Revionics
REVENUE BIONICS

WHITE PAPER

Science Propels a New Era of Retail Price Optimization

Why -- and how -- mathematics, statistics, and econometrics should matter for retailers

By Jim Sills, Ph.D. and Jeff Moore

Table of Contents

Jim Sills is an experienced software development executive with over 20 years of experience. He is currently vice president of Engineering at Revionics <www.GetRevionics.com>. Sills has also served as vice president of Trade Development at SAP, where he managed a staff of over 70 employees working on planning applications for retail environments. He is widely credited with pioneering scientific retailing at Khimetrics, where he served as Vice President of Research. A former faculty member at the University of Texas, San Antonio, Sills received his Doctorate and Masters in electrical engineering from Georgia Institute of Technology. He has a Bachelors in lectrical engineering from the University of Dayton. He holds six patents and has published over 20 papers.

Jeff Moore comes from an electrical engineering background with 13 years of experience. He joined Revionics early in 2008 as Director of Research. He was the lead architect of Demand Management Science at SAP where he led a core team of 10 scientists and engineers in the integration of Demand Forecasting with numerous retail applications. He was a researcher and systems engineer at pricing pioneer Khimetrics, designing solutions for markdown, promotions, and replenishment as well as developing core demand modeling and forecasting science. He holds a Masters in electrical engineering with a minor in mathematics from the Georgia Institute of Technology. He holds a Bachelors in electrical engineering from the University of Arizona.

Abstract

Modeling and analytics are now the hot topic in a vast array of formerly non-scientific environments: Internet pioneers feverishly seek to uncover the mathematical roots behind "viral" marketing; physicists are being employed by publishers to forecast how a favorable New York Times book review sends Amazon.com sales skyrocketing; geology specialists are helping some fast-moving consumer goods retailers re-create sales aftershock effects. In each case, non-scientific environments are being transformed by modeling, forecasting, and predictive analytics science – namely because in the absence of these powerful disciplines, it would be nearly impossible for retailers to handle the complexity of data and variables associated with these tasks.

Most retailers know that technology has played an increasingly important role in helping retailers set prices. But until recently, these efforts have been rooted in advances in computing technology, rather than in newfound applications of scientific principles. Real science is a powerful, pervasive force in retailing today, particularly so for addressing the complex challenge of retail pricing. Done right, the application of scientific principles to the creation of a true price optimization strategy can lead to significant sales, margin, and profit lift for retailers. This paper explains why retailers can no longer thrive without a science-based pricing system, defines and illustrates the right science-based approach, and calls out the key features and functionalities of leading science-based price optimization systems.

"Traditional pricing methodologies use target margin percentages and/or competitor pricing strategies as the core elements of base price, and most retailers employ systems that are incapable of considering consumer demand intelligence."

What Is Retail Pricing Science - and Why Is It So Important?

Of all the challenges facing retailers today, pricing strategy is often cited as the most complex and demanding – yet it is also the discipline most responsible for making the difference between profitability and insolvency. For most retailers, pricing has long been at best a poorly automated process and more typically a highly manual process. Category managers and pricing analysts today continue to overly depend on their intuition and experience to determine the price for every product in every store. Given the volume of items that exist within most retail formats today, this "gut feel" approach is no longer adequate.

These traditional pricing methodologies use target margin percentages and/or competitor pricing strategies as the core elements of base price, and most retailers employ systems that are incapable of considering consumer demand intelligence in their pricing processes - which means they cannot confidently determine which items they should raise the price on without having a detrimental impact on demand, or which items they should lower the price on to increase sales – the key to increased profit. Most retailers established a price strategy long ago based on a margin percentage over costs, and they have simply adjusted that price over time as costs increased or when they have seen movement in their competitor's price for the same item.

Today's increasingly complex pricing environment, and the lack of adequate automation to create or manage a sophisticated pricing strategy, forces many retailers to play the game of "follow the leader", where pricing is set directly to primary competitors. This pattern of reactive pricing "leaves money on the table." -- Retailers are bound by a pricing regime that fails to steer consumer behavior to the most profitable items. As such, well-known national brands are often priced such that they do not capture the value associated with their brand names, and private label products are often haphazardly priced, often failing to encourage switching to more profitable alternatives.

Over the past two decades, price optimization science has advanced tremendously (see Revionics' white paper library for more information). Front-end point-of-sale systems have enabled large-scale retailers to collect and analyze reams of consumer purchase behavior data. More recent advances in the early 2000's – the "fourth generation" of pricing systems – took advantage of technological breakthroughs in computing speed and data processing power (enabling faster number crunching), vastly increased data compression and transmission (enabling greater data storage and manipulation), and access to data (through the proliferation of PCs and increased ease-of-use via user-friendly software platforms). Further, improved communications and computing systems, widespread adoption of PCs and backend-systems, and development of new scientific optimization techniques brought price optimization within the reach of retailers of all sizes. The limitations of first-generation price optimization systems, including high costs, maintenance of large and complex technical infrastructures, and extensive training times and learning curves, have been eliminated. Robust price optimization solutions are now available to any retailer with basic retail technology and internet access.

These advances mentioned above, however, are rooted in technology, not in retail science. Unlike the sophisticated modeling and analytics platforms and techniques developed for optimizing consumer flight reservations (e.g., SABRE – which bred Orbitz, Expedia, etc.) or facilitating online Internet search (Google), retail pricing had yet to integrate new technological capabilities with advanced statistics, mathematics, physics, and econometrics – core scientific disciplines that can, if applied in concert as an integrated unit to the challenge, create a price optimization system far beyond the capabilities of any traditional or typical "fourth generation" system.

"New-era retail price optimization regimes are derived from integrating advanced statistics, mathematics, physics, and econometrics with traditional retailer best practices and heuristics."

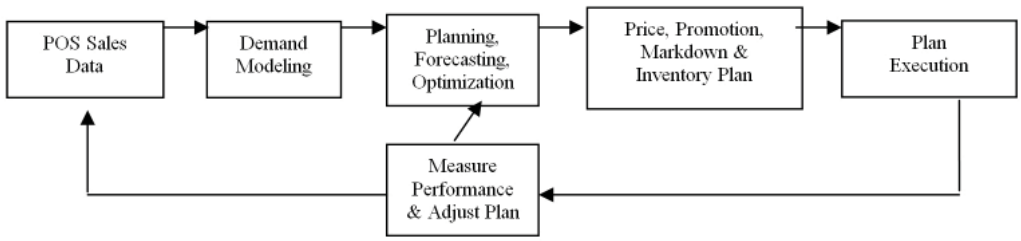

Figure 2. Key Stages of the Advanced Retail Pricing Science Process

The Advanced-Science Approach

New-era retail price optimization regimes are derived from integrating advanced statistics, mathematics, physics, and econometrics with traditional retailer best practices and heuristics. The new-era pricing regime, however, is more than just a mix of formulas; it is an adaptive process that integrates advanced modeling, analytics and forecasting, and workflow processes designed to provide retailers with a simple-to-use, easy-to-understand price optimization system. Figure 1.0 depicts the basic structure of the advanced-science approach:

Step 1: Obtain a Clean Master Item Data File
Ultimately, every decision that a retailer makes should be informed by customer demand. Obtaining comprehensive sales data is the first step to enabling a science-based price optimization system. This data file – usually generated from front-end POS data capture – is the key ingredient to determining where the most prominent item price elasticity resides (described in greater detail below). Raw customer behavior data, however, usually includes a small number of extreme or misaligned data points – such as price outliers, out-of-stock items, items with unidentified promotions- that require inferencing to be "cleaned" or removed to create a more statistically reliable data set for demand modeling. Data cleansing is the first and most critical element of creating a "trustworthy" price optimization system.

Step 2: Modeling – Employ a Series of Algorithms to Produce Parameters of Price Elasticity
While consumer purchase behavior at the individual level can vary widely, collective purchase behavior is, over time, products, and stores, far more consistent and, therefore, predictable. Using the cleaned data, it is possible to develop a demand model - a set of parameters and demand-influencing factors that together form a mathematical expression that predicts customer demand.

The goal of modeling is to produce a set of parameters associated with a mathematical formula that can be used to predict unit sales for any given combination of price, promotion, markdown, or inventory strategy. This requires understanding item-specific sensitivities. Identifying specific parameters (e.g., parameters for price sensitivity, promotional lift, and cannibalization) enables the system to generate price change recommendations based on specific retailer goals (such as margin targets or profit and revenue levels). The power of having such a model is that it allows retailers to predict purchase behavior (Steps 3 and 4 below) with a high degree of confidence, enabling better decision making in business planning and execution.

Demand modeling uses an observational history of purchase behavior (sales history) to produce an explanation of future customer behavior that depends on many factors, including:

- **Velocity**
  Velocity is the nominal sales rate of a product. Since business impact is proportional to velocity, decisions for which products to promote, regular pricing decisions, replenishment, and markdown are all heavily influenced by velocity.

- **Price Elasticity** *(described in greater detail below)*
  Price elasticity is the response of the item movement to price changes. Elasticity relates quantity sold to the price seen by the customer. The elasticity impacts any decision relating to the price, including regular pricing, promotion, and markdown.

- **Promoting Response**
  Promotional response measures how customers respond to item promotion above and beyond the impact of the pricing effect. Promotions typically produce "extra-elastic" lift due to the added visibility of putting up signs, running print advertisements, and building in-store displays. Promotional response determines how customers respond to the various promotional activities independent of the price that is charged. Promotional response impacts the selection of products to promote, and the medium and manner in which they are promoted.

"The goal of modeling is to produce a set of parameters associated with a mathematical formula that can be used to predict unit sales for any given combination of price, promotion, markdown, or inventory strategy."

- **Seasonality / Holidays**
  Seasonality refers to how time of year impacts demand. Cyclic patterns are present for many classes of products (hot chocolate sells more in the winter, while popsicles sell more in the summer). Many products are also strongly influenced by holidays. Baking goods tend to have very large "spikes" immediately preceding Thanksgiving and Christmas. Eggs have a very large lift for Easter. Seasonality can impact replenishment, promotion planning, markdown, and labor planning activities.

- **Trending**
  Trending refers to a relative change in the popularity of a product or group of products over time (independent of price, promotion, and availability). Migration of shoppers away from milk chocolate and toward dark chocolate in the United States is a good example of a demand trend that reflects a change in customer preference that is not driven by pricing effects.

- **Cannibalization**
  Cannibalization is an inter-product effect that measures the change in demand for a product as a function of demand changes for other products. For instance, if a national brand of tortilla chips is promoted, the increased sales may detract from demand for the similar private-label tortilla chips. Cannibalization is an important driver in pricing and promotion decisions, determining the behavior of entire groups of products in relation to one another.

- **Affinity / Halo**
  Affinity is the flip side of cannibalization. Complementary products can see boosted sales due to an increase in sales of another item. As an example in retail grocery, promoting hot dogs may result in increased sales of other items including buns, mustard, catsup, and pickle relish. These additional sales (sometimes called "drag-along") can have an important impact on the overall profitability of pricing or promotion decisions.

"A forecasting engine uses the previously generated models on demand to create an updated scenario forecast."

This list is by no means exhaustive. Weather effects, competitor pricing and behavior, shelf placement, and street traffic can all impact customer demand in measurable ways, and can therefore be incorporated into demand models. Most of these effects, however, are not observable from sales data alone, and in some cases provide little or no predictive benefits (all of these effects can provide a good explanation for historical demand patterns, but unless we can also accurately predict them in the future they don't provide any additional insight to our decision-making process).

The bulleted list above is presented roughly in the order of difficulty or sophistication involved in modeling the effect. Basic velocity alone can be gauged with simple or time-weighted averages. Elasticity and promotional response can be approached with fairly straightforward regression techniques. Seasonality and trending require more sophisticated time-series approaches along with holiday calendars. Cannibalization is a subtle effect involving many-to-many relationships among models' causes and effects. Affinity is also a subtle effect, but is more difficult even than cannibalization to measure because the set of candidate products for positive interaction with a given product forms a very large pool of potential relationships, making causal attribution extremely difficult.

Figure 2.0 illustrates the workflow relationships between sales history data, demand modeling, and the individual models generated by associated business factors:

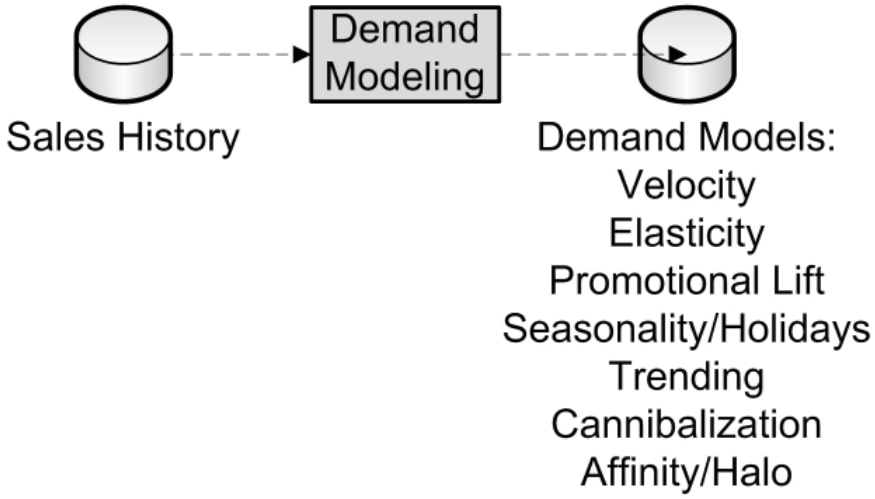

Figure 2. Demand Modeling

"Price elasticity is the single most powerful driver of demand modeling, and is the critical enabler of the forecasting and predicting attributes of new-era price optimization systems."

Step 3: Forecasting: Using Models to Predict the Impact of Price Changes on Customer Behavior

This step extends modeling outputs to predict likely customer response to pricing changes in real-time by enabling "what-if" scenario forecasting. Figure 3.0 illustrates a typical forecasting workflow including "what-if" scenario forecasting as the central component. Scenario forecasting approval/disapproval is the fulcrum point in the decision-making process, triggering either execution of recommendations and scenarios or a recycling of the modeling and forecasting loop.

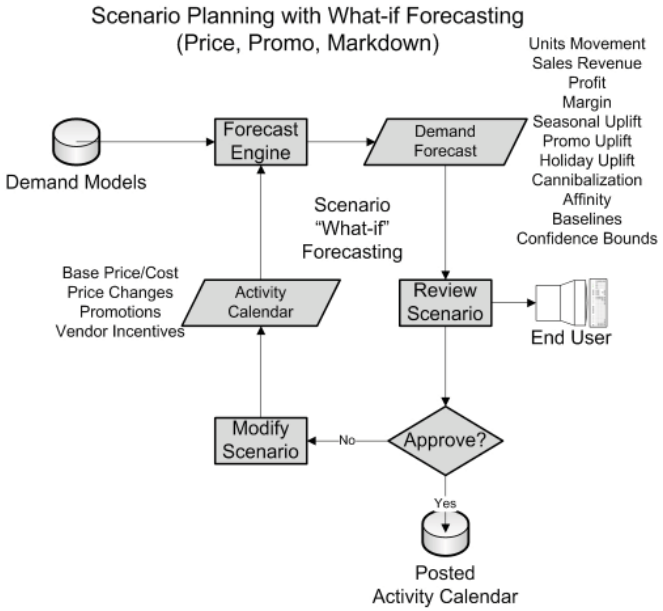

Figure 3. What-if Scenario Planning

Scenario forecasting is an iterative process. In this workflow, the user creates and modifies an "activity calendar" consisting of pricing and promotion decisions. A forecasting engine uses the previously generated models "on demand" to create an updated scenario forecast. Forecasts are made available in the user interface, where users can examine the impact of their decisions at various levels of aggregation. If satisfied with projected results, users approve the scenario for implementation, which then feeds into subsequent workflows.

In this manner, scenario forecasting re-defines the concept of optimization to mean "automatic" decision-making produced by scientific algorithms.

Example Scenario Forecasting Workflow: Promotion Planning

The scenario forecasting workflow can support promotion planning by allowing users to assess projected promotional decisions. In the "Modify" step, the user selects products to be promoted; sets prices, offers, and promotion media; and then receives an updated forecast of demand. The user can continue to make adjustments to the promotion scenario until the forecasted results meet desired business goals.

At the item level, users are able to envision sales and projected profit lift due directly to the promotion. If an item has poor uplift, the user may choose not to promote it in favor of other products that will generate better promotional response. Profit, revenue, margin, and unit sales are all provided by the forecast. The price and promotional offer parameters can be modified to find results that best match the planner's goals for the promotion.

"New-era price optimization systems are able to analyze data across multiple product categories and subcategories at any point in a product's lifecycle to determine specific demand causalities."

The item's impact on related products due to cannibalization and affinity can also be seen. In some cases, these effects may influence promotional decisions. As an example, for retail grocers, it may be worthwhile to take extremely deep cuts on hot dogs if there is a good expectation that the increase in sales of buns will offset the margin impact.

The planner will also want to know the impact of the promotional activity at higher levels of aggregation. A planner may want to know the total additional revenue or profit that will be generated by the promotion, or the overall margin of promoted products relative to their regular-price values. The planner may also wish to view these values by product category, or by ad zone, or even by store. Demand forecasting forms the basis of all of these views of the impact of a promotion.

Price Elasticity

Price elasticity is the single most powerful driver of demand modeling, and is the critical enabler of the forecasting and predicting attributes of new-era price optimization systems. Price elasticity applies advanced math, statistics, and analytics to measure consumer response - sensitivity - to changes in price. The formula for price elasticity in its simplest form is:

$$\frac{\%\ \text{change in quantity demanded}}{\%\ \text{change in price}}$$

The science behind this formula is simple. For example, if the price elasticity is 1, then a 10% increase in price will cause a 10% decrease in unit sales. Similarly, if the price elasticity is 2, a 10% drop in price will cause a 20% increase in unit sales.

Figure 4 illustrates how item-level price elasticities are typically distributed in a retail store.

In this framework, if every item in a retailer's store achieved an elasticity rating of 1, every price increase would result in a proportional increase in demand – the retailer would be operating at maximum revenue. This is a retailer's goal. Determining elasticity at the item, subcategory, or category level enables retailers to establish consistent pricing decisions.

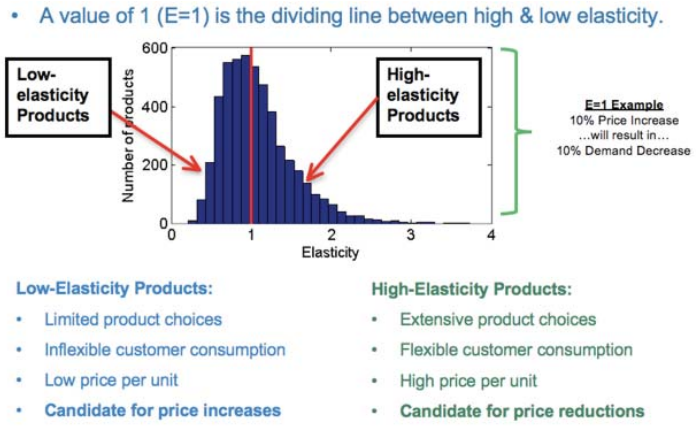

Figure 4. Pricing Elasticity and Individual Item Pricing

Step 4: Predicting Customer Behavior from Modeling and Forecasting

In addition to analyzing consumer demand signals, modeling price changes to recommend new ones, and forecasting customer behavior based on recommended price changes, new-era price optimization science allows retailers to actually predict the impact of recommended price changes to future sales, margin, or profit metrics.

Figure 5 below illustrates how raising the price of a particular item – 2% low fat milk in a retail grocery store – lowers overall product revenue but increases profit and margin. The opportunity curve represented in this illustration is actually a visualization of the price elasticity of 2% low fat milk. It is derived from the modeling of all the related pricing factors (i.e., base price, past customer demand, cost, seasonality, etc.), and is presented here to show how retailers are able to forecast price change effects to achieve targeted business goals.

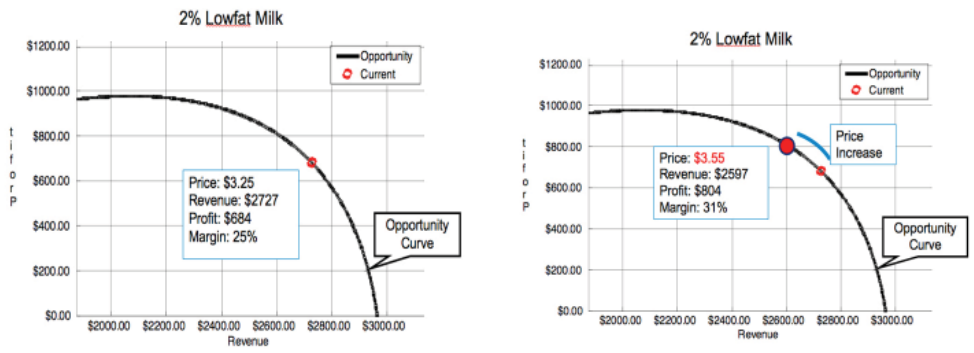

Figure 5. Pricing Elasticity and Individual Item Pricing

"Retailers need to be able to discern the features and functionalities that differentiate one system from another to ensure they not only find the system that best suits their specific needs but also use the system to its highest capacity."

This predictive ability is the latest addition to the system of retail pricing brought about by the application of scientific disciplines that now includes mechanisms for not only generating prices, but also monitoring the effectiveness of price changes, learning from those results, and then adopting the underlying mathematical models that drive the science. Indeed, retail pricing software is now self-teaching.

The most robust new-era price optimization systems de-couple pricing effects between variables. The most advanced systems can solve the co-linearity problem normally associated with variables such as cannibalization, promotions, or seasonality – where pricing effects are often "masked", making it often difficult if not impossible for retailers to determine with even a moderate degree of confidence if the demand changes they experienced on a particular item was due to any one particular variable. New-era price optimization systems are able to analyze data across multiple product categories and subcategories at any point in a product's lifecycle to determine specific demand causalities. This ability enables retailers to create pricing strategy consistency

Further, the best systems will recommend prices based on advanced demand forecasting, competitor analysis, group/KVI(Key Value Item) analysis, brand analysis, relational pricing analysis, promotions/TPR (Temporary Price Reduction) analysis, price-per-unit analysis, as well as targets for volume margin and category margin. Naturally, every retail environment is different, and the pricing objectives of retailers can vary from one store to another. This raises the importance of having a highly configurable system with the right up-front support to determine the best mix of demand intelligence (science) and heuristics (strategies, rules, and best-practices) in the creation and executing of your pricing strategy.

"Advanced science embedded in these systems is capable of providing specific pricing answers but only in conjunction with the "art" of how a retailer wants their store to be positioned in the marketplace."

Using sales data to produce mathematical models of customer demand, then making informed, high-confidence predictions of customer behavior based on those models, allows the retailer to make the best decisions for pricing, promotion, markdown, and replenishment in light of their strategic goals for the business as well as their own individual "rules" and best-practices. Decisions based on a good understanding of customer demand (through elasticity modeling) allow retailers to boost revenue and profit, reduce waste, and save valuable time and effort across the entire organization, from planning to in-store execution.

Features and Functions of the Ideal Science-based Price Optimization System

Science-based price optimization systems do exist, but there is a wide variety of differences between them. Retailers need to be able to discern the features and functionalities that differentiate one system from another to ensure they not only find the system that best suits their specific needs, but also use the system to its highest capacity. Here is a brief list of key differentiation attributes:

1. Real science versus technology packaged as science. Some providers have developed systems they promote and publicize as being grounded in the most advanced science, but that are in reality classic, off-the-shelf regression engines.

   In one example, a provider employs a system that identifies customer-purchasing patterns that exist between groups of products. In this framework, over time this "neural net" system will identify trends in the data that are then used to produce price recommendations. New-era pricing systems, by contrast, provide significantly deeper analytical processes described above to measure and relate how individual items behave individually and as a group under specific pricing scenarios. This system is able to account for "unclean" data streams that would normally misalign neural net systems. Further, neural net type systems reflect how items may appear to respond similarly to price changes but in reality do not. For example, a neural net type system will price chocolate pudding differently than pistachio pudding because their demand curves reflect vastly different consumer behavior.

   New-era systems are able to differentiate each pricing factor associated with the difference in consumer demand and apply greater analysis power to the pricing task – under most scenarios, both flavors would be priced the same but the price level could be changed for all flavors to reflect purchase behavior differences (the increase in the price of pistachio will not deter demand enough to offset the increase in revenue associated with lifting the price of chocolate to optimize margins or profit).

2. The effectiveness of any new-era price optimization system is a direct result of the quality of the data source. The scientific principles and processes described above that are responsible for modeling and forecasting are actually measuring source data volatility. The more volatile the data, the less confidence the retailer has in the recommendations and predictions produced by the system.

3. In today's hyper-competitive retail landscape, retailers must have the ability to respond to market conditions with extreme speed and accuracy. Science-based price optimization systems enable retailers to react immediately to any situation by producing scenario forecasts and new pricing recommendations that can be executed every day - as opposed to older or less capable systems that can only review and analyze source data quarterly.

4. Similarly, new-era systems of choice should be customizable for specific retailer needs. Most existing systems have been built for general purposes and adapted for retail use. In many cases, software has not been designed and developed by retail experts. Retailers should exert time and energy to understand the extent of retail know-how from their provider prior to purchasing by asking the question: has the vendor hired retail experts AFTER developing the system in order to promote the system as a fit for retail, or was the system developed by retail experts and scientists with significant knowledge of retail environments?

5. Scalability is another critical factor retailers need to consider. Not only can new-era systems determine pricing changes weekly, these systems are highly scalable at multiple levels: at the item level by graphically exposing key information to individual pricing specialists throughout individual and category lifecycles, for any size retailer with any number of stores, and for retailers across a variety of industries.

It should be noted that science alone, however, is not sufficient to provide a complete solution to the challenge of retail pricing. Done right, new-era price optimization systems take the guesswork out of pricing – at every stage of a product's life. Advanced science embedded in these systems is capable of providing specific pricing answers – but only in conjunction with the "art" of how a retailer wants their store to be positioned in the marketplace. Retailers grappling with price-image issues, for example, can focus on product mix, promotions, brand and marketing – all the other components of running a business – and use their pricing technology to achieve category and product pricing that addresses the price-image goal in line with demand signals from customers.

Given the power of the new tools and techniques available to retailers, the ideal new-era price optimization system should provide the following benefits to retailers:

- Aligns all pricing decisions with retailer business goals and objectives
- Allows retailers to customize the system to their specific business needs and attributes
- Automates price changes and updates weekly (at a minimum) or as often as is required
- Accounts for all identifiable business variables and conditions
- Incorporates past customer demand and purchase behavior
- Enables "what-if" scenario planning for price recommendations
- Is able to scale the number of prices recommended to the retailer's implementation capabilities
- Predicts the effects of price changes on future customer behavior
- Enables pricing across a retailer's stores and between categories and subcategories
- Is universally accessible and easy to use
- Includes ample supplier support and retail expertise
- Is cost-effective, allowing retailers to pay only for services they use

The Formula for Future Success: Embrace Technology, Find the Right Partner Bill Gates, Founder and former CEO of Microsoft, said recently,

"Information technology and business are inextricably interwoven. It is no longer possible to talk meaningfully about one without the talking about the other."

This perspective aptly describes the world we live in today. Consumers increasingly use sophisticated technologies in their everyday lives – sometimes, in ways they may not even fully understand. For most, their lives are forever changed – technology deployed with the right user experience creates transformation.

It is the same for retailers of fast-moving consumer goods. Smart retailers who proactively embrace new technology find, in general, that their business is transformed. But there are two key factors to the transformation: 1. Retailers must carefully evaluate and select the right technology solution. Today's pricing science is scalable, affordable, and should be delivered in a highly consumable fashion. Due diligence to determine fit is essential. 2. Science or technology alone is incapable of solving the massive challenge of pricing – no system can generate profit lift in the absence of retailer commitment and best practices. Experienced retailers will tell you that these systems do not run by themselves and need to be managed – but that the time and effort required is more than paid for by the business lift generated.

The formula for success is simple: Retail laggards who continue to dismiss or delay implementing a price optimization system will continue to struggle and "leave money on the table." Retailer winners understand the power of leveraging pricing science, and will see their investments quickly reflected in profit gains and tremendous return on their investment.

For more information, please visit **www.revionics.com**.

Revionics is a leading provider of full-lifecycle price and promotion optimization technology for retailers and distributors in the fast-moving consumer goods industry. The Revionics Advanced Pricing System (RAPS) generates increased sales and profits through sophisticated demand intelligence and proprietary pricing science. The system optimally determines base pricing, promotional and ad pricing, temporary price reductions (TPRs) and markdowns. The Revionics offering is available as a Software-as-a-Service (SaaS) subscription offering over the Internet. The service includes advanced price modeling, optimization on-demand, scenario forecasting, and advanced category analytics.