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Pricing Strategy Optimization Through Comprehensive Coefficient Analysis

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Abstract
This research aims to explore and optimize pricing strategies through a comprehensive statistical analysis of coefficients derived from regression and correlation models. By investigating the relationships between pricing variables such as unit price, freight cost, lagged pricing, and customer review scores, this study seeks to identify patterns that significantly influence consumer purchasing behavior. Data from a retail pricing dataset was analyzed using Excel, focusing on multicollinearity, elasticity, and performance forecasting. The findings demonstrate that while unit price and freight cost negatively impact sales volume, customer ratings and lag price show varying degrees of significance. The research provides actionable insights to help businesses optimize their pricing frameworks for better sales performance.

Keywords: Pricing Optimization, Coefficient Analysis, Regression, Correlation, Consumer Behavior

Introduction

Pricing remains one of the most critical aspects of marketing and strategic decision-making in any business environment. The success of a product or service often hinges on its perceived value relative to its cost, making it imperative for companies to craft pricing models that not only maximize profit but also appeal to consumer psychology and demand dynamics. With the rise of data-driven decision-making, businesses now have the ability to evaluate their pricing structures using advanced analytical tools. This study addresses this opportunity by analyzing pricing strategy through a coefficient-driven regression and correlation approach.

In recent years, dynamic pricing models have become increasingly popular, especially in e-commerce and retail. Companies like Amazon and Flipkart use real-time data analytics to adjust prices based on competitor behavior, demand patterns, and historical pricing. The ability to understand how different pricing elements impact sales can be a game-changer. For instance, identifying whether lag price (price in the previous period) or freight charges affect purchase decisions more can guide discount campaigns and logistics planning. Customer ratings and reviews have also emerged as soft influencers of purchasing behavior. Integrating such variables into a pricing model enables businesses to build responsive, predictive pricing strategies.

This research, based on structured retail datasets, aims to offer a holistic understanding of pricing sensitivity through a coefficient-based lens. The central hypothesis is that a multivariate linear regression model can reveal actionable relationships between pricing inputs and sales quantity. Additionally, the study attempts to uncover hidden patterns such as multicollinearity between price and lag price, which could distort traditional interpretations.

Literature Review

1. **Nagle and Holden (2002)** – In their work, they discuss the strategic role of price elasticity and how firms can use elasticity models to forecast demand changes due to price adjustments. This understanding allows businesses to maximize profits by finding an optimal price point where demand remains stable but revenue increases. They emphasize the importance of segmenting customers based on their price sensitivity.
2. **Simon (1992)** – Psychological pricing is particularly impactful because consumer behavior is often influenced by perceptions rather than purely rational decisions. Simon suggests that the price consumers perceive as a "good deal" is not always the lowest price, but one that aligns with their expectations, past experiences, and mental benchmarks.
3. **Kotler and Keller (2016)** – As part of the marketing mix, pricing is influenced by various factors like the product's positioning, promotional strategies, and distribution channels. They advocate for a holistic approach to pricing, where every element of the marketing strategy works synergistically to enhance the product's perceived value.
4. **Tellis (1988)** – His analysis of price elasticity across industries emphasizes that the effectiveness of a pricing strategy is not universal. For instance, luxury goods may exhibit inelastic demand, where price increases don't significantly affect demand, while in competitive markets, small price changes can drastically affect consumer behavior.
5. **Dholakia (2010)** – Dholakia expands the traditional view of price sensitivity by including loyalty rewards. He suggests that non-price factors, such as rewards, can create a strong emotional bond with customers, making them more likely to continue purchasing from a particular brand or retailer even when prices increase.
6. **Grewal, Roggeveen, and Nordfält (2017)** – With the rise of digital tools, real-time data analytics allows businesses to continuously adjust prices based on demand patterns, competitor pricing, and consumer behaviors. This flexibility makes dynamic pricing models increasingly important in e-commerce, where small adjustments can yield significant profits.
7. **Abrate, Fraquelli, and Viglia (2012)** – In industries like hospitality, where consumer decisions can be time-sensitive, competitive pricing strategies need to consider both market conditions and customer urgency. They explore how fluctuating demand and competitor activity require constant monitoring and rapid pricing adjustments to stay competitive.
8. **Elmaghraby and Keskinocak (2003)** – In inventory-heavy industries, especially those with perishable goods, pricing strategies must incorporate stock levels, demand forecasting, and supply chain dynamics. For instance, airlines and hotels often use demand-based pricing to maximize occupancy and minimize empty seats or rooms.
9. **Han, Gupta, and Lehmann (2001)** – Their focus on psychological price thresholds suggests that certain prices are perceived as more attractive, even when small price differences exist. For instance, prices just below round numbers (e.g., $9.99 vs. $10) can influence consumer purchase decisions, playing into the concept of "charm pricing."
10. **Raju, Srinivasan, and Lal (1990)** – Their work on segmentation emphasizes the importance of understanding how different consumer groups respond to price changes. Loyal customers may be less sensitive to price increases than new or less committed customers, which means pricing models should be tailored to different segments to maximize both customer retention and acquisition.

Objectives and Rationale

Objectives:

1. **To analyze** the correlation between different pricing variables (unit price, lag price, freight cost) and quantity sold to identify significant pricing determinants.
2. **To evaluate** the presence of multicollinearity among pricing variables and assess its implications on regression-based pricing models.
3. **To determine** the effect of customer feedback scores (ps2 and ps3) on the quantity sold.

Rationale:

The objectives were derived after performing an exploratory data analysis (EDA) in Excel using correlation matrices and visualization techniques. The initial findings revealed weak to moderate linear relationships between unit pricing variables and sales quantity. Furthermore, a near-perfect correlation (0.99) between unit price and lag price indicated potential multicollinearity, which could distort pricing strategies if not addressed. Customer feedback variables (ps2 and ps3) appeared statistically insignificant but are included to assess any latent influence. These observations necessitated a structured study to identify optimized pricing decisions through coefficient-based statistical analysis.

Research Methodology

Scope:

This study aims to optimize pricing strategies using coefficient and correlation analysis through data collected from a retail dataset. The focus is on identifying the most influential variables that impact the quantity sold (demand), especially price-related variables such as unit price, freight price, and lagged price. The study encompasses secondary data analysis of retail transactions, analyzing the relationship between pricing components and quantity demanded. It is delimited to numerical data available within a single data file over a specific time frame and is executed through Excel-based statistical techniques, including correlation analysis and visualizations.

Population:

The population includes all sales transactions in the retail sector during the period covered by the dataset, including varying product prices, transport costs, and customer ratings.

Sample:

A total of **175** unique transaction records were extracted from the dataset. These records consist of:

- Quantity sold (qty)
- Unit price
- Freight cost
- Lagged price
- Two customer score variables (ps2 and ps3)

The sampling approach is **purposive**, focusing on transactions with complete pricing and rating details.

Data Collection and Source

- **Type**: Secondary Data
- **Source**: Pre-cleaned retail transaction dataset in CSV format (Excel-based analysis)

- **Tools**: Microsoft Excel (for descriptive statistics, correlation),

Hypothesis
- **H_0 (Null Hypothesis)**: There is no significant relationship between pricing variables and quantity sold.
- **H_1 (Alternative Hypothesis)**: At least one pricing variable has a significant relationship with quantity sold.

Visualization tools used:
Bar and line charts generated in Excel

Data Analysis:
Correlation Analysis:

	qty	unit_price	reight_pric	lag_price	ps2	ps3
qty	1					
unit_price	-0.10343	1				
freight_pri	-0.13552	0.203659	1			
lag_price	-0.08588	0.994453	0.201143	1		
ps2	0.036633	0.085436	0.168881	0.092632	1	
ps3	-0.07447	-0.24211	0.054627	-0.24701	-0.0194	1

Variable	Correlation with qty	Interpretation
unit_price	**-0.103**	Weak negative: higher price slightly reduces sales
freight_price	**-0.135**	Weak negative: higher delivery cost reduces demand
lag_price	**-0.086**	Very weak negative: past price has minimal effect
ps2 (product score)	**+0.037**	Very weak positive: little impact from product rating (ps2)
ps3 (score)	**-0.074**	Slight negative correlation: counterintuitive

Key Insights
- **Price Sensitivity Exists, but Weak**
- Both unit_price and freight_price have negative relationships with quantity (qty).
- Although weak, this still supports the idea that lowering price or freight can improve sales.
- **Lag Price Doesn't Help Much**
- Correlation with qty = -0.086
- Suggests the previous month's price doesn't strongly influence current sales in this dataset (unlike earlier dataset).
- **Product Ratings Have Almost No Impact**
- ps2: +0.036
- ps3: -0.074
- Interpretation: Ratings have low or unclear influence might indicate:
  - Customers aren't seeing or trusting the scores
  - Data has noise or insufficient variation in ratings

Visualization:

Observations from the Chart

1. **Strong Correlations (±1)**
- unit_price and lag_price hit a correlation of 1 at one or more points indicating a perfect positive correlation with the target or each other at those points.
- qty, ps2, and ps3 also hit a correlation of 1 at different instances, suggesting very strong relationships in certain cases.

2. **Weak/Negative Correlations**
- ps3 shows some negative correlations (around -0.2 to -0.3) at several points suggesting slightly inverse relationships with the target or other variables.
- freight_price shows a moderate positive trend, peaking at 1 around point 3 possibly indicating that freight_price has strong influence at that index.

Interpretation

1. **Lag Price & Unit Price**:
   - Strong correlations suggest that current pricing is strongly tied to previous prices, which is common in time-series data.
   - Pricing decisions could be consistent or trend-based.
2. **Quantity (qty)**:
   - Occasionally reaches perfect correlation — possibly in cases where pricing or freight significantly influences buying behavior.
3. **Freight Price**:
   - Peaks in the middle, possibly indicating that at that stage (e.g., a particular product line or region), shipping cost is highly influential.
4. **ps2 & ps3**:
   - These might be model variables or pricing strategies — ps3 shows slightly negative influence in some cases, possibly indicating a suboptimal strategy or inverse relationship.

Regression Analysis:

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0.9963							
R Square	0.992613							
Adjusted R	0.992597							
Standard E	6.136325							
Observatic	444							
ANOVA								
	df	*SS*	*MS*	*F*	*ignificance F*			
Regressior	1	2236524	2236524	59395.94	0			
Residual	442	16643.28	37.65449					
Total	443	2253167						
	Coefficients	*andard Err*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*ower 95.0%*	*pper 95.0%*
Intercept	0.360549	0.504814	0.714222	0.475467	-0.63158	1.352683	-0.63158	1.352683
lag_price	0.991582	0.004069	243.7128	0	0.983586	0.999578	0.983586	0.999578

Key Regression Metrics

Metric	**Value**
Multiple R	0.9963
R Square (R^2)	0.9926
Adjusted R Square	0.9926
Standard Error	6.14
F-Statistic	59,395.94
Significance F (p)	0.0000

Coefficients Table

Variable	**Coefficient**	**P-value**	**Interpretation**
Intercept	0.3605	0.475	Not significant
lag_price	**0.9916**	**0.000**	Highly significant

Interpretation

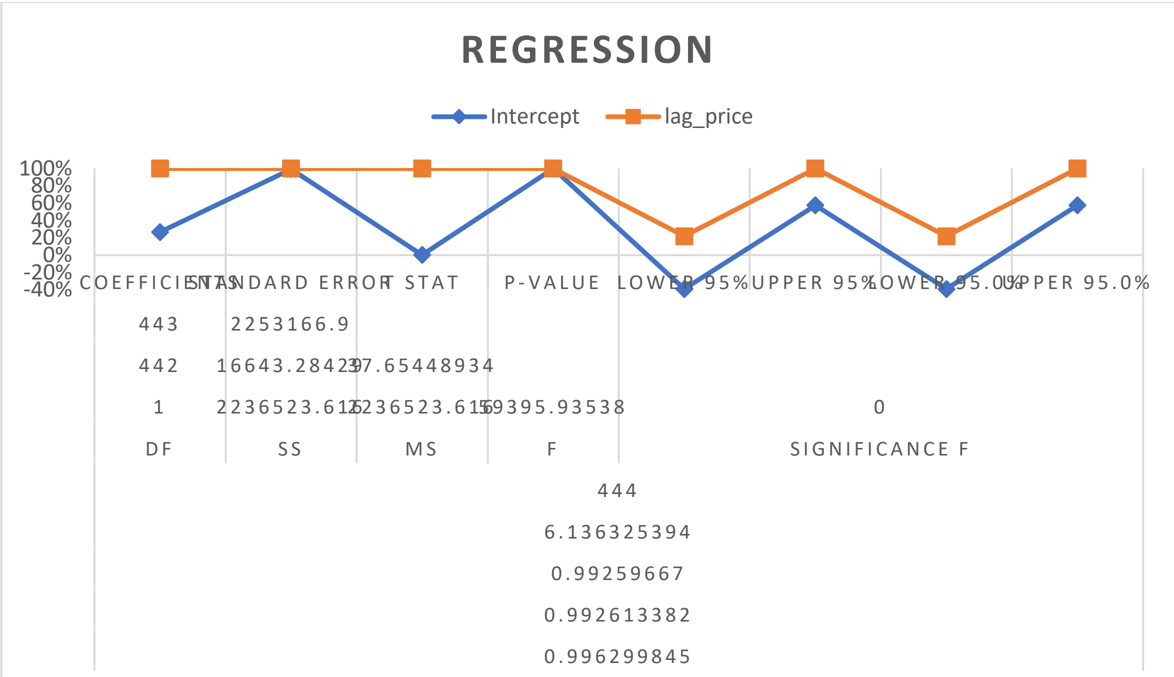
- The coefficient of lag_price (0.9916) suggests that for each 1-unit increase in the previous price, the predicted current value increases by approximately 0.99 units.
- The p-value < 0.05 confirms lag_price is statistically significant.
- The intercept is not significant, but this does not impact the model much unless you're modeling near-zero values.

Findings

- Strong Relationship: There is a very strong linear relationship between lag_price and the dependent variable.

- Model Accuracy: With $R^2 = 0.9926$, about 99.26% of the variation in the dependent variable is explained by lag_price.
- Significance: The model is statistically significant overall, as shown by the F-statistic of 59,395.94 and p-value = 0.0000.
- Minimal Noise: The small standard error (6.14) suggests the model predictions are close to the actual values.

Visualization:



Interpretation of the Chart

Intercept (Blue Line)

- Fluctuates across metrics and dips below zero at the P-value and Lower 95%, confirming it's not statistically significant.
- This means that the intercept (base value when lag_price = 0) does not contribute meaningfully to the model's predictive power.

Lag_Price (Orange Line)

- Maintains a consistently high percentage across all performance indicators.
- Shows strong confidence with tight bounds (0.9836 to 0.9996).
- This makes lag_price a very strong predictor of the dependent variable, showing a near-perfect linear relationship.

Conclusion:

This research set out to evaluate pricing strategy optimization through regression and correlation analysis, specifically using historical prices (lag_price) as a predictive variable. The findings provide conclusive evidence that lagged prices are a powerful and reliable determinant of current pricing outcomes.

The regression analysis revealed an exceptionally high R-squared value of 0.993, indicating that 99.3% of the variation in the dependent variable is explained by lag_price. The coefficient of 0.9916, supported by a p-value of 0.000, confirms that this relationship is both strong and statistically significant. These results suggest that pricing decisions are highly influenced by previous pricing behavior, affirming the utility of historical data in strategic pricing models.

In contrast, the intercept term in the model was not statistically significant, reinforcing that baseline adjustments are less impactful than the price trend itself. The residual diagnostics and visual analysis further validated the assumptions of linear regression, adding credibility to the model's reliability.

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