Price Predictor™
Reimagined Price Elasticity

TABS Analytics A division of Blacksmith Applications

DECISION INSIGHT

Price Elasticity Analytics Reimagined

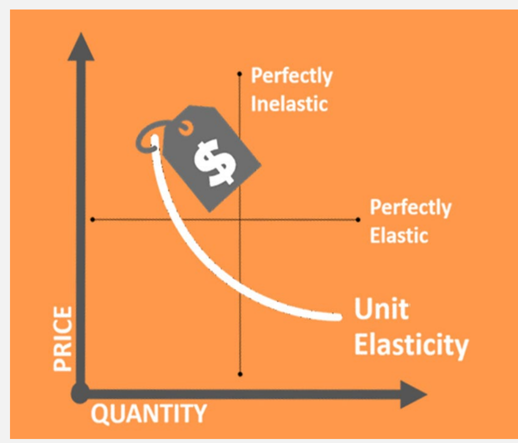
Elasticity measures the change in demand when economic factors like price are adjusted. For CPGs, elasticity is a key concept in improving pricing strategy to determine the increase or decrease in demand for a good when its price is manipulated. Price elasticity can be a useful tool when it comes to understanding the market, specifically consumer behavior.

However, historical data is not adequate in determining price elasticity because there is not enough variation, or you need to raise prices beyond what is currently in the marketplace. TABS and Decision Insight have come together to create a solution that combines the predictive benefits of Virtual Shopping with analytics powered by Machine Learning to achieve the optimal price.

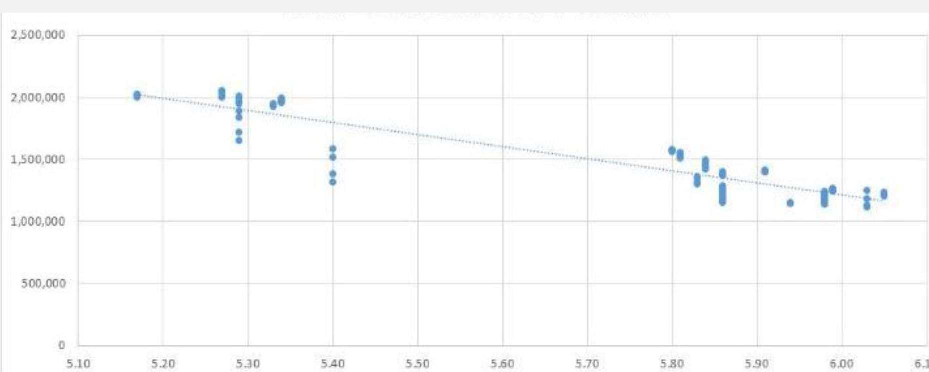
To begin, *what is the traditional approach to price elasticity? And what are its shortcomings?*

Traditional Elasticity Analysis

Price Elasticity is a measure of how sensitive demand is to changes in price. For products with high elasticity, a change in price results in a change of demand (examples: luxury items, commodity products). Products that see no change in demand even if price changes are inelastic (examples: gasoline, medications). If demand increases when prices go up, then the price elasticity of demand is positive. If demand decreases when price goes up, then the price elasticity of demand is negative. Traditionally, price and quantity are evaluated to understand elasticity. But while the traditional price elasticity analysis works in certain contexts, the approach has four key shortcomings.

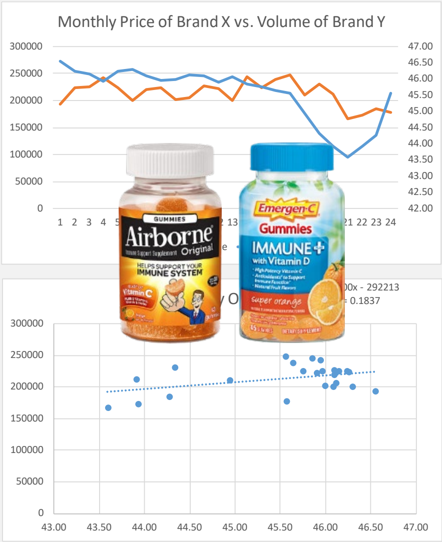


Price Elasticity: The higher the absolute value, the more sensitive consumers are to change.



Shortcomings of Traditional Elasticity Analysis

1. **Sales data alone is at risk from market shocks**
2. **Pricing variation needed for projections is often lacking in historical scanner data**
3. **Analytical complexity increases exponentially across shopper consideration factors, i.e., multiple promotions across multiple brands**
4. **Cost & timing currently limit market response**



Shortcoming #1: COVID (External) Impacts
Sales data collected during COVID can not be used in analysis since it provides an inaccurate reflection of the market. The pandemic placed significant strain on the CPG industry, as consumers rushed to stock up on such products. In the preliminary data, it appears that consumers during that bump became less price sensitive. This is corroborated by the fact that overall demand in the industry went up roughly 7% while average pricing went up 7%. That is a whole year of data that can't be used to make projections. At least for the next two to three years, it will be problematic to try to use the typical scan data to determine price elasticity effects.

Shortcoming #2: Lack of Pricing Variation
Another issue with the traditional approach is that there is a lack of pricing variation. While it is a common belief that changes in pricing occur frequently in order to respond to the demand of customers, in reality there is chain-wide pricing that stays consistent for an extended period of time. Therefore, the data is not useful for making projections since there are minimal fluctuations in pricing.

Shortcoming #3: Cross Elasticity
The concept of cross elasticity describes how sensitive the demand for a product is to changes in the price of another similar product. For example, if the price of Brand X increases, demand for Brand Y may decrease, and vice versa. Cross elasticity affects products across multiple segments – consider a category with 10 brands, 50 brand sizes, across 30 geographies… 73,500 cross elasticities to analyze – that's an unmanageable number of analytics to conduct with in-market scan data. An additional problem occurs when there is synchronous movement in pricing, as competitors often price match. This eliminates the ability to have an isolated analysis on a situation where if Brand X increases price, what is the impact on their competitor, Brand Y, when their price does not change in response.

Shortcoming #4: Timing & Cost
Most elasticity studies are conducted only once per year, take several months to complete, and are expensive. CPGs must then rely on this one study all year, even as things change in the marketplace, making it difficult to capture any kind of exogenous shock or change to the pricing environment as it is happening. Ideally, it would be better to track elasticity like market share or brand health: on an ongoing basis.

Our New Price Elasticity Solution

Price Predictor™ was developed to get quicker and more dynamic results, have more granularity, with the ability to isolate variables and the ability to easily respond to any changes. To understand the optimal price, the new Price Predictor system combines Virtual Shopping and Machine Learning.

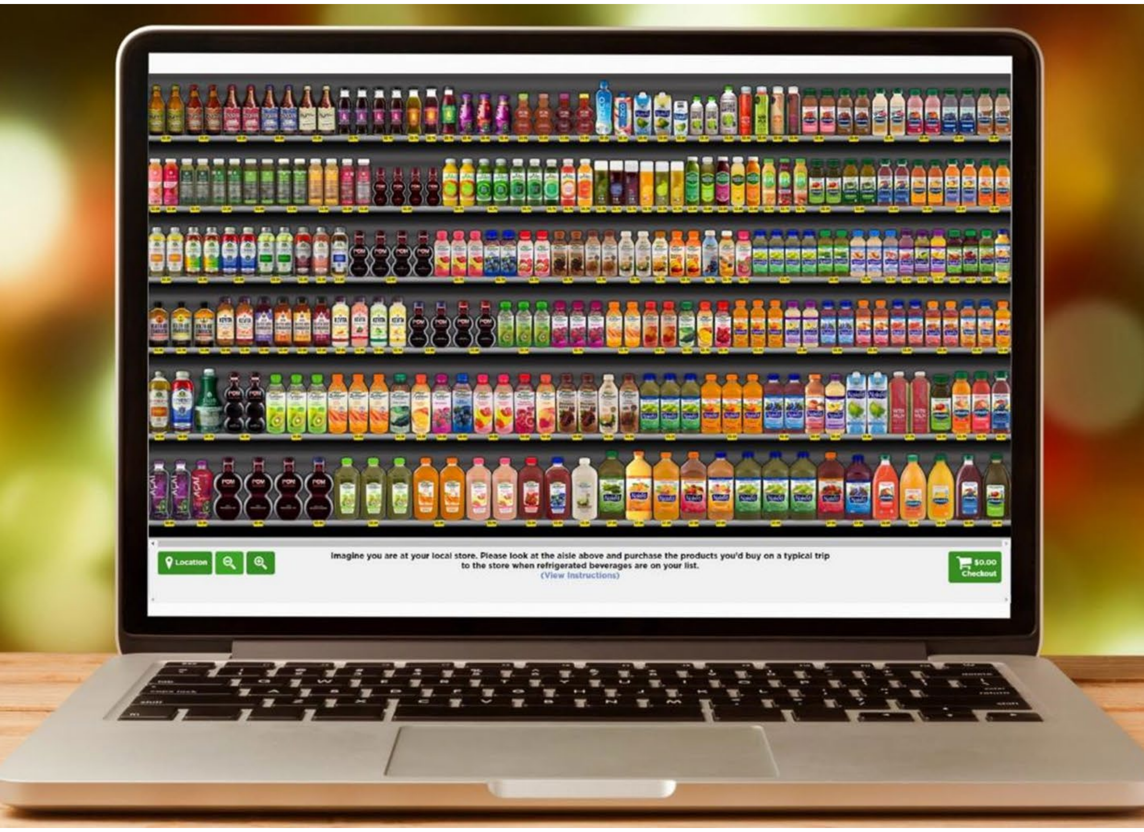
Virtual Shopping is ideal for testing pricing because it puts shoppers in the context of an actual purchasing decision with a realistic set of competitive alternatives. Virtual sales data correlates to in-market data at .90 or greater.

Machine Learning then efficiently runs multiple simulations to explore possible scenarios for future market conditions. Results are forward-looking and can be updated regularly.

The Price Predictor™ process:

1. Virtually test price variations and competitive response with shoppers.
2. Feed research sales data into analytical engine.
3. Machine Learning efficiently analyzes multiple future scenarios.
4. Future market data powers simulation tool.

Our new approach removes the effects of market shocks to achieve the perfect price.



How Virtual Shopping Works

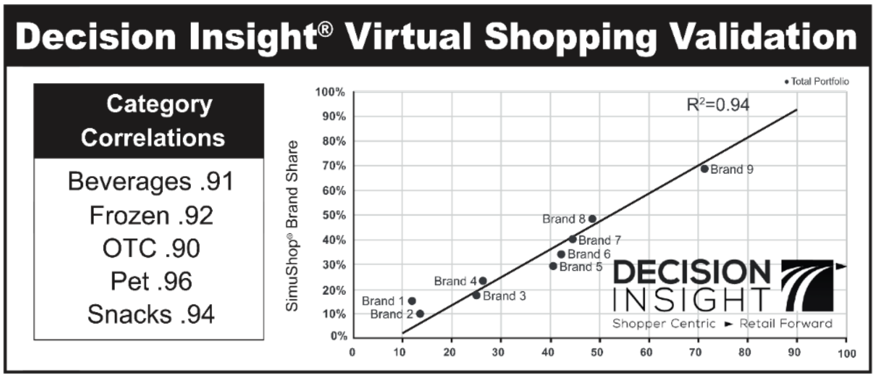
A virtual shopping environment resembles an actual store, where respondents shop from a selection of shelf variations. Shoppers can click on products to see a larger image with product details and choose which (if any) items to add to their shopping cart.

Virtual Shopping for Price Elasticity Analysis

Virtual Shopping offers a solution to limitations of the traditional approach. It allows us to understand the impact of potential *new* pricing tactics by testing shoppers' response to a broader set of value offerings.

It also eliminates the volatility from COVID that has exacerbated the flaws in historical sales data. Scanner data can't isolate structural shock events or keep pace with current pricing evolution.

Decision Insight developed this proprietary online Virtual Shopping platform over 15 years ago, with virtual sales data consistently correlating to in-market data at a very high level of 0.90 or higher. This is true across categories throughout the store, demonstrating that the platform accurately predicts what is going to happen in the marketplace. The high level of confidence from these correlations provides the foundation for Price Predictor, which combines the predictive benefits of virtual testing with machine learning.



Example: Simulating Cross-Elasticity Effects

A controlled virtual shopping environment can test multiple combinations of variables, such as pricing, assortment, arrangement, and promotions. Results determine how performance is driven by each variable or combination. For example, it's possible to develop and test alternative size/price configurations so brands can determine what occurs at important price thresholds, such as what will happen if the price is shifted from 99 cents to $3.

Benefits of Virtual Shopping

- ✓ **Correlates to in-market data at .90 or greater** (predictive and reliable)
- ✓ **Measures actual sales** (same as in-market test)
- ✓ **Reduces risk** (isolates test variables for targeted cross elasticity effects)
- ✓ **Forward-looking data can be regularly updated**
- ✓ **Timing and cost efficiencies** (response can be based on current conditions)

Machine Learning for Modeling Cross-Elasticity of Consumer Products

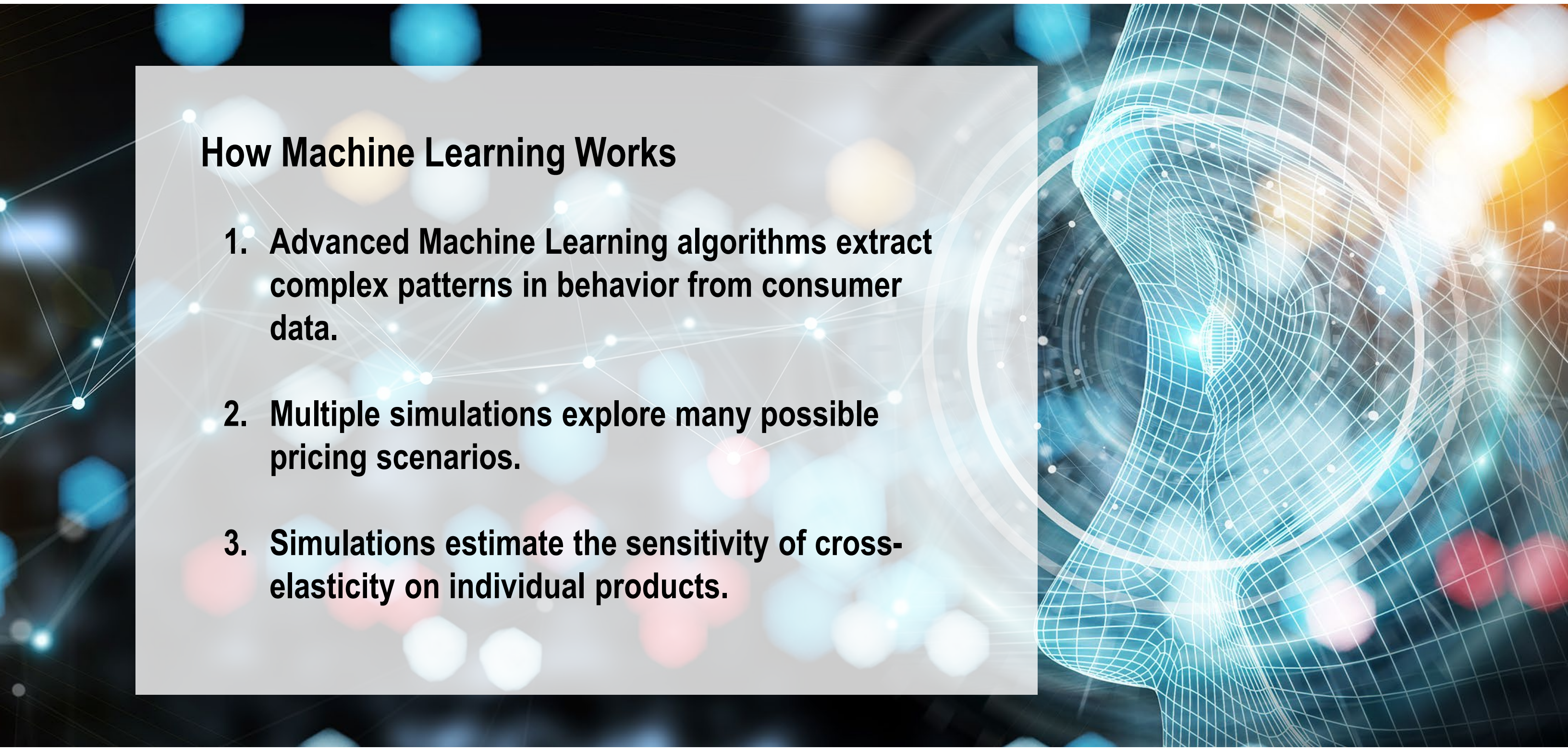
Machine Learning models trained on historical consumer data are used to simulate cross-elasticity effects on demand within the marketplace. Advanced algorithms are applied to extract complex patterns in consumer behavior.

Price Predictor goes a step further and, in addition to linear regression, takes an approach that provides a richer, fuller picture of how different products within a given market are interacting with one other. Multiple simulations are generated to explore many possible pricing scenarios. The simulations are used to estimate the sensitivity of cross-elasticity on individual products.

You get realistic market trends based on variables like distribution, promotions and marketing

Example: Non-Linear Approach

The concept of cross elasticity is fundamentally non-linear: How does the demand for Product A change as the price of Product B changes? For example, if product A increases price by $1 versus $2, the magnitude of that effect on a different product is not going to be the same at each of those price points. This is essentially impossible to pick up through traditional linear regression, but through a machine learning approach it’s possible to capture some of those nonlinearities.



How Machine Learning Works

1. **Advanced Machine Learning algorithms extract complex patterns in behavior from consumer data.**

2. **Multiple simulations explore many possible pricing scenarios.**

3. **Simulations estimate the sensitivity of cross-elasticity on individual products.**

Advanced Analytics: Explore All Scenarios

Simulations provide the ability to explore any set of product prices within the market assuming competitors don’t respond at all. The user selects a set of prices to explore and then the application runs multiple simulations in real-time to compute the outcome.

When experimenting with pricing impact, the results can be used to optimize the consumer response. For example, if the price of a product is increased, the simulation projects and predicts how demand for other products will change if no competitor changes their prices. For some product categories where prices change very slowly, this could be appropriate; for faster moving categories, machine simulations could be added to gain key insights.

Considering the Salty Snacks category, where prices can change very quickly, this approach is more appropriate to determine how competitors might respond.

For example, when the price of Cheese Puffs is increased, it’s likely that a competitive cheese snack will increase their price as well. In this framework, results illustrate how demand for all products in the category (including within own portfolio) are impacted at various levels, including tortilla and potato chips.

While common belief is that cross elasticity happens on a one-to-one basis, this example demonstrates that a price change for one product can impact demand for a lot of different products, even products that one wouldn’t consider initially.

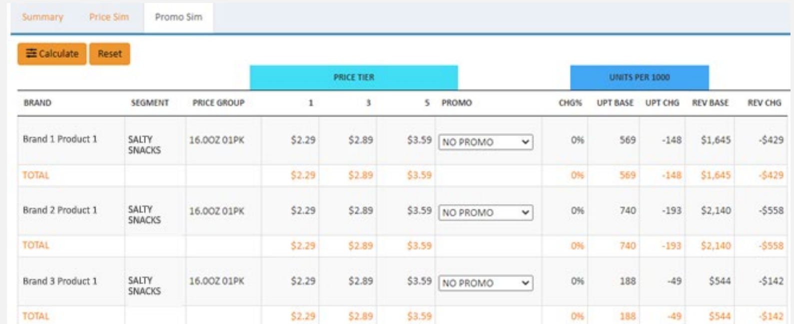
This is a powerful approach, especially with the volatility from COVID, and allows manufacturers to test with reliability.

Sample Study: How it Works

1. Shoppers exposed to multiple scenarios of randomized Shelf Prices for major Price Groups (3 or 5 prices tested)
2. Simulations explore possible pricing scenarios.
3. Machine Learning algorithms extract complex patterns in behavior from consumer data.
4. Results estimate the Sales and Profit impact of any scenario by Product, Brand and Category.

Interactive Simulator Delivery

- **User controls the price changes of products**
- **Competitor response is modeled in simulations**



Summary | Price Sim | Promo Sim

Calculate | Reset

			PRICE TIER				UNITS PER 1000				
BRAND	SEGMENT	PRICE GROUP	1	3	5	PROMO	CHG%	UPT BASE	UPT CHG	REV BASE	REV CHG
Brand 1 Product 1	SALTY SNACKS	16.0OZ 01PK	$2.29	$2.89	$3.59	NO PROMO	0%	569	-148	$1,645	-$429
TOTAL			$2.29	$2.89	$3.59		0%	569	-148	$1,645	-$429
Brand 2 Product 1	SALTY SNACKS	16.0OZ 01PK	$2.29	$2.89	$3.59	NO PROMO	0%	740	-193	$2,140	-$558
TOTAL			$2.29	$2.89	$3.59		0%	740	-193	$2,140	-$558
Brand 3 Product 1	SALTY SNACKS	16.0OZ 01PK	$2.29	$2.89	$3.59	NO PROMO	0%	188	-49	$544	-$142
TOTAL			$2.29	$2.89	$3.59		0%	188	-49	$544	-$142

Conclusion

While the traditional price elasticity approach can be useful in certain situations, historical data is not adequate in determining price elasticity because there is not enough variation, or prices need to be raised beyond what is currently in the marketplace. Price Predictor™ combines Virtual Shopping with Machine Learning to solve this problem and offers superior advantages, such as identifying cross-price elasticity.

With a traditional elasticity analysis approach, the process is limited in terms of how many different scenarios can be sampled and considered. On the other hand, this new solution analyzes how the market would behave across a variety of different scenarios. Valuable insights can be derived from conducting numerous simulations. The machine learning method provides more freedom in terms of investigating how the market might respond to a given condition.

Not every pricing question requires a machine learning process. To test a more limited number of price points, a dedicated Virtual Shopping study can be conducted with Decision Insight. For more complex analysis, Machine Learning may be the most efficient and effective model.

Price Predictor™ Advantages:

- ✓ Strong correlation of Virtual Shopping research to in-market performance with 90% accuracy
- ✓ Findings based on current market conditions
- ✓ Results are forward-looking and can be updated regularly

About TABS Analytics

Tabs Analytics is a technology-enabled analytics firm servicing the consumer products industry. Our mission is to simplify and improve the way analytics is conducted through analytical innovation, which translates into a competitive advantage for our clients. TABS is the leading outsourced sales and marketing analytics firm in the consumer-packaged goods (CPG) industry.

About Decision Insight

Decision Insight (DI), a division of TABS Analytics, is a leading shopper insights and retail strategy firm that uncovers shopper behaviors and motivations. Twenty years of partnering with leading CPG companies have groomed the team at DI to actively anticipate emerging needs to deliver solutions that lead to activation, triggering higher shopper satisfaction and increased sales. Our Test & Learn research is forward-looking and based on shopper behavior.

For more information about this white paper or TABS+Decision Insight research offerings, email Leslie Downie at leslie@decisioninsight.com.

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