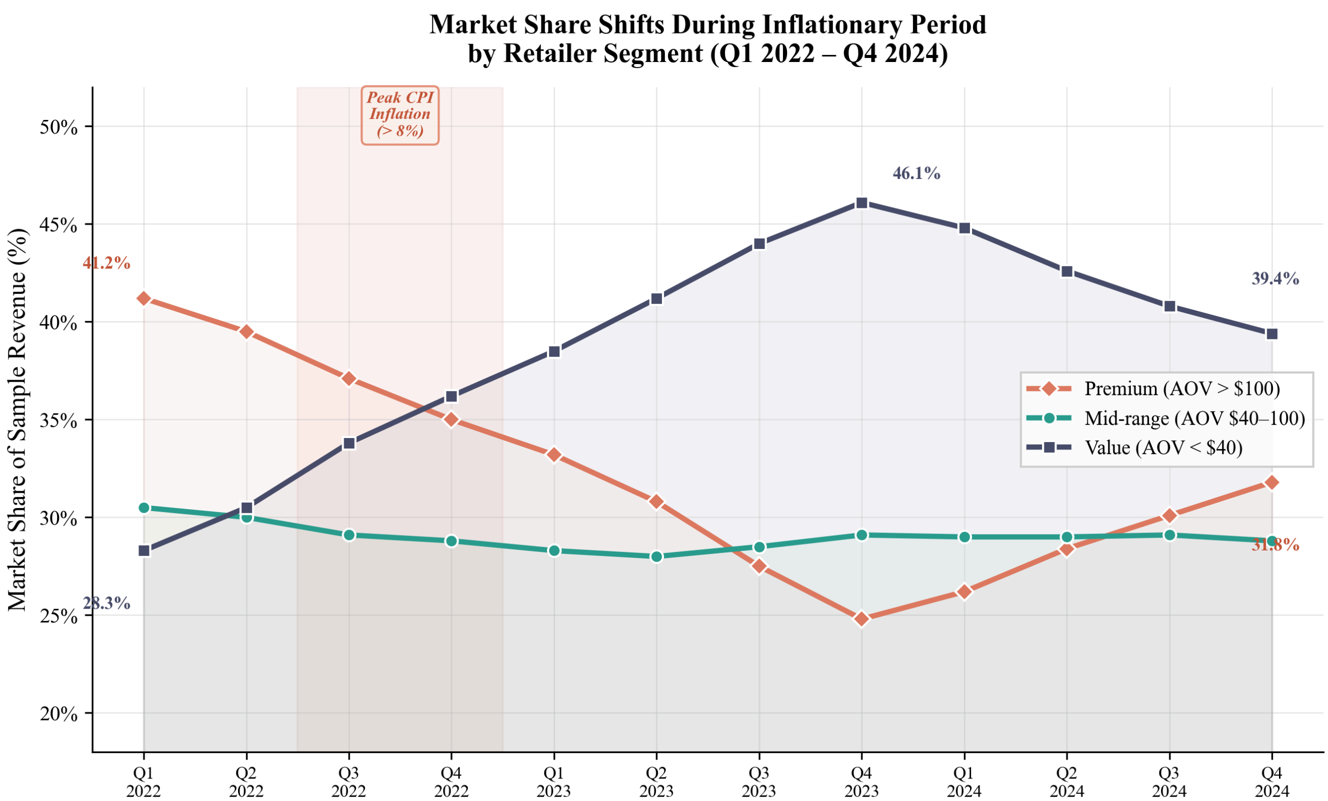

Figure 4. Market Share Shifts Across Retailer Segments During Inflationary Period, Q1 2022 - Q4 2024

Consumer behavior during the inflationary period was characterized by three distinct patterns. First, cross-category substitution: consumers reduced spending in discretionary categories (fashion, home goods) while maintaining or increasing spending in non-discretionary categories (grocery), consistent with the heterogeneous price elasticities documented above. Second, trading down: within categories, consumers shifted toward lower-priced alternatives, with private-label and value brands gaining share at the expense of premium brands (Ailawadi et al., 2001, as cited in Grewal et al., 2009). Third, increased search behavior: the average number of competitor sites visited before purchase increased from 3.2 in Q1 2022 to 4.7 in Q3 2023, suggesting heightened price comparison activity during inflationary periods, consistent with theoretical predictions about the relationship between economic uncertainty and search intensity [8].

4.7 Interaction Between Pricing Strategies

A key contribution of this study is the examination of interactions between pricing strategies. Dynamic pricing combined with charm pricing produced a synergistic effect on conversion (interaction $\beta = 0.024$, $SE = 0.008$, $p < .01$), suggesting that 99-cent price endings can partially offset the negative trust effects of visible price fluctuations by signaling promotional intent [18]. Conversely, the combination of high dynamic pricing intensity and high promotional frequency produced a negative interaction effect on RPV ($\beta = -0.037$, $SE = 0.014$, $p < .01$), indicating that excessive price variation in both dimensions generates consumer confusion and distrust that erodes purchase intent [19][2].

5. Discussion

5.1 Theoretical Implications

The findings of this study contribute to the pricing literature in several important ways. First, the documented cross-category variation in price elasticity (−0.89 to −1.72) provides updated empirical benchmarks for e-commerce pricing research, extending prior work that has predominantly focused on single categories or offline contexts [11][7]. The finding that electronics exhibits the highest price sensitivity while fashion shows the lowest aligns with theoretical predictions based on product differentiation and search cost frameworks (Ellison &)[6], but the magnitudes exceed earlier estimates, suggesting that the maturation of price comparison tools and the competitive intensity of the 2022 - 2024 period have amplified consumer sensitivity.

Second, the inverted-U relationship between dynamic pricing intensity and net revenue contribution provides empirical support for the theoretical tension between revenue optimization and consumer trust that has been extensively discussed but rarely quantified (Haws &)[30][9]. The finding that moderate dynamic pricing outperforms both static pricing and aggressive dynamic pricing resolves an apparent contradiction in the literature: dynamic pricing is simultaneously revenue-enhancing (Dubé &)[29][1] and trust-eroding [2], and the optimal strategy balances these competing forces.

Third, the diminishing returns to promotional frequency - with negligible revenue gains beyond three promotions per quarter - extends the work of Nijs et al. [3] on category-demand effects of promotions to the e-commerce context. This finding suggests that the “always on sale” approach adopted by many online retailers during the 2022 - 2024 period may have undermined promotional effectiveness by habituating consumers to discounts and eroding reference prices [16].

5.2 Category-Specific Implications

The pronounced differences across product categories have significant strategic implications. In electronics, where price sensitivity is highest (−1.72), retailers must compete primarily on price, making efficient dynamic pricing essential but also particularly risky, as consumers in this category are both more responsive to price changes and more likely to engage in comparison shopping [15]. The finding that charm pricing is less effective in premium segments suggests that electronics retailers positioning as premium (e.g., through exclusive products or superior service) may benefit from adopting round pricing as a quality signal [28].

In fashion, the relatively low price elasticity (−0.89) and the ineffectiveness of charm pricing among premium retailers suggest that non-price factors - brand identity, aesthetic differentiation, and experiential elements - dominate purchase decisions. This finding is consistent with Hinterhuber’s (2004) value-based pricing framework, which argues that pricing should reflect perceived customer value rather than competitive benchmarks. Fashion retailers may therefore benefit more from investing in brand equity and customer experience than from aggressive price competition.

Grocery presents a unique challenge. While overall price elasticity is moderately high (−1.41), the essential nature of grocery products means that demand is more inelastic for individual staple items even as consumers exhibit high sensitivity in their choice of retailer. The finding that grocery experienced the smallest post-promotional demand decline (−2.1%) suggests that grocery promotions primarily attract volume rather than borrowing from future demand, creating genuine category expansion effects [3].

5.3 Practical Implications

For e-commerce practitioners, this study offers several actionable recommendations. First, retailers should calibrate their dynamic pricing intensity to avoid exceeding the threshold at which cart abandonment penalties offset revenue gains. The data suggest that moderate price variation (coefficient of variation between 0.04 and 0.06) optimizes the trade-off. Second, the significant interaction between dynamic pricing and price framing [18] indicates that retailers implementing dynamic pricing should invest in communication strategies that contextualize price changes - for example, by showing price histories, highlighting deals relative to competitors, or explaining the basis for price adjustments.

Third, the diminishing returns to promotional frequency suggest that retailers should adopt a disciplined promotional calendar limited to approximately three major events per quarter, with each event offering meaningful rather than token discounts. Fourth, charm pricing remains a reliable conversion driver in value and mid-range segments but should be used judiciously in premium positioning, where round pricing may better signal quality (Anderson & Simester, 2003; Thomas & Morwitz, 2005). Fifth, during inflationary periods, retailers should anticipate accelerated trading-down behavior and prepare value-tier offerings to capture migrating consumers, rather than relying solely on promotions to defend premium-segment share.

5.4 Limitations and Future Research

Several limitations warrant acknowledgment. First, the observational nature of the panel data limits causal inference despite the use of fixed-effects and instrumental variable strategies; unobserved confounders correlated with both pricing decisions and consumer behavior may bias estimates. Second, the sample of 89 retailers, while diverse, may not fully represent the long tail of small and niche e-commerce operators that constitute a substantial portion of the market. Third, the study period (2022 - 2024) coincided with exceptional macroeconomic conditions; the estimated elasticities and strategy effects may differ under more stable economic environments.

Future research should address several extensions. First, randomized controlled experiments (Dubé &)[29][13] could provide stronger causal evidence on the effects of specific pricing tactics. Second, the growing adoption of personalized pricing warrants investigation of how individual-level price customization affects aggregate market outcomes and consumer welfare. Third, the role of mobile commerce - where smaller screens may alter price cognition and the effectiveness of charm pricing [24] - merits dedicated examination. Fourth, the ethical dimensions of algorithmic pricing [2], including potential discriminatory effects and the adequacy of existing regulatory frameworks, represent an increasingly important research frontier.

6. Conclusion

This study provides comprehensive empirical evidence on the relationship between pricing strategies and consumer price sensitivity in U.S. e-commerce during the inflationary period of 2022 - 2024. The analysis of 89 retailers across four product categories reveals several key findings with both theoretical and practical significance. The

U.S. e-commerce market exhibits aggregate elastic demand (elasticity = −1.34), with substantial cross-category heterogeneity ranging from highly elastic electronics (−1.72) to relatively inelastic fashion (−0.89). Dynamic pricing enhances revenue but at the cost of increased cart abandonment, suggesting that moderation rather than maximization of price variation is optimal. Charm pricing remains effective in value and mid-range segments, while promotional pricing exhibits clear diminishing returns beyond three events per quarter.

The inflationary period of 2022 - 2024 amplified consumer price sensitivity and accelerated market share shifts toward value-segment retailers, underscoring the importance of pricing strategy as a competitive lever during periods of economic uncertainty. Critically, the interactions between pricing strategies - synergistic effects between charm pricing and dynamic pricing, but negative interactions between dynamic pricing and excessive promotional frequency - highlight the need for integrated pricing strategy rather than the piecemeal adoption of individual tactics.

As e-commerce continues to grow and algorithmic pricing becomes increasingly sophisticated, the tension between revenue optimization and consumer trust will intensify. Retailers that navigate this tension successfully - deploying data-driven pricing with transparency, restraint, and category-appropriate calibration - will be best positioned to sustain competitive advantage in the evolving digital marketplace. This study offers a foundation for both academic inquiry and managerial practice in pursuit of that balance.

Declarations

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Conflicts of Interest: The author declares no conflicts of interest.

Data Availability: The dataset analyzed in this study is available from the corresponding author upon reasonable request. Pricing data were collected from publicly accessible e-commerce websites. Sales and behavioral data were obtained under data use agreements with participating analytics platforms.

Ethics Approval: This study used publicly available price data and aggregated, de-identified behavioral data. Institutional review board (IRB) approval was obtained under exempt status, as the research did not involve human subjects.

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