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The revenue growth analytics partner to executives driving pricing, sales, and marketing excellence

Mastering Price Elasticity Modeling: A Comprehensive Guide for Pricing, Analytics and Finance Professionals.

White Paper

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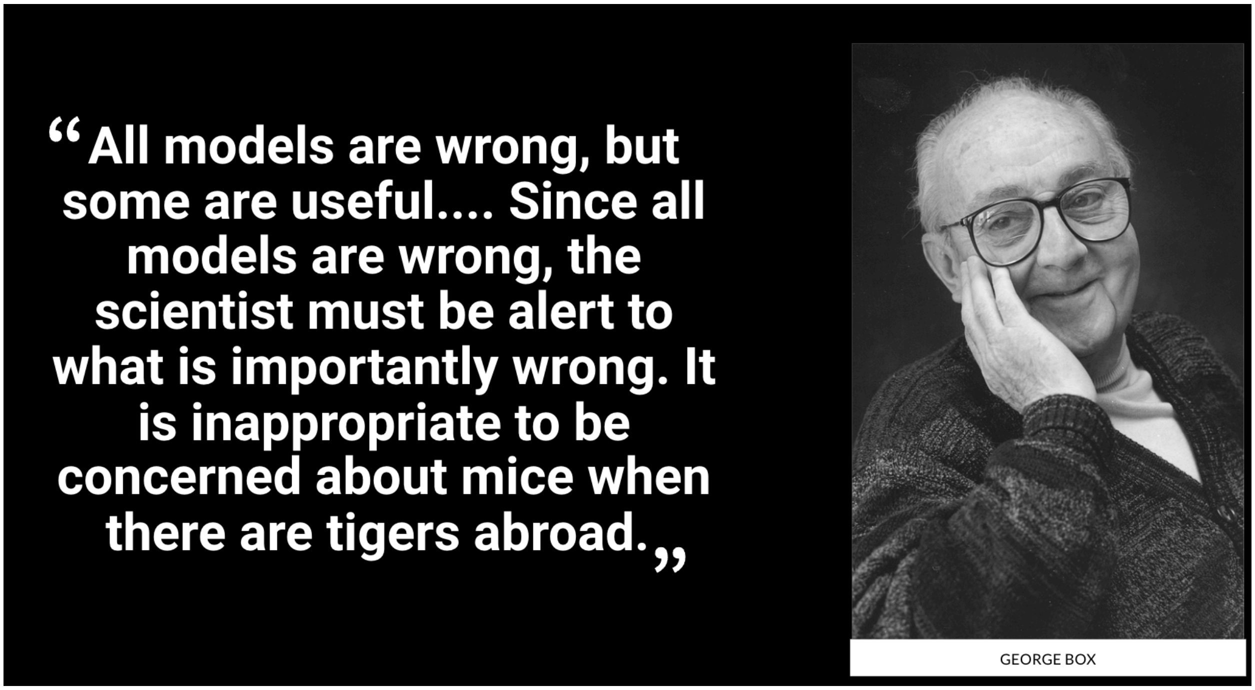
Mastering Price Elasticity Modeling: A Comprehensive Guide



Understanding price elasticity modeling has become crucial for companies aiming to optimize their pricing strategies and maximize profits. The Price Elasticity modeling approach empowers organizations to gauge how price changes affect demand for their products or services, providing invaluable insights for commercial decision-makers. By leveraging advanced techniques in price elasticity modeling, businesses can navigate market fluctuations, anticipate customer (both consumer and professional buyer) behavior, and stay ahead of the competition in an increasingly dynamic economic environment.

Our guide provides valuable information about price elasticity modeling, covering everything from fundamental concepts to cutting-edge machine learning methods. Readers will gain a deep understanding of both linear regression and machine learning-based approaches, data aggregation strategies, and strategic implications. Topics extend to advanced approaches, including random forest and gradient boosting, shedding light on their applications in estimating price sensitivities. By mastering various aspects of Price Elasticity modeling, pricing, marketing, and finance, professionals and data scientists can make more informed decisions, ultimately leading to enhanced profitability and market positioning in a world characterized by being data-rich but insights-poor.

George Box's famous quote, ***"All models are wrong, but some are useful,"*** captures an essential truth about price elasticity modeling. No model can perfectly capture every nuance of market behavior or predict exact outcomes - because all models are simplifications of reality.

For price elasticity modeling, this translates into focusing on what matters: identifying the key drivers of demand, understanding the relationship between price and volume, and being aware of the limitations of the data and assumptions used.

Rather than seeking perfection, we use these models to gain actionable insights that help us optimize pricing strategies, anticipate customer reactions, and understand the potential financial impact of price changes. The goal is to be aware of the limitations, continuously validate the model's assumptions, and update it as new data comes in.

Parsimony is critical in Price Elasticity modeling; in other words, you need to create a useful model with the least number of variables you can. As long as it's directionally correct and allows you to make the right pricing decision, a simpler model can often be more beneficial than a complicated ML model that is entirely black-box and may overfit your training data.

Understanding Price Elasticity

Price elasticity is a cornerstone concept in pricing strategy. It offers invaluable insights into customer behavior and market dynamics. This foundational analytical approach empowers businesses to make informed pricing, product positioning, revenue, and profit optimization decisions.

Definition and Importance

Price elasticity demonstrates the responsiveness or sensitivity of customer demand for a specific product or service based on its price. It is quantified as a numerical value, typically negative, indicating the percentage change in quantity demanded resulting from a 1% change in price. This metric is paramount in pricing strategy, as it directly influences how value is distributed between a firm and its customers.

The significance of price elasticity lies in its ability to guide strategic pricing decisions. While the precise numerical value may not always be critical, understanding where a product or service falls on the elasticity spectrum is crucial for effective pricing strategies. This knowledge allows businesses to anticipate market reactions to price changes and adjust their strategy accordingly.

Types of Price Elasticity

Price elasticity manifests in various forms, each offering unique insights into market dynamics:

Elasticity Type	Description	Example
Own-Price Elasticity	Measures how demand for a product changes in response to changes in its own price.	Demand for a soft drink drops when its price rises.
Cross-Price Elasticity	Examines how the demand for one product is affected by price changes in another, often related, product.	Demand for tea rises when the price of coffee increases.
Competitive Price Index Elasticity	Assesses how demand responds to changes in relative price competitiveness.	Market share declines when our price gap (or index) to competition increases.
Promotional Price Elasticity	Focuses on how temporary price reductions or promotions impact demand.	Increased demand during a "Buy One, Get One Free" offer.
Inelastic Demand (Elasticity < 1)	Significant price changes have minimal impact on demand.	Essential goods like insulin, fuel, or tires.
Elastic Demand (Elasticity > 1)	Minor price changes have a significant impact on demand.	Most consumer products, luxury goods, non-essential items like designer clothing

Factors Affecting Price Elasticity

Several factors influence the price elasticity of a product or service:

1. **Availability of substitutes:** Products with readily available alternatives tend to have higher elasticity.
2. **Necessity vs. luxury:** Essential goods typically have lower elasticity than luxury items.
3. **Brand loyalty:** Strong brand loyalty can reduce price sensitivity, leading to lower elasticity.
4. **Time horizon:** Elasticity can increase or decrease over time as consumers have more opportunity to adjust their behavior.
5. **Proportion of income:** Products that constitute a larger portion of consumer income tend to have higher elasticity.

Understanding these factors allows businesses to more accurately anticipate and model consumer responses to price changes. For instance, beef exhibits high elasticity due to the availability of substitutes like pork or chicken, whereas insulin, being an essential medication, displays inelastic demand.

Significance of Price Elasticity

Comprehending price elasticity is crucial for businesses to make informed pricing decisions and optimize revenue generation. Understanding where a product falls on the elasticity spectrum empowers companies to:

- **Maximize Revenue and Profits:** By knowing the elasticity of demand, companies can strategically adjust prices to maximize revenue and gross profit. For elastic goods, lowering prices or implementing promotions might substantially increase sales volume, offsetting the lower per-unit profit. Conversely, increasing prices might lead to higher profits for inelastic goods despite a slight decrease in sales volume.
- **Minimize Pricing Risk:** Knowing the Price Elasticity coefficients by SKU, Customer, and Product enables the Finance team to conduct practical what-if scenario analyses of key price changes or discount actions. It also allows the Strategy team to run scenarios around competitor price changes to observe volume and profit impacts.
- **Optimize Inventory and Liquidity:** Price Elasticity-based scenario analyses give the Supply Chain team visibility into how specific promotional or clearance pricing actions would impact inventory levels or how deep clearance price discounts need to be to deplete over-bought inventory that's not selling.

- **Inform Product Development:** Price elasticity insights can guide product development decisions. Inelastic demand suggests a loyal customer base willing to pay a premium, encouraging investments in product differentiation and innovation.
- **Optimize Marketing Strategies:** Understanding price sensitivity helps tailor marketing campaigns and promotional offers. Companies can target price-sensitive customers with discounts and bundles while focusing on value propositions for customers with inelastic demand.
- **Competitive Advantage:** Accurately gauging price elasticity helps businesses respond to competitive pricing strategies. Companies can make strategic pricing adjustments to maintain or gain market share by understanding their products' elasticity relative to competitors.

Why is it critical to know my Price Elasticities?

The Concept of Volume Hurdles

Price elasticity modeling also serves as a critical tool in profit sensitivity analysis. This approach explores the effects of price changes on both customer behaviors and the firm's profitability. A vital component of this analysis is the concept of volume hurdles, which represent the minimum growth in sales volume necessary to counteract the decrease in per-unit profit due to a price reduction.

Pricing for profitability involves a fundamental analysis of how price changes impact customer behavior and the firm's bottom line. The concept of volume hurdles is crucial here—it defines the required volume changes needed to justify a price change.

Before implementing any pricing action, checking if these volume hurdles are realistically attainable is essential. Strategic considerations might lead you to pursue or avoid a pricing action, depending on competitive dynamics or market share objectives, even if the volume hurdle isn't met.

Volume hurdles are a critical first-line analysis for pricing decisions, ensuring that price changes align with your profitability goals.

Volume Hurdle for a Price Decrease

The size of this volume increase depends on the initial contribution margin.

A high contribution margin means a smaller increase in sales volume is needed, while a low margin requires a much more significant volume increase to make the price cut profitable. Understanding these dynamics is critical, especially when planning tactical price cuts like discounts or promotions.

Volume Hurdle for a Price Increase

Conversely, a price increase allows for a reduction in volume while maintaining profitability up to a certain point.

The volume that can be forfeited depends on the contribution margin—smaller margins can tolerate more significant volume decreases, while larger margins require more careful management of volume declines.

Understanding these thresholds ensures that any price increase decision is made with a clear view of its impact on profitability.

Price Increases and Decreases Have Non-Symmetrical Effects on Profit

It's important to note that the effects of price changes are not symmetrical. Price reductions often require much more significant increases in unit sales to maintain profitability than the volume loss that can be tolerated with price increases.

For example, with a 50% contribution margin, a 15% price increase might only need a 23% volume loss or less to be more profitable, while a 15% price cut could require a 43% volume growth to break even.

This asymmetry means that price cuts are often riskier than price increases.

Break-Even Volume Hurdles for Price Increases

Price Change %

Initial Contribution Margin %	5%	10%	15%	20%	25%	30%	35%	40%	45%	50%	55%
10%	-33%	-50%	-60%	-67%	-71%	-75%	-78%	-80%	-82%	-83%	-85%
15%	-25%	-40%	-50%	-57%	-63%	-67%	-70%	-73%	-75%	-77%	-79%
20%	-20%	-33%	-43%	-50%	-56%	-60%	-64%	-67%	-69%	-71%	-73%
25%	-17%	-29%	-38%	-44%	-50%	-55%	-58%	-62%	-64%	-67%	-69%
30%	-14%	-25%	-33%	-40%	-45%	-50%	-54%	-57%	-60%	-63%	-65%
35%	-13%	-22%	-30%	-36%	-42%	-46%	-50%	-53%	-56%	-59%	-61%
40%	-11%	-20%	-27%	-33%	-38%	-43%	-47%	-50%	-53%	-56%	-58%
45%	-10%	-18%	-25%	-31%	-36%	-40%	-44%	-47%	-50%	-53%	-55%
50%	-9%	-17%	-23%	-29%	-33%	-38%	-41%	-44%	-47%	-50%	-52%
55%	-8%	-15%	-21%	-27%	-31%	-35%	-39%	-42%	-45%	-48%	-50%
60%	-8%	-14%	-20%	-25%	-29%	-33%	-37%	-40%	-43%	-45%	-48%
65%	-7%	-13%	-19%	-24%	-28%	-32%	-35%	-38%	-41%	-43%	-46%
70%	-7%	-13%	-18%	-22%	-26%	-30%	-33%	-36%	-39%	-42%	-44%
75%	-6%	-12%	-17%	-21%	-25%	-29%	-32%	-35%	-38%	-40%	-42%
80%	-6%	-11%	-16%	-20%	-24%	-27%	-30%	-33%	-36%	-38%	-41%

Break-Even Volume Hurdle Matrix for Price Increases. You can lose up to this volume percentage and still be better off after the price increase in Gross Profit dollars.

Break-Even Volume Hurdles for Price Decreases

Price Change %

Initial Contribution Margin %	-5%	-10%	-15%	-20%	-25%	-30%	-35%	-40%	-45%	-50%	-55%
10%	100%										
15%	50%	200%									
20%	33%	100%	300%								
25%	25%	67%	150%	400%							
30%	20%	50%	100%	200%	500%						
35%	17%	40%	75%	133%	250%	600%					
40%	14%	33%	60%	100%	167%	300%	700%				
45%	13%	29%	50%	80%	125%	200%	350%	800%			
50%	11%	25%	43%	67%	100%	150%	233%	400%	900%		
55%	10%	22%	38%	57%	83%	120%	175%	267%	450%	1000%	
60%	9%	20%	33%	50%	71%	100%	140%	200%	300%	500%	1100%
65%	8%	18%	30%	44%	63%	86%	117%	160%	225%	333%	550%
70%	8%	17%	27%	40%	56%	75%	100%	133%	180%	250%	367%
75%	7%	15%	25%	36%	50%	67%	88%	114%	150%	200%	275%
80%	7%	14%	23%	33%	45%	60%	78%	100%	129%	167%	220%

Break-Even Volume Hurdle Matrix for Price Decreases. You need to gain at least this much more unit volume to break even on Gross Profit dollars.

By leveraging price elasticity insights, businesses can develop more nuanced pricing strategies that balance consumer demand with profitability goals. This approach enables companies to optimize their pricing decisions, potentially leading to increased market share, improved customer satisfaction, and enhanced overall financial performance.

The Fundamentals of Price Elasticity Modeling

Profit sensitivity analysis evaluates how changes in critical variables impact profitability, while price elasticity modeling specifically measures the responsiveness of demand to price changes. By integrating these approaches, businesses can develop actionable insights into optimizing pricing strategies to align with profit goals.

Data Requirements

To conduct effective price elasticity modeling, organizations need to gather and analyze specific data points. These include:

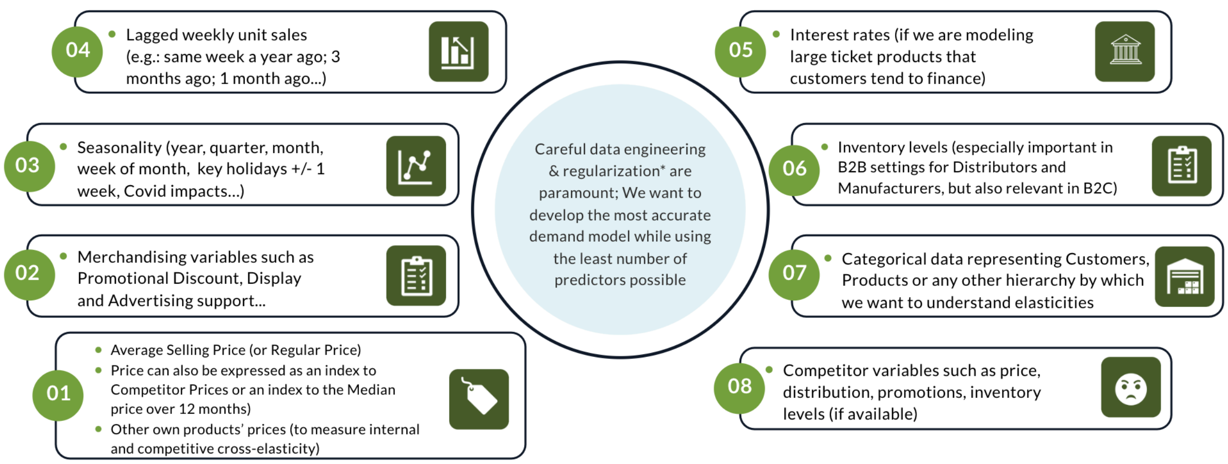
1. **Average Selling Price**: Use as a direct measure or indexed against competitors to assess pricing strategies.
2. **Promotional Pricing**: Measure the ratio of discounted to regular prices to capture promotional effects.
3. **Inventory Levels**: Monitor stock levels for manufacturers and distributors, which is crucial in B2B settings.
4. **Customer and Product Segmentation**: To refine granular elasticity estimates, include categorical data on customers, products, or market segments.
5. **Merchandising Variables**: Account for promotions, displays, and advertising efforts that influence price sensitivity.
6. **Seasonality and Lagged Sales**: Factor in seasonal demand patterns and historical sales to account for time-based variations.
7. **Competitor Variables**: Include competitor pricing, promotions, and positioning to understand market dynamics.

Integrating the Profit Equation:

By combining Price Elasticity modeling with the profit equation **Pr = Q(P-V) - F**, businesses can develop a comprehensive understanding of how different pricing strategies affect volume and profitability.

1. Quantity Sold (Volume): Represented as Q in the profit equation
2. Price: Denoted as P in the equation
3. Variable Costs: Indicated by V in the profit formula
4. Fixed Costs: Represented as F in the equation

Understanding Price Elasticities enables firms to predict new sales volumes when prices change, allowing them to forecast the resulting profit and revenue shifts. This can facilitate dynamic scenario analyses, where different pricing strategies can be evaluated to understand their profit implications, helping refine strategies to maximize profit dollars while balancing potential trade-offs between volume and profit margins.



Typical variables used for Price Elasticity modeling

Understanding the key variables and their interplay is crucial for accurate price elasticity modeling:

1. **Direct Impact on Profit**: Price changes immediately influence revenue and profit through their effect on sales prices.
2. **Indirect Impact on Profit**: Adjusting prices affects the quantity sold, which can lead to changes in overall profit.
3. **Cost Implications**: Price changes can impact costs indirectly; for example, lowering prices might boost demand, leading to better economies of scale and reduced per-unit costs

The laws of economics suggest that as the price of everyday goods increases, volume decreases, resulting in fewer purchases. This relationship forms the basis of volume hurdles identified through profit sensitivity analysis.

Model Selection

Selecting the appropriate model for price elasticity analysis is critical. While traditional methods like linear regression have been widely used, advanced machine-learning approaches are gaining traction in most industries. However, it's essential to understand the limitations of ML methods:

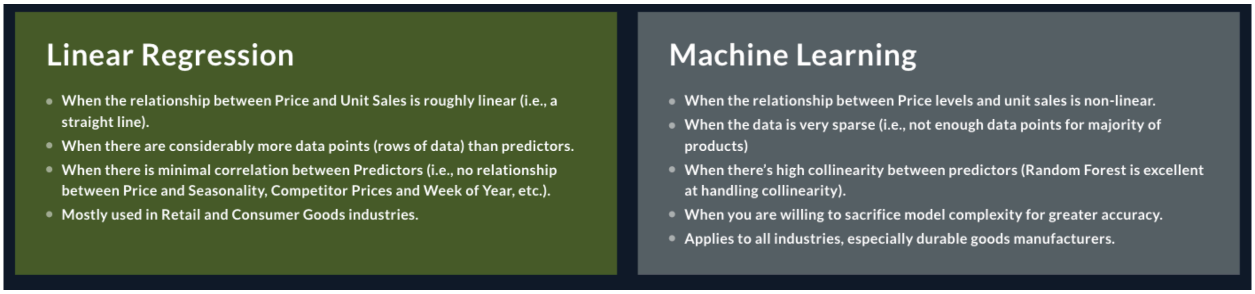
1. **Traditional Machine Learning Methods:**
   - Great for solving prediction problems as a “baseline” approach
   - It may not provide good estimators of causal parameters
   - ***Example:*** Random Forest models can identify correlations between price and unit sales but struggle to distinguish causality from confounding factors
2. **Double Machine Learning (DML):**
   - A hybrid approach combining econometrics and machine learning
   - Tailored for causal inference in the presence of many confounders
   - Provides faster learning rates and robust behavior across a broader range of probability distributions
   - Ideal, when focusing on a single price elasticity coefficient

When selecting a model, it's crucial to consider the presence of confounding variables. These factors influence the independent variable (price) and the dependent variable (sales), potentially leading to biased estimates if not accounted for properly.

Model Type	Strengths	Limitations
Traditional ML	Excellent for predictions	May struggle with causal inference
DML	Strong causal inference capabilities	More complex implementation

Linear Regression Techniques

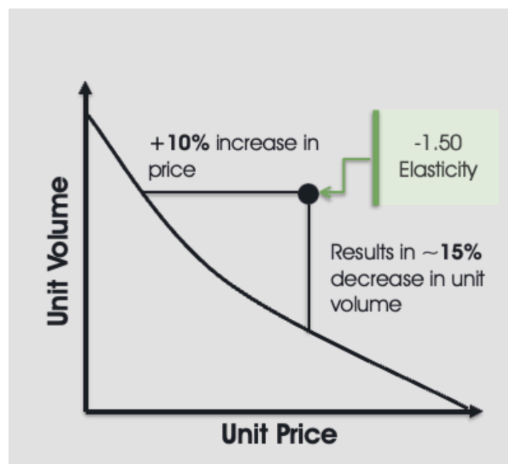
Linear regression techniques are fundamental in [price elasticity modeling](). They offer a straightforward approach to estimating the relationship between price changes and demand. These methods have evolved from simple linear regression to more sophisticated approaches, each with its strengths and applications in pricing strategy.



When to use Linear Regression vs. Machine Learning to estimate Price Elasticities

Simple Linear Regression

Simple linear regression is a foundational technique in price elasticity modeling, analyzing the relationship between price and quantity demanded. By plotting these variables on a graph, analysts identify the line of best fit that represents this relationship. The slope of the line indicates the rate of change in quantity demanded concerning price changes, but it is not the price elasticity coefficient. To determine price elasticity, the slope is adjusted by the price to the quantity ratio, reflecting the percentage change in demand relative to price changes.



Multiple Linear Regression (mid-point method)

Building upon simple linear regression, the multiple linear regression approach incorporates additional variables that may influence demand. This method allows for a more comprehensive analysis of price elasticity by considering factors such as promotional activities, seasonality, and competitor pricing. The mid-point method calculates elasticity using the average of two or more price points and their corresponding quantities, providing a more accurate estimate of price sensitivity.

Log-Log Regression

Log-log regression has become a widespread technique in price elasticity modeling because it handles non-linear relationships between price and demand better than regular linear regression. By transforming the dependent and independent variables into logarithmic form, this method allows for a more accessible, straightforward interpretation of elasticity coefficients. The resulting coefficients directly represent the percentage change in quantity demanded for a 1% change in price, making it particularly useful for comparing elasticities across different products or markets.

[redacted]	Function	Elasticity Estimation
Linear model (mid-point method)	Units ~ a + b*Price	b * (avg Price) / (avg Units)
Log-Linear	log(Units) ~ a + b*Price	b * (avg Price)
Linear-Log	Units ~ a + b*log(Price)	b / (avg Units)
Log-Log (most popular)	log(Units) ~ a + b*log(Price)	b

Estimating Price Elasticity with Regression Models (simplified)

Regularized Regression (ElasticNet)

As pricing strategies have grown more complex, regularized regression techniques like ElasticNet have gained prominence in price elasticity modeling. ElasticNet combines the benefits of Lasso and Ridge regression, addressing multicollinearity issues and preventing overfitting. This method is beneficial when dealing with high-dimensional data sets, as it can effectively handle a large number of predictors while maintaining model stability.

To illustrate the differences between these regression techniques, consider the following comparison:

Technique	Strengths	Limitations
Simple Linear Regression	Easy to implement and interpret	May oversimplify complex relationships
Multiple Linear Regression	Incorporates multiple factors	Can be sensitive to multicollinearity
Log-Log Regression	Directly interprets elasticity coefficients	Assumes constant elasticity across all price points
ElasticNet	Handles high-dimensional data, prevents overfitting	It may require more computational resources

While these linear regression techniques provide valuable insights into price elasticity, it's important to note their limitations. Traditional machine learning methods, including these regression approaches, excel at solving prediction problems but may not always provide accurate estimators of causal parameters. For instance, a Random Forest model might identify correlations between price and unit sales but struggle to distinguish causality from confounding factors.

More advanced approaches like Double Machine Learning (DML) have emerged to address these limitations. DML combines econometrics and machine learning, tailored for causal inference in the presence of many confounders. This hybrid approach offers faster learning rates and robust behavior across a broader range of probability distributions, making it particularly useful when focusing on a single price elasticity coefficient.

Industries	Retail (Grocery, Mass, Merch)	Consumer Products	Durable Goods Wholesalers	Manufacturers (Capital Equipment)
Typical Industry Characteristics	High transaction volume; typically strong relationship between price-volume; sales & customer data-rich (+ competitor pricing/inventory). Price-Volume relationship often linear.	Fast moving products; strong relationship between price-volume; rich internal and market data (comp. pricing, sales, market share, in-store support metrics). Price-Volume relationship often linear.	Fast moving for ~ 5% of SKU assortment; highly sparse transaction for bottom 80% rivh internal data (and often scraped competitor pricing & inventory data). Price-Volume relationship mostly non-linear.	Relatively sparse transactions (high ticket products) with long purchase cycle and product lifecycle; demand can be seasonal and influenced by interest rates. Price-Volume relationship mostly non-linear.
Multi-linear Regression(additive)	★☆☆☆☆	★⯪☆☆☆	☆☆☆☆☆	☆☆☆☆☆
Multiplicative Regression(aka, log-log regression)	★★☆☆☆	★★☆☆☆	★☆☆☆☆	★☆☆☆☆
Multiplicative Regression with Regularization (Lasso, Ridge or ElasticNet Regression)	★★★★☆	★★★★☆	★★☆☆☆	★⯪☆☆☆
Ensemble Models (Random Forest, XGBoost)	★★★★☆	★★★★☆	★★★★☆	★★★☆☆
Weighted or Stacked Models (Traditional States + ML)	★★★★★	★★★★★	★★★★★	★★★★★

Ranking of modeling approaches for price elasticity estimations by Industry

Advanced Machine Learning Approaches

As price elasticity modeling has evolved, advanced machine-learning techniques have emerged as powerful tools for analyzing complex market dynamics. These sophisticated approaches offer enhanced predictive capabilities and the ability to handle large, multidimensional datasets. We'll explore some of the most prominent advanced machine learning methods in price elasticity modeling.

Random Forest

Random Forest has become a popular technique for estimating price elasticities due to its ability to handle non-linear relationships and interactions between variables. This ensemble learning method combines multiple decision trees to create a robust predictive model. In the context of price elasticity modeling, Random Forest excels at capturing the intricate relationships between price changes and sales volume.

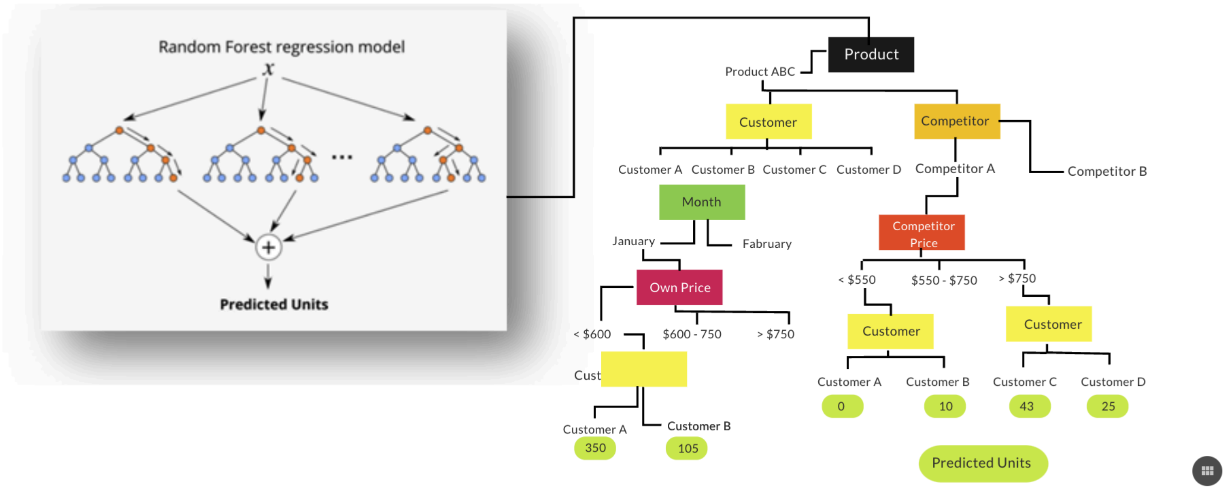
To estimate price elasticities using Random Forest, analysts employ a "model perturbation" approach. This process involves several steps:

1. **Train the Model:** Use historical sales data to train a Random Forest or GBM model, incorporating various features like price, promotions, competitor pricing, and seasonality.
2. **Simulate Price Ranges:** For each product, generate a range of simulated price points above and below the current price.
3. **Predict Demand:** Use the trained model to predict demand at each simulated price point, keeping other variables constant.
4. **Calculate Elasticity:** Calculate the price elasticity of demand by observing the percentage change in predicted demand for each percentage change in simulated price.

Example: Price Perturbation with Random Forest
Imagine a company selling high-end winter jackets. They've trained a Random Forest model to predict demand based on factors including price, competitor pricing, and weather conditions.
1. The current price of a specific jacket is $600.
2. They simulate price points ranging from $400 to $700 in increments of $50.
3. The model predicts the corresponding demand for each simulated price point. For instance, at $400, the model predicts a demand of 540 units, while at $650, the predicted demand drops to 200 units.
4. By calculating the percentage change in demand for each price change, the company can estimate the price elasticity of demand at different price levels and overall (across price ranges) using straight or revenue-weighted averages.

This method enables the calculation of dynamic, product-level price elasticities that account for various factors such as price ranges, channels, customers, and seasonality.

In a Random Forest (RF) regression model, Unit Predictions from hundreds or thousands of Decision Trees are averaged out (aka "the wisdom of the crowd").Rough depiction of how a partial Decision Tree may look like (~ 1 out of 1,000). In your model, depending on how many predictors you have, even one Decision Tree may be 10-50x larger. Think of a Decision Tree as a collection of simple IF-ELSE-THEN statements.



How to estimate Price Elasticities from a ML Demand model: Random Forest Example

So how do we calculate Price Elasticities from Predicted Units?

Using "price perturbations"...

Step 1: We develop ~ multiple Random Forest models for each Product and pick the one with the best accuracy against a test data set (a data set that the model has not seen).

2: For each Product (or Channel-Product, etc.), we input 5-20 simulated price ranges. We leave the other predictor values unchanged.

3: We run predictions for each Product (or Customer-Product) combination for each of the 5-20 simulated price points. ...

4: We calculate the implied elasticity based on a) Simulated Price Ranges and b) Predicted Units (we can aggregate using straight or weighted averages)

Simulated Prices	Predicted Units	Implied Elasticity (by Price Range)
$ 400.00	540	...
$ 500.00	400	1.04
$ 550.00	305	2.38
$ 600.00	250	1.98
$ 650.00	200	2.40
$ 700.00	180	1.30
	Average P/E	1.82

Implied elasticities using model perturbation approach from a Random Forest model.

Pros:

- **Non-Linear Relationships:** Random Forest can naturally handle non-linearities in the data.
- **Interactions:** Automatically captures interactions between variables.
- **Robust to Overfitting:** Especially when the number of trees is sufficiently large.

Cons:

- **Black-Box:** More difficult to interpret than linear regression.
- **Computational Overhead:** Especially with large datasets or a large number of trees.
- **Doesn't Directly Measure Causality:** Without specific techniques or designs (like DML or matched designs), a Random Forest might just show associations and not causal relationships.

Price Elasticity Modeling with Random Forest: Pros and Cons

Gradient Boosting Machines

Gradient Boosting Machines (GBMs) represent another powerful ensemble learning technique used in price elasticity modeling. GBMs build a series of weak learners, typically decision trees, sequentially, with each new model correcting the errors of its predecessors. This approach has demonstrated exceptional performance in capturing complex, non-linear relationships between prices and demand.

Pros:

- **Handling Non-Linearities:** Like DML and Random Forest, GBM can model complex non-linear relationships.
- **Performance:** Often provides high predictive accuracy and can outperform Random Forest if tuned properly.
- **Feature Importance:** Provides measures of feature importance, which can be insightful for understanding the model.

Cons:

- **Overfitting:** If not carefully tuned, GBMs can overfit to the training data, especially when the data is noisy.
- **Interpretability:** While better than some other machine learning models, GBMs are still less interpretable than linear models.
- **Computational Demand:** Training GBMs can be computationally expensive due to the sequential nature of boosting.

Price Elasticity Modeling with Gradient Boosting: Pros and Cons

Neural Networks

Neural Networks, particularly deep learning architectures, have gained traction in price elasticity modeling due to their ability to capture highly complex patterns in data. These models can automatically learn intricate relationships between various factors influencing demand, including price, promotions, seasonality, and external market conditions. Neural Networks excel at handling large volumes of data and can adapt to changing market dynamics over time.

Double Machine Learning

Double Machine Learning (DML) represents a significant advancement in price elasticity modeling, addressing some of the limitations of traditional machine learning approaches. DML combines econometrics and machine learning, making it particularly well-suited for causal inference in the presence of many confounding variables.

DML's Two-Step Approach:

1. **Prediction:** DML utilizes machine learning algorithms like Random Forest or GBM to predict the outcome variable (e.g., demand) and the treatment variable (e.g., price) based on potential confounders. This step effectively removes the influence of confounders from both variables.
2. **Estimation:** After controlling for confounders in the prediction step, DML performs a linear regression analysis on the residuals (differences between predicted and actual values) of the outcome and treatment variables. This residual-on-residual regression isolates the causal effect of price on demand.

Benefits of DML:

- **Confounder Control:** DML effectively accounts for the impact of confounding variables, leading to unbiased estimations of the causal effect of price on demand.
- **Non-Linear Relationships:** Using machine learning, DML can capture non-linear relationships between variables, providing more accurate elasticity estimations than linear regression models.
- **High-Dimensional Data:** DML excels in handling datasets with many variables, making it suitable for complex pricing scenarios with numerous factors influencing demand.

Example: DML for Price Elasticity Estimation

A grocery store chain wants to estimate the price elasticity of demand for its organic apples. It has data on apple sales, prices, seasonality, promotions, competitor pricing, and customer demographics.

1. **Prediction:** They train two separate Random Forest models: one to predict apple sales based on confounders and another to predict apple prices based on the same confounders.
2. **Residualization:** They use the trained models to predict sales and prices, then calculate the residuals by subtracting predicted values from actual values.
3. **Estimation:** They perform a linear regression analysis on sales and price residuals. The coefficient of the price residual represents the unbiased estimate of the price elasticity of demand for organic apples.

Pros:

- **Dealing with High-Dimensional Covariates:** DML is designed to handle situations where there are many predictors.
- **Non-Linear Relationships:** By leveraging machine learning, DML can capture non-linear relationships between variables.
- **Control for Confounding:** DML can help isolate the causal effect of a treatment by removing the variation in the treatment that's due to confounding variables.
- **Handles Omitted Variable Bias**: the more advanced version (aka "chernozhukov" Double ML model, implemented in the DML package in R and Python) can handle model bias very well.

Cons:

- **Complexity:** DML is more complex to implement and understand than traditional linear regression.
- **Computationally Intensive:** Since it involves multiple stages of predictions and regressions with potentially complex machine learning models.

Price Elasticity Modeling with Double Machine Learning: Pros and Cons

Future Trends in Price Elasticity Modeling

Price elasticity modeling will continue to evolve, driven by technological/algorithmic advancements and increasing data availability. Some notable future trends include:

- **Hyper-Personalization:** AI models will become increasingly sophisticated in analyzing customer data, enabling micro-segmentation and hyper-personalized pricing strategies based on real-time context, behavior, and preferences.
- **Contextual Pricing:** Pricing models will incorporate real-time contextual data, like weather, location, and even social media trends, to adjust prices dynamically and optimize revenue for every transaction.
- **Explainable AI (XAI):** As AI models become more complex, explainability will gain importance. XAI techniques will make the decision-making process of AI-powered pricing models transparent and understandable, building trust and facilitating human oversight.
- **Integration with IoT and Wearables:** Data from connected devices and wearables will provide insights into customer behavior and preferences, enriching pricing models with real-time context and personalized insights.

As pricing professionals embrace these advanced techniques, machine learning models will provide far more accurate elasticity estimates, which are essential for dynamic pricing strategies. By integrating hyper-personalization, contextual data, and real-time inputs from IoT and wearable devices, businesses can dynamically adjust prices with precision. Incorporating explainable AI will ensure these models remain transparent, fostering trust and enhancing decision-making. Leveraging these innovations will enable companies to optimize pricing in real-time, responding effectively to market changes and maximizing revenue potential.

Data Aggregation Strategies

Store-Level vs. Chain-Level Data

For most price elasticity modeling, the level of data aggregation plays a crucial role in determining the accuracy and applicability of the results. Researchers have extensively examined the appropriateness of data aggregation by estimating models at various levels: store, chain, and market. The SCAN*PRO model, a widely used framework in price elasticity analysis, has been applied across these different aggregation levels to assess its performance.

At the store level, models utilize granular data from individual retail locations, capturing the nuances of local market dynamics. In contrast, chain-level models aggregate data across multiple stores within a retail chain. For instance, a chain-level model might explain sales for a specific brand in a particular chain during a given week as a function of variables such as the weighted average price for the brand (calculated as chain-level revenue divided by chain-level unit sales) and the proportion of stores in the chain featuring a promotion for that brand.

Pros and Cons of Aggregation

Data aggregation in price elasticity modeling presents both advantages and challenges:

Pros:

1. **Simplified analysis:** Aggregated data can reduce computational complexity.
2. **Broader market insights:** Chain-level data may provide a more comprehensive view of overall market trends.
3. **Reduced noise:** Aggregation can smooth out individual store anomalies.

Cons:

1. **Loss of granularity:** Store-specific nuances may be obscured in aggregated data.
2. **Potential bias:** Aggregation can mask heterogeneity in consumer behavior across different locations.
3. **Reduced ability to capture local promotional effects**: Store-level promotions may not be accurately represented in aggregated models.

Challenging the Norms with Retail Chain-level Data

Traditional sales and price elasticity modeling methods in the Retail, CPG, and Distribution industries have relied heavily on detailed store (or warehouse) and product-level models to estimate critical factors in pricing decisions, such as baseline sales or regular and promotional price elasticities.

These approaches have been around for the past few decades. While they have contributed significantly to our understanding of price-volume dynamics for Retail and Consumer Products industries, they present substantial challenges and limitations.

The primary issue is data access for Distributors and CPGs (or other manufacturers): disaggregated, store-level data is available for POS data aggregators like Nielsen and IRI, who have traditionally charged a hefty sum for things like Price Elasticity models or Pricing Scenario Analysis tools. Even if companies can access store-level sell-through data, there are issues related to data quality, storage, and the complexity of ongoing, large-scale data management.

We propose reconsidering the data we use for Price & Promotional Elasticity modeling and related Demand Models (e.g., Baseline vs. Incremental Sales). Instead of focusing on detailed, disaggregated data, we advocate using aggregated, Retail Chain level (or often Retail Chain and Region level) data.

In terms of modeling techniques, we advocate for adopting modern ML approaches, moving away from derivations of log-log regressions or mixed-effect linear models that many data providers still rely on.

Our proposal is nothing new, albeit still not widely accepted in the Retail and CPG communities. Kurt Jetta and Erick Rengifo wrote an excellent paper over a decade ago titled "A Model to Improve the Estimation of Baseline Retail Sales," which supports our point of view on this topic.

	Avg. Price Elasticities	Notes
Consumer Non-Durables	1.5 - 5	Higher for frequently purchased items (e.g., groceries), promotional price elasticities > regular price elasticities
Consumer Durables	1.5 - 3	Lower for infrequent purchases (e.g., appliances)
Pharmaceuticals	0.2 - 2.5	Highly variable, depends on innovation and competition
Industrial Products	2-10	Highly variable, depends on product specialization and competition
Airlines	>2	Sensitive to price changes, especially in competitive markets
Telecom	0.7-1.7	Variable, depends on service type (e.g., airtime vs. subscriptions)
Restaurants	2-3	Highly elastic, sensitive to price and alternatives
Automobiles	0.7 - 2	Lower for luxury vehicles

Typical Price Elasticity coefficients by Industry (source: Power Pricing by Simon and Dolan)

Disaggregated Data and Traditional Models: A Critical Review

For decades, the CPG and retail industry has extensively relied on detailed store and product level data for sales and price elasticity modeling. Many predictive models still in use by industry and consultancies have been derived from old-school models like "Scan*Pro" and "PromotionScan," traditionally used by Nielsen and IRI.

These models have contributed significantly to shaping the field of Revenue Growth Management and pricing analytics, providing actionable insights to inform pricing, promotional, and marketing strategies.

However, the reliance on these models and the use of disaggregated data presents several limitations:

1. We often observe sharp increases in modeled baseline sales during Price Promotions, which should not be the case. Baseline sales are independent of promotional activity and are primarily a factor of brand strength, distribution depth/breadth, and seasonality.
2. Store-level data have high dimensionality and multi-collinearity that are hard to control, even if you use regularization.
3. Most small- to mid-size CPGs don't have the budget to shell out $100K-150K on a 2-3 month Price Elasticity Study using store-level disaggregated data.
4. Most retail pricing, promotions, and marketing are executed at the retail chain (e.g., Harris Teeter) or chain-market level (e.g., Kroger Atlanta). Therefore, store-level

modeling is unnecessary and doesn't align with how execution or management thinking occurs.

Aggregated Data: An Overlooked Resource

In contrast to the highly granular, store-level data that has dominated the field, we propose a sharp turn towards aggregated retail chain-level data. This logic also applies to the distribution industry, where more aggregated methods will suffice instead of complex models built at the Distribution Center - Product level (i.e., Regional or National models).

As mentioned above, modeling demand and price elasticity at a higher, aggregated level aligns with management thinking and accountability, and model accuracy is often as good or better than models built on granular, more complex data.

Furthermore, using aggregated data offers several practical advantages:

1. It is more readily available and less costly to acquire and manage than disaggregated data.
2. It allows for greater modeling flexibility, reducing processing time and computational resources. You can build sophisticated price & promotion elasticity models in a matter of hours or a few days vs. the usual 1-3 month long process that has characterized these modeling efforts.
3. Models and insights are available for smaller CPGs and retailers, who otherwise wouldn't have the budget or the resources to procure complex models.
4. It allows for complete in-sourcing of all demand and price modeling efforts, building critical, sustainable capabilities for Revenue Growth Management instead of relying on 3rd parties.

Interpreting and Applying Model Results

The interpretation and application of price elasticity model results are crucial in shaping effective pricing strategies. By understanding the nuances of elasticity coefficients and their implications, businesses can make informed decisions that optimize revenue and profitability.

Elasticity Coefficients

Elasticity coefficients serve as numerical indicators of customer responsiveness to price changes. These values, which can be either positive or negative, represent the percentage change in quantity demanded resulting from a 1% change in price. For instance, an elasticity coefficient of -1.5 suggests that a 1% increase in price would lead to a 1.5% decrease in demand.

To interpret these coefficients effectively, consider the following guidelines:

1. **Inelastic Demand (Elasticity < 1):** Products with inelastic demand experience minimal impact on demand despite significant price changes. Essential goods, such as insulin, typically fall into this category.
2. **Elastic Demand (Elasticity > 1):** Products with elastic demand see substantial changes in demand with small price adjustments. Luxury goods and non-essential items, like designer clothing, often exhibit elastic demand.

Cross-Price Elasticity

Cross-price elasticity examines how changes in the price of one product affect the demand for another, often related, product. This concept helps businesses understand the interplay between different products in their portfolio or competitive offerings.

Types of Cross-Elasticity

- **Positive Cross-Elasticity (Substitutes):** This indicates that an increase in the price of one product leads to a rise in demand for another. These products are considered substitutes, fulfilling similar consumer needs.
    - **Example:** Imagine two popular cola brands, Cola A and Cola B. If the price of Cola A increases, consumers may switch to the now relatively cheaper Cola B, leading to increased demand for Cola B. The higher the positive cross-elasticity, the stronger the substitution effect.

- **Negative Cross-Elasticity (Complementary Goods):** This implies that an increase in the price of one product leads to a decrease in demand for another. These products are considered complements and are often used together.
  - **Example:** Consider printers and ink cartridges. If printer prices increase significantly, demand for ink cartridges may decrease as fewer people buy printers. This negative cross-elasticity reflects the complementary nature of the products.
- **Zero Cross-Elasticity (Unrelated Goods):** This indicates that a change in the price of one product has no impact on the demand for another. The products are considered unrelated in terms of consumer usage and preferences.
  - **Example:** Changes in the price of luxury cars are unlikely to affect the demand for toothpaste. These products cater to different needs and consumer segments, resulting in zero cross-elasticity.

Modeling Cross-Elasticity

Cross-elasticity can be modeled using various statistical techniques, most commonly regression analysis. The demand for one product is regressed on the price of another product (or the price index or price gap to the other product), along with other relevant factors like own-price, seasonality, and marketing efforts. Loosely stated, the coefficient of the other product's price in the regression equation represents the cross-elasticity.

Example: Regression Model for Coffee Brands:

log(Demand for Coffee Brand B) = $\beta 0$ + $\beta 1$*log(Price of Coffee Brand A) + $\beta 2$*log(Price of Coffee Brand B) + $\beta 3$ * Seasonality + $\beta 4$*log(Advertising Spend) + ε

In this model, $\beta 1$ represents the cross-elasticity of demand for Coffee Brand B with respect to the price of Coffee Brand A.

Strategic Implications of Cross-Elasticity:

Understanding cross-elasticity empowers businesses to:

- **Anticipate Competitive Impact:** By knowing the cross-elasticity between their products and competitors' products, companies can predict how competitor price changes might affect their sales.

- **Optimize Pricing Strategies:** High positive cross-elasticity suggests a competitive market where price adjustments should be made carefully, considering competitor reactions. Negative cross-elasticity presents opportunities for bundling or cross-promotional activities.
- **Identify New Market Opportunities:** Analyzing cross-elasticity patterns can reveal hidden product relationships, leading to innovative product bundles or market expansion strategies.

Competitive Price Index Elasticity: Gauging Price Sensitivity Relative to Price Competitiveness

CPI Elasticity, where CPI stands for **Competitive Price Index**, is a powerful metric that measures the sensitivity of a product's demand to changes in its price relative to competitor prices. It helps businesses understand how customers respond to shifts in their competitive pricing position.

The CPI is calculated as: (Our Price / Competitor Price) x 100

A CPI of around 100 indicates that a product is priced at the same level as its competitors. A CPI greater than 100 implies a premium pricing strategy, while a CPI less than 100 signifies a discount pricing approach.

Understanding CPI Elasticity:

- **Positive CPI Elasticity**: Demand also increases as the CPI increases (our price becomes relatively higher). This may happen for luxury or premium products where higher prices signal exclusivity or quality.
- **Negative CPI Elasticity**: Demand decreases as the CPI increases. This is typical for most products where consumers are price-sensitive and prefer lower-cost alternatives.
- **Zero CPI Elasticity**: Changes in CPI have little to no impact on demand, which is common for products with strong brand loyalty or unique features that reduce price sensitivity.

Modeling CPI Elasticity:
Similar to cross-elasticity, CPI Elasticity can be modeled using regression analysis. The demand for a product is regressed on the CPI, along with other relevant variables such as own absolute price, seasonality, promotions, and advertising efforts. The coefficient of the CPI in the regression equation represents the CPI Elasticity.

Example: Regression Model for Demand and Competitive Pricing:
$\log(\text{Demand for Product Y}) = \beta 0 + \beta 1 * \log(\text{CPI}) + \beta 3 * \text{Seasonality} + \beta 4 * \log(\text{Promotion Intensity}) + \varepsilon$

In this model, $\beta 1$ represents the CPI Elasticity of demand for Product Y.

Strategic Implications of CPI Elasticity

Understanding CPI Elasticity empowers businesses to

- **Optimize Competitive Pricing Strategies:** Understanding CPI Elasticity enables businesses to optimize competitive pricing strategies. Maintaining competitive pricing is crucial for products with **negative CPI Elasticity** (where demand decreases as prices rise relative to competitors). A premium pricing strategy might be effective for products with **positive CPI Elasticity** (where demand increases as relative prices rise, often due to perceived value or exclusivity). The correct understanding of CPI Elasticity helps companies align their pricing with market demand and customer perception.

- **Assess Price Sensitivity in Competitive Contexts:** CPI Elasticity provides a more nuanced understanding of price sensitivity than own-price elasticity alone. It lets us understand customer sensitivity to price differences relative to competitors, allowing for more informed pricing decisions in competitive markets.
- **Develop Targeted Marketing Strategies:** By understanding how CPI Elasticity varies across different geographies, product categories, and customer segments, businesses can tailor marketing campaigns and promotional offers to target specific groups based on their sensitivity to competitive price positioning.

By incorporating CPI Elasticity into their pricing models, businesses can move beyond a simplistic view of own-price elasticity by considering how competitive dynamics influence consumer behavior. This enables them to develop more sophisticated and effective pricing strategies that maximize revenue and market share in a competitive landscape.

Break-Even Price Elasticity: A Powerful Tool for Pricing Decisions

Break-even price elasticity (B/E P/E) is a crucial concept in pricing strategy that goes beyond simple break-even analysis. While it's widely used in the Consumer Products industry, it's often underutilized in other sectors. This concept serves as a powerful sanity check for pricing decisions, helping businesses avoid potentially damaging price investments.

There are two essential versions of B/E P/E that pricing and commercial teams should consider:

1. **Revenue Break-Even Price Elasticity:** calculates the price elasticity required for a product to remain revenue-neutral after a price change. In other words, it determines the elasticity needed to generate the same revenue at the new price compared to the old price.

Formula: Revenue B/E P/E = -(Current Price / New Price)

2. **Gross Profit Break-Even Price Elas:** calculates the price elasticity required for a product to maintain the same gross profit after a price change.

Formula: Gross Profit B/E P/E = -1 / (Current GP% + Price Change %)

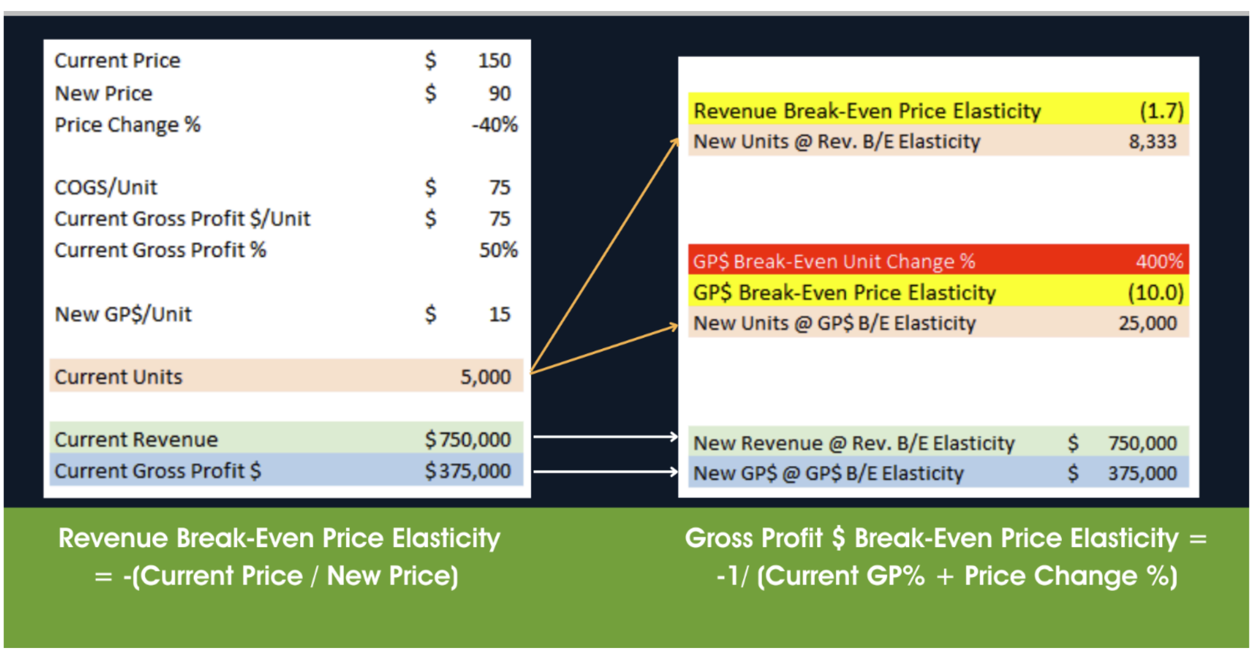
To illustrate the power of this concept, let's consider a fictional example of a 40% price investment:

Imagine a company is considering offering a 40% discount on one of its anchor products for a year-end promotion. The current gross profit margin is 50%, which would decrease to about 20% after the discount.

Using the B/E P/E calculations:

1. **Revenue B/E P/E = -(100 / 60) = -1.7**
   This means that to break even on revenue, the price elasticity would need to be -1.7. If historical price elasticities in the industry range from -4 to -0.5, this number seems reasonable, and the company might feel comfortable with this price investment.
2. **Gross Profit B/E P/E = -1 / (50% + (-40%)) = -10**
   To break even on gross profit, the price elasticity would need to be -10. This is significantly higher than the revenue break-even and likely outside the industry's historical range of elasticities. It suggests that the units sold would need to increase by 400% (-10 P/E x -40% Price Investment) to maintain the same gross profit, which seems highly improbable.

The stark difference between these two break-even points highlights the importance of considering both revenue and profit implications when making pricing decisions. While the revenue break-even might seem achievable, the gross profit break-even reveals the potential for substantial profit losses.



Break-Even Price Elasticities: a simple, but powerful sanity check on your pricing decisions

Upper Bound P/E to Meet B/E Volume Hurdles

Price Change % (Increase)

Initial Contribution Margin %	5%	10%	15%	20%	25%	30%	35%	40%	45%	50%	55%
10%	(6.67)	(5.00)	(4.00)	(3.33)	(2.86)	(2.50)	(2.22)	(2.00)	(1.82)	(1.67)	(1.54)
15%	(5.00)	(4.00)	(3.33)	(2.86)	(2.50)	(2.22)	(2.00)	(1.82)	(1.67)	(1.54)	(1.43)
20%	(4.00)	(3.33)	(2.86)	(2.50)	(2.22)	(2.00)	(1.82)	(1.67)	(1.54)	(1.43)	(1.33)
25%	(3.33)	(2.86)	(2.50)	(2.22)	(2.00)	(1.82)	(1.67)	(1.54)	(1.43)	(1.33)	(1.25)
30%	(2.86)	(2.50)	(2.22)	(2.00)	(1.82)	(1.67)	(1.54)	(1.43)	(1.33)	(1.25)	(1.18)
35%	(2.50)	(2.22)	(2.00)	(1.82)	(1.67)	(1.54)	(1.43)	(1.33)	(1.25)	(1.18)	(1.11)
40%	(2.22)	(2.00)	(1.82)	(1.67)	(1.54)	(1.43)	(1.33)	(1.25)	(1.18)	(1.11)	(1.05)
45%	(2.00)	(1.82)	(1.67)	(1.54)	(1.43)	(1.33)	(1.25)	(1.18)	(1.11)	(1.05)	(1.00)
50%	(1.82)	(1.67)	(1.54)	(1.43)	(1.33)	(1.25)	(1.18)	(1.11)	(1.05)	(1.00)	(0.95)
55%	(1.67)	(1.54)	(1.43)	(1.33)	(1.25)	(1.18)	(1.11)	(1.05)	(1.00)	(0.95)	(0.91)
60%	(1.54)	(1.43)	(1.33)	(1.25)	(1.18)	(1.11)	(1.05)	(1.00)	(0.95)	(0.91)	(0.87)
65%	(1.43)	(1.33)	(1.25)	(1.18)	(1.11)	(1.05)	(1.00)	(0.95)	(0.91)	(0.87)	(0.83)
70%	(1.33)	(1.25)	(1.18)	(1.11)	(1.05)	(1.00)	(0.95)	(0.91)	(0.87)	(0.83)	(0.80)
75%	(1.25)	(1.18)	(1.11)	(1.05)	(1.00)	(0.95)	(0.91)	(0.87)	(0.83)	(0.80)	(0.77)
80%	(1.18)	(1.11)	(1.05)	(1.00)	(0.95)	(0.91)	(0.87)	(0.83)	(0.80)	(0.77)	(0.74)

Price Elasticity needs to be this number or lower (i.e. "less elastic") for Break-Even Volume Hurdle to be achievable (and for Gross Profit dollars to be the same before/after the price change).

Lower Bound P/E to Meet B/E Volume Hurdles

Price Change % (Decrease)

Initial Contribution Margin %	-5%	-10%	-15%	-20%	-25%	-30%	-35%	-40%	-45%	-50%	-55%
10%	(20.00)										
15%	(10.00)	(20.00)									
20%	(6.67)	(10.00)	(20.00)								
25%	(5.00)	(6.67)	(10.00)	(20.00)							
30%	(4.00)	(5.00)	(6.67)	(10.00)	(20.00)						
35%	(3.33)	(4.00)	(5.00)	(6.67)	(10.00)	(20.00)					
40%	(2.86)	(3.33)	(4.00)	(5.00)	(6.67)	(10.00)	(20.00)				
45%	(2.50)	(2.86)	(3.33)	(4.00)	(5.00)	(6.67)	(10.00)	(20.00)			
50%	(2.22)	(2.50)	(2.86)	(3.33)	(4.00)	(5.00)	(6.67)	(10.00)	(20.00)		
55%	(2.00)	(2.22)	(2.50)	(2.86)	(3.33)	(4.00)	(5.00)	(6.67)	(10.00)	(20.00)	
60%	(1.82)	(2.00)	(2.22)	(2.50)	(2.86)	(3.33)	(4.00)	(5.00)	(6.67)	(10.00)	(20.00)
65%	(1.67)	(1.82)	(2.00)	(2.22)	(2.50)	(2.86)	(3.33)	(4.00)	(5.00)	(6.67)	(10.00)
70%	(1.54)	(1.67)	(1.82)	(2.00)	(2.22)	(2.50)	(2.86)	(3.33)	(4.00)	(5.00)	(6.67)
75%	(1.43)	(1.54)	(1.67)	(1.82)	(2.00)	(2.22)	(2.50)	(2.86)	(3.33)	(4.00)	(5.00)
80%	(1.33)	(1.43)	(1.54)	(1.67)	(1.82)	(2.00)	(2.22)	(2.50)	(2.86)	(3.33)	(4.00)

Price Elasticity needs to be this number or higher (i.e. "more elastic") for Break-Even Volume Hurdle to be achievable.

By incorporating B/E P/E analysis into their pricing strategies, businesses can:

1. Quickly assess the reasonableness of proposed price changes
2. Avoid damaging impacts on operating profits
3. Make more informed decisions about promotional strategies
4. Better understand the relationship between price changes, sales volume, and profitability

Adding the B/E Price Elasticity sanity check to their price investment evaluation toolkit can be invaluable for pricing, finance, and sales operations professionals. It's a simple yet powerful concept that can either reaffirm a pricing decision or prevent potentially harmful actions that could significantly impact operating profits.

While driving unit sales through deep discounts might seem attractive for meeting short-term targets, we must always consider the long-term impact on profitability and overall business health.

Optimizing Pricing Strategies

To optimize pricing strategies based on elasticity insights, consider the following steps:

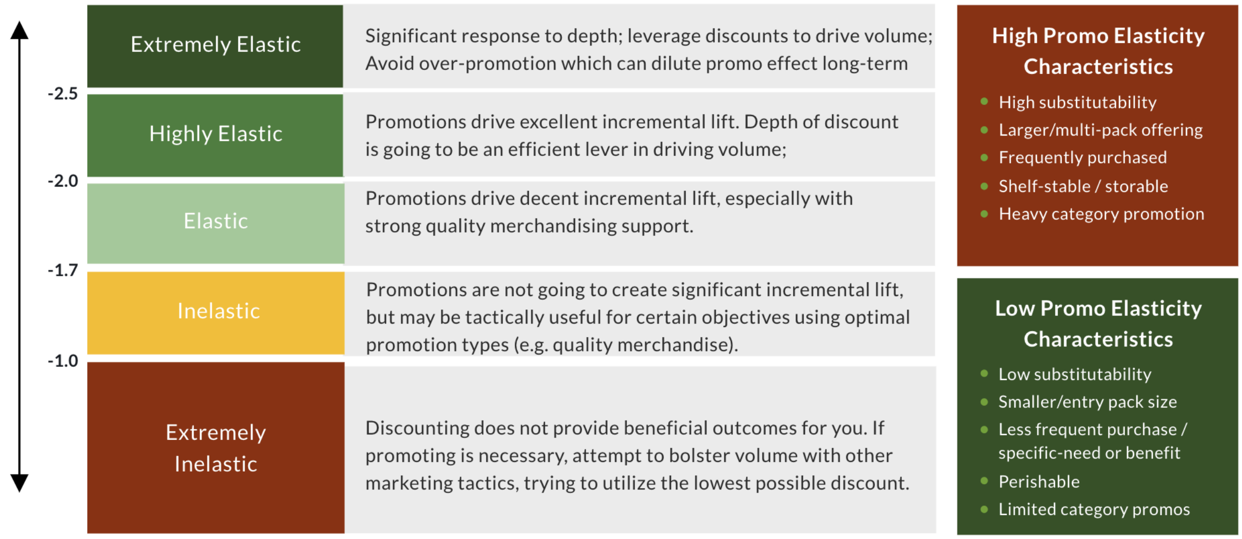
1. **Analyze volume hurdles:** Calculate the minimum growth in sales volume necessary to counteract decreased per-unit profit from a price reduction.
2. **Evaluate strategic context:** Consider factors beyond immediate profitability, such as market share preservation or avoiding price wars.
3. **Balance short-term and long-term goals:** Weigh the immediate impact of pricing actions against potential long-term consequences on brand perception and customer loyalty.
4. **Segment-specific approach: Tailor** pricing strategies to different customer segments based on their unique elasticity profiles.

Regular (Base) vs. Promoted Price Elasticity (in CPG and Retail)

In consumer packaged goods (CPG) and retail industries, it's essential to distinguish between regular (base) price elasticity and promotional price elasticity. [The SCAN*PRO model](), a widely used framework in price and promotion elasticity analysis, helps capture these differences:

Elasticity Type	Description	Application
Regular Price Elasticity	Measures long-term demand response to changes in base price	Informs overall pricing strategy
Promotional Price Elasticity	Captures short-term demand shifts due to temporary discounts	Guides promotional planning

Base Price Elasticity Strategy Guide



Promo Price Elasticity Strategy Guide

Scan*Pro: A Pioneer in Promotion Modeling

ACNielsen's Scan*Pro has been a groundbreaking model of sales promotion analytics, offering a detailed understanding of how promotional activities impact brand performance. The model's strength lies in its ability to leverage granular store-level scanner data, enabling detailed analysis of promotional impacts on a week-by-week basis.

Unpacking the Scan*Pro Model

The core of ScanPro is a multiplicative model that expresses the unit sales of a brand as a function of several factors, including price, promotional activities, seasonality, and store-specific effects. Here's the formula for the original ScanPro model:

$$q_{kjt} = \left[\prod_{r=1}^{n} \left(\frac{p_{krt}}{\bar{p}_{kr}} \right)^{\beta_{rj}} \prod_{l=1}^{3} \gamma_{lrj}^{D_{lkrt}} \right] \left[\prod_{t=1}^{T} \delta_{jt}^{X_t} \right] \left[\prod_{k=1}^{K} \lambda_{kj}^{Z_k} \right] e^{u_{kjt}}$$

$$k = 1, \ldots, K, \quad t = 1, \ldots, T$$

where: q_{kjt} is unit sales (e.g. number of pounds) for brand j in store k, week t, p_{krt} is the unit price for brand r in store k, week t,

$p\text{–}_{kr}$ is the median regular unit price (in non-promoted weeks) for brand r in store k,

D_{1krt} is an indicator variable for feature advertising: 1 if brand r is featured (but *not* displayed) by store k, in week t; 0 otherwise,

D_{2krt} is an indicator variable for display: 1 if brand r is displayed (but *not* featured) by store k, week t; 0 otherwise,

D_{3krt} is an indicator variable for the simultaneous use of feature and display: 1 if brand r is featured *and* displayed; 0 otherwise,

X_t is an indicator variable (proxy for missing variables and seasonal effects): 1 if the observation is in week t; 0 otherwise,

Z_k = an indicator variable for store k: 1 if the observation is from store k; 0 otherwise.

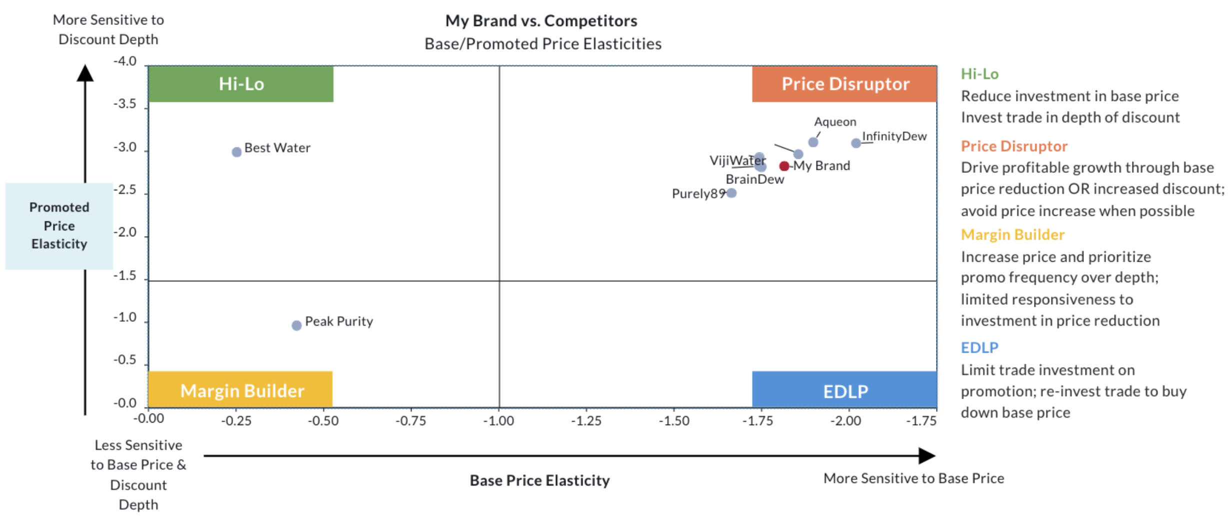
Key Features of Scan*Pro

- **Store-Level Data Analysis**: Scan*Pro performs analysis at the individual store level, capturing the granular impact of promotional activities and accounting for store-specific variations in promotional response. However, as we discussed earlier, it can be easily modified to fit more aggregated data.
- **Promotion Effect Quantification**: The model quantifies the sales lift attributable to specific promotional tactics, including temporary price cuts, feature advertising, and special displays. This allows managers to measure the effectiveness of different promotional strategies and optimize their promotional mix.
- **Dynamic Baseline Estimation**: Scan*Pro incorporates dynamic baseline sales estimation, accounting for seasonality, trends, and other factors influencing sales independent of promotions. This allows the model to isolate the true promotional impact, providing a more accurate assessment of promotional effectiveness.
- **Chain-Specific Parameterization**: The model can be customized with chain-specific parameters, recognizing that different retail chains may have unique promotional responses. This allows for a more precise understanding of how promotions work within specific retail environments.

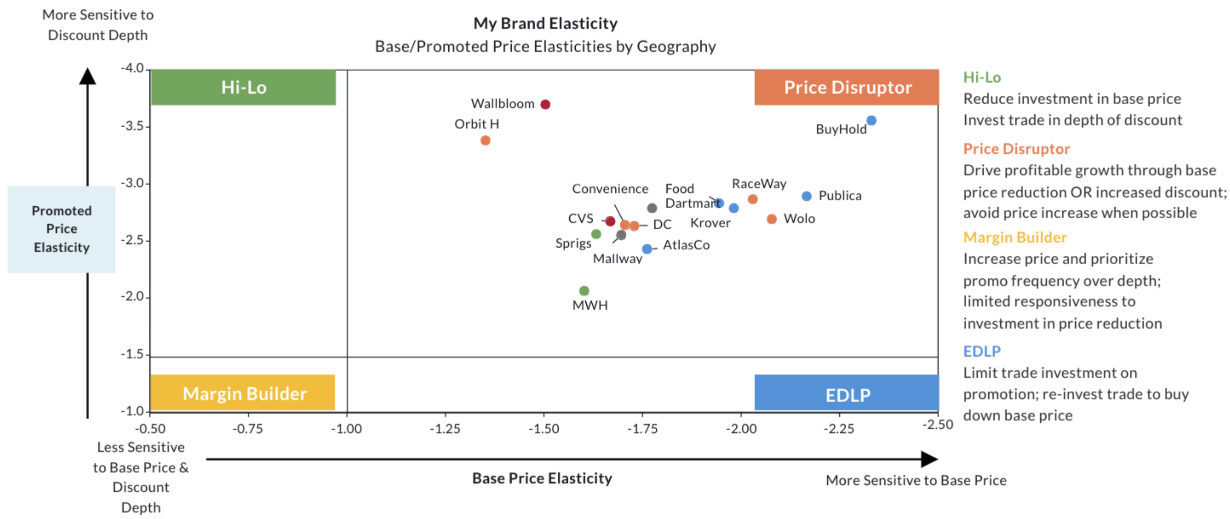
Evolution of Scan*Pro

Since its inception, Scan*Pro has undergone continuous refinements and enhancements to improve its accuracy and analytical power:

- **Dynamic Parameterization**: Scan*Pro models now incorporate dynamic parameterization, allowing promotion effects to vary over time based on factors like the recency and frequency of past promotions. This approach captures the dynamic nature of consumer response to promotions.
- **Leads and Lags Incorporation**: Advanced Scan*Pro models include leads and lags for promotional variables, capturing the impact of promotions on sales not only during the promotional week but also in the weeks leading up to and following the promotion. This helps understand stockpiling behavior (increased sales before a promotion) and post-promotion dips (decreased sales after a promotion).
- **Flexible Deal Effect Curves**: The model has incorporated semiparametric estimation methods to capture non-linear relationships and interaction effects in deal effect curves. This allows for a more accurate representation of how sales respond to varying discount levels and offers nuanced insights into pricing and promotion strategies.
- **Sales Decomposition**: Scan*Pro models decompose promotional sales lift into various sources, including cross-brand effects (sales taken from competitors), stockpiling (sales shifted from future periods), and category expansion (new sales generated by attracting new buyers to the category). This decomposition provides a deeper understanding of the drivers of promotional effectiveness and allows managers to assess the overall impact of promotions on the category as a whole.



Basic framework to understand the optimal price and promo strategy for My Brand within a Retail chain



My Brand's base and promo elasticity across various Retail chains guide Retail price investment strategy.

Conclusion

Through its ongoing evolution and enhancements, Scan*Pro remains a powerful tool for understanding promotional effectiveness. It empowers businesses to make insights- and ML-driven decisions about their promotional strategies, optimize their promotional mix, and maximize the return on their promotional investments. The model's ability to adapt to different retail environments and account for dynamic promotional effects makes it an indispensable asset in sales promotion analytics.

Challenges and Limitations

While price elasticity modeling serves as a powerful tool for pricing strategies, it comes with its own set of challenges and limitations that pricing professionals must navigate carefully. Understanding these constraints is crucial for making informed decisions and interpreting model results accurately.

Data Quality Issues

The accuracy of price elasticity models heavily depends on the quality and reliability of input data. Challenges in this area include:

- **Missing Values:** Data can have gaps due to various reasons, like errors in data entry, system glitches, or simply unavailable information. Ignoring missing values can lead to biased estimations and inaccurate predictions.
- **Outliers:** Outliers are extreme values that deviate significantly from the rest of the data. They can arise from measurement errors, data entry mistakes, or genuine but unusual events. Outliers can disproportionately influence model training, skewing results.
- **Inconsistencies:** Data inconsistencies can take various forms, such as different units of measurement, varying data formats, or conflicting information from different sources. Such discrepancies can lead to errors in analysis and misinterpretations.

Addressing Data Challenges:

- **Handling Missing Data:** Several techniques can handle missing data, including:
    - **Deletion:** Removing rows or columns with missing values, although this can lead to information loss.
    - **Imputation:** Replacing missing values with estimated values based on other data points. Common methods include mean/median imputation, regression imputation, and K-nearest neighbors imputation.
- **Dealing with Outliers:** Outliers can be addressed by:
    - **Removal:** Deleting outliers if they are clearly due to errors or are very few in number.
    - **Transformation:** Applying mathematical transformations (like logarithmic or square root transformations) to reduce the impact of outliers.
    - **Winsorization:** Replacing extreme values with less extreme values, essentially capping the outliers.
- **Ensuring Data Consistency:** Data consistency involves:
    - **Standardization:** Converting data into a uniform format, including units of measurement, data types, and naming conventions.
    - **Validation Rules:** Implementing data validation rules to prevent inconsistencies during data entry or data integration.

- **Data Reconciliation:** Resolving conflicting information from different sources by applying logical rules or expert judgment.

Feature Engineering: Enhancing Model Power

Beyond cleaning and preparing raw data, feature engineering plays a crucial role in improving the accuracy and insights derived from price elasticity models. Feature engineering involves creating new variables (features) from existing data, capturing relevant information and relationships that might not be immediately apparent.

Examples of Feature Engineering for Price Elasticity:

- **Lag Variables:** Creating lag variables for price and promotions (e.g., price of the product in the previous week or month) captures the impact of past pricing decisions on current demand.
- **Rolling Averages:** Calculating rolling averages of sales, prices, or competitor pricing smooths out short-term fluctuations and captures longer-term trends, providing more stable model inputs.
- **Interaction Terms:** Creating interaction terms between variables (e.g., price and promotion interaction) captures the combined effect of multiple factors on demand.
- **Time-Based Features:** Extracting features like day of the week, month of the year, or holiday indicators incorporates seasonality and temporal patterns into the model.

By investing in thorough data preparation, cleaning, and feature engineering, businesses can significantly enhance the accuracy, reliability, and predictive power of their ML-powered price elasticity models. This will lead to more informed pricing decisions and improved business outcomes.

Model Assumptions

Price elasticity models often rely on certain assumptions that may not always hold true in real-world scenarios. Some key assumptions and their potential limitations include:

1. Linearity: Many models assume a linear relationship between price changes and demand, which may oversimplify complex market dynamics.
2. Constant elasticity: The assumption that elasticity remains constant across all price points can lead to inaccurate predictions, especially for products with varying price sensitivities at different price levels.
3. Ceteris paribus: Models often assume "all else being equal," which rarely occurs in dynamic market environments.

To address these limitations, analysts should consider using more advanced modeling techniques, such as non-linear regression or machine learning approaches like Random Forests or Gradient Boosting. These methods can capture more nuanced relationships between price and demand.

Evaluating and Selecting the Right Price Elasticity Model

Developing various price elasticity models is only the first step. The next crucial stage involves evaluating their performance and selecting the model that best suits your specific business needs and data characteristics. This requires understanding common evaluation metrics and considering the trade-off between model complexity and interpretability.

Model Evaluation Metrics:

- **R-squared:** Measures the proportion of variation in the dependent variable (demand) explained by the independent variables (price and other factors). Higher R-squared values indicate a better model fit, but a high R-squared doesn't guarantee predictive accuracy.
- **Mean Absolute Error (MAE):** Calculates the average absolute difference between predicted and actual demand values. MAE is less sensitive to outliers compared to RMSE.
- **Root Mean Squared Error (RMSE):** This measure measures the square root of the average squared difference between predicted and actual demand values. Larger errors are given a higher weight.

Choosing the Right Model:

The choice of the best model depends on several factors:

- **Data Complexity:** For datasets with non-linear relationships and complex interactions, models like Random Forest, GBM, or DML, are often more suitable. Linear Regression might suffice for simpler, linear relationships.
- **Interpretability:** Linear Regression offers easier interpretability, as the coefficients directly represent the impact of each variable. More complex models can be challenging to interpret, but techniques like feature importance analysis can help.
- **Computational Resources:** More complex models demand more computational resources and time for training and prediction. Simpler models are computationally less intensive.
- **Business Objectives:** A simple linear model might suffice if the primary goal is to understand the directional impact of price changes. If precise demand prediction is paramount, we may prefer more complex models.

Cross-Validation: Ensuring Generalizability:

Cross-validation is a technique used to assess a model's ability to generalize to unseen data, preventing overfitting. It involves splitting the data into multiple folds, training the model on some folds, and testing it on the remaining fold. This process is repeated multiple times, with different folds used for training and testing. The average performance across folds gives a more reliable estimate of the model's true predictive ability.

By carefully evaluating different models using relevant metrics and considering factors like interpretability, complexity, and business objectives, businesses can select the most suitable price elasticity model for their needs. Regularly evaluating model performance and updating models as needed ensures continuous improvement and adaptation to evolving market dynamics.

Implementing Price Elasticity Modeling: Practical Tips and Best Practices

Embarking on the journey of price elasticity modeling requires more than just understanding the technical aspects. Successful implementation requires a strategic approach, starting with a clear understanding of business objectives and incorporating continuous evaluation and improvement.

Practical Tips and Best Practices:

- **Start Simple:** Don't get overwhelmed by complex models from the outset. Begin with a basic model, like Linear Regression, to gain initial insights and understand the fundamental relationships. Gradually increase complexity as needed based on data characteristics and business objectives.
- **Iterate and Improve:** Price elasticity is not a static concept. Consumer behavior, market dynamics, and competitor actions are constantly evolving. Continuously evaluate model performance, refine models by adding new data or features, and adapt your approach to ensure ongoing accuracy and relevance.
- **Invest in Data Infrastructure:** Robust data collection, storage, and management systems are essential for successful price elasticity modeling. Invest in tools and technologies that ensure data quality, consistency, and accessibility for analysis. This includes integrating data from various sources, like sales transactions, customer relationship management (CRM) systems, web analytics, and external market data.
- **Collaboration between Data Scientists and Business Experts:** Collaborate closely with data science teams and business stakeholders. Data scientists bring technical expertise, while business experts provide domain knowledge and understand market nuances. This synergy ensures that models are aligned with business objectives, are interpretable by business users, and lead to actionable insights.

Moving Beyond the Model: Translating Insights into Action

Price elasticity modeling is not merely an academic exercise. The ultimate goal is to translate model insights into actionable pricing strategies. This involves:

- **Communicating Insights Effectively:** Present model results in a clear and concise way, highlighting key findings and their implications for pricing decisions. Use visualizations, dashboards, and storytelling to make insights accessible and compelling for business users.
- **Integrating with Pricing Processes:** Incorporate price elasticity modeling into existing pricing workflows. This might involve using model outputs to inform price optimization software, adjust pricing rules, or guide negotiations with retailers.
- **Monitoring and Adapting:** Continuously monitor the impact of pricing decisions based on model insights. Track key metrics like sales volume, revenue, and profitability to assess the effectiveness of pricing strategies. Be prepared to adapt your approach as needed based on real-world outcomes and evolving market dynamics.

Market Dynamics

The dynamic and often disruptive nature of markets poses significant challenges for price elasticity modeling:

1. **Competitive actions**: Sudden price changes or promotions by competitors can disrupt demand patterns and render elasticity estimates less reliable.
2. **Seasonality:** Fluctuations in demand due to seasonal factors can complicate the interpretation of elasticity coefficients.
3. **External events:** Economic shifts, regulatory changes, or unforeseen events (e.g., pandemics) can dramatically alter consumer behavior and pricing dynamics.

To account for these factors, pricing and commercial analytics professionals should:

1. Regularly update models with fresh data to capture recent market trends
2. Incorporate competitive intelligence and market indicators into their analyses
3. Use scenario planning to anticipate potential market disruptions and their impact on elasticity estimates

Challenge	Impact on Modeling	Mitigation Strategy
Data Quality	Inaccurate elasticity estimates	Implement robust data management systems or advanced imputation methods
Model Assumptions	Oversimplification of market dynamics	Employ advanced modeling techniques using machine learning
Market Dynamics	Reduced reliability of elasticity coefficients	Regular model updates and scenario planning

By acknowledging these challenges and implementing appropriate strategies to address them, businesses can enhance the effectiveness of their price elasticity modeling efforts and make more informed pricing decisions.

Conclusion

Mastering price elasticity modeling is no longer just an analytical exercise - it's a strategic imperative for businesses seeking to thrive in an increasingly competitive and insights-driven marketplace. This comprehensive guide has outlined the fundamental concepts, advanced methodologies, and practical applications of price elasticity modeling, highlighting its critical role in pricing strategy, revenue optimization, and market positioning. By understanding the nuances of different elasticity types, data aggregation strategies, and model selection techniques, businesses can craft more dynamic and effective pricing approaches tailored to their unique market conditions.

However, the true value of price elasticity modeling extends beyond theoretical insights. It offers a framework for making informed decisions directly impacting the bottom line. Organizations can optimize pricing decisions by integrating elasticity analyses into their strategic planning processes to maximize short-term and long-term profitability. For example, businesses can use elasticity insights to balance revenue growth with profit margins, fine-tune promotional strategies, and enhance inventory optimization (and liquidity). These models also provide critical guidance for new product development, marketing campaigns, and competitive positioning, ensuring pricing strategies align with consumer behavior and market dynamics.

To leverage the full potential of price elasticity modeling, businesses should consider a few actionable steps:

1. **First, they must invest in building robust data infrastructures** that support continuous data collection, integration, and analysis. This involves not only maintaining high-quality datasets but also developing the right tools and capabilities to model price sensitivities effectively. Employing advanced machine learning techniques such as Double Machine Learning or Gradient Boosting Machines can provide deeper insights into complex, non-linear relationships, offering a more nuanced understanding of consumer behavior and market reactions.
2. **Second, businesses should foster collaboration between data scientists, pricing analysts, and business leaders**. Pricing decisions should be informed by a blend of empirical data and market insights, ensuring that elasticity models are both technically sound and contextually relevant. Regular cross-functional workshops, advanced analytics-driven strategy sessions, and the use of visualization tools can help bridge the gap between analytical findings and strategic decision-making.
3. **Third, adopting elasticity modeling should be seen as a continuous process rather than a one-time effort.** Market conditions, consumer preferences, and competitive landscapes constantly evolve, necessitating ongoing model updates and scenario analyses. Businesses must remain agile and ready to adapt their pricing strategies in response to external disruptions, seasonal fluctuations, and competitor actions. Leveraging near real-time data and incorporating contextual variables such as social

media sentiment, weather patterns, or geopolitical events can further refine model accuracy and ensure that pricing strategies remain resilient.

4. **Lastly, organizations should consider the importance of effectively communicating elasticity insights to all stakeholders.** We should present clear, actionable findings that resonate with decision-makers, using visualizations and scenario simulations to demonstrate the potential impact of different pricing decisions. This not only aids in making data-driven decisions but also enhances organizational buy-in and fosters a culture of transparency and accountability.

As the field of price elasticity modeling continues to evolve, embracing these best practices will be key to unlocking new opportunities for profitable growth. Businesses that master elasticity modeling in-house will be better positioned to navigate market uncertainties, respond to competitive pressures, and drive sustained operating profit growth. To stay ahead of the curve, it is crucial for pricing professionals to keep up with emerging trends in both pricing and AI/ML, continuously refine their methodologies, and leverage advanced tools and technologies.

For a deeper exploration of these concepts and access to our full suite of pricing and revenue growth management insights, we invite you to explore our additional resources or reach out to our advisory team. By mastering price elasticity modeling, businesses can transform complex data into strategic pricing intelligence, driving smarter decisions and stronger financial performance.

To build internal capabilities, any business looking to train their commercial and analytics/data science staff in price elasticity modeling using their data should consider our tailored corporate training programs. We designed these programs to enhance analytical skills and equip teams with practical tools to apply advanced pricing strategies effectively. For more information, visit our corporate training page.

Coding Resources

By downloading our whitepaper, you have received exclusive access to our growing suite of price elasticity modeling resources.

1. **TOOLS ➢ B2B Price Elasticity Modeling (R)**
    - Download R scripts for demand modeling and price elasticity in B2B, using linear regression, multiplicative models, and random forests.
2. **TOOLS ➢ Price Elasticity - Linear to ML (B2C)**
    - Access tools for B2C demand modeling with linear and machine learning approaches.
3. **TOOLS ➢ Price Elasticity with ElasticNet (R & Python)**
    - Scripts for estimating B2C price elasticity, combining linear regression and ML.
    - Link to R code
    - Link to Python code
4. **TOOLS ➢ Price Elasticity Using Double ML (Python)**
    - Python-based advanced double machine learning models for elasticity estimation.
5. **SLIDES ➢ Modeling Price Elasticities**
    - Presentation slides on price elasticity modeling techniques.
6. **SLIDES ➢ Double ML for Price Elasticities**
    - Slides detailing double machine learning methods for price elasticity.
7. **SLIDES ➢ Volume Hurdles and Strategic Implications**
    - Slides detailing the concept of profit sensitivity analyses and break-even volume hurdles.
8. **SLIDES ➢ Random Forest and Gradient Boosting Tutorial**
    - Tutorial slides on how Random Forest and Gradient Boosting algorithms work.

For more Revenue Growth Analytics tools and resources, visit the Revology Analytics Tools page.

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