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Intermittent Demand Forecasting and Multi-tiered Causal Analysis

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ABSTRACT

The use, limits, and misuse of statistical models in different industries are propelling new techniques and best practices in forecasting. Until recently, many factors such as data collection and storage constraints, poor data synchronization capabilities, technology limitations, and limited internal analytical expertise have made it impossible to forecast intermittent demand. In addition, integrating consumer demand data (that is, point-of-sale [POS]/syndicated scanner data from ACNielsen/ Information Resources Inc. [IRI]/Intercontinental Marketing Services [IMS]) to shipment forecasts was a challenge. This presentation gives practical how-to advice on intermittent forecasting and outlines a framework, using multi-tiered causal analysis (MTCA), that links demand to supply. The framework uses a process of nesting causal models together by using data and analytics.

INTRODUCTION

Since the early 1990s the CPG industry has been moving from a manufacturing "push" to a consumer "pull" strategy. In the past, companies would make the products they thought consumers wanted and needed to purchase, and would push those into the marketplace. If the products didn't sell, they would discount them until they sold, which reduced margins and lowered profits. Today, CPG manufacturers rely on consumers pulling products through the supply chain, which requires a better understanding of consumer behaviors and choice selections.

Most manufacturers agree that integrated supply chain management initiatives are driving these changes in the supply chain. The accurate prediction of consumer demand has been cited as the most critical factor in the improvement of replenishment forecasts, which directly impact supply chain efficiencies. Furthermore, most companies are struggling with how to implement causal techniques such as multiple linear regression (MLR) to model and predict consumer behavior along with short-term volume lifts associated with sales promotions. Finally, sales forecasting methods and applications currently being implemented have been evolving from simple time series extrapolations of past sales history to more sophisticated causal techniques such as ordinary least squares regression (OLS) and applied micro-econometrics.

Prior to the past decade, under the traditional push philosophy, simple time series technique, such as Winter's three-parameter exponential smoothing, could adequately predict sales demand. This was even more evident in markets with little competition, requiring no great marketing efforts to stimulate consumer demand. In these situations, minimal segmentation was needed and price increases were taken as an annual prerequisite to doing business. Sales demand essentially increased as the population of the masses expanded, consuming virtually all of the supply. In fact, for the most part, manufacturers' supply capabilities were at full capacity. Keeping the product on the shelf was the main focus, along with expanded shelf presence (that is, added variations of the same product). As a result, manufacturers pushed their products to retailers through the supply chain by offering cash incentives (for example, off-invoice allowances, cash discounts and co-op advertising). This process enabled retailers to stockpile inventories at low costs for future consumption. It also required little mathematical expertise to predict replenishment inventories (shipments) to retailers, as the manufacturer merely increased the cash incentives to meet volume targets required to satisfy shareholders' volume and profit expectations.

As competitive pressure increased within the marketplace and consumers began to demand higher quality products at lower prices, retailers were forced to carry more alternatives (product facings) with lower margins. This situation created a proliferation of stock keeping units (SKUs) that were forced onto the retailers' shelves along with pools of inventories, stifling the manufacturer's abilities to push inventories through the channels of distribution using cash incentives. In time, carrying the costs associated with holding large volumes of inventories forced retailers to cut back on reorders to manufacturers (shipments) and/or to divert the inventories to other retailers. The end result was lower margins for the manufacturers and lower volume for the retailers when they sold products at regular prices, as consumers bought only during promotions, stockpiling products for future consumption.

Finally, manufacturers began shifting their marketing investments to drive consumer demand by increasing local and national advertising, adding more in-store promotional materials and providing more support to increase product categories, thus pulling products through the channels of distribution rather than pushing them through the system.

This new focus on the consumer not only increased brand volumes at retail and expanded product categories, but it also increased margins for the manufacturers and profits for the retailers as store volumes increased. As a result of the manufacturer refocus on the consumer, the role of sales forecasting evolved into a broader, more business analysis function that used advanced causal analysis to identify the factors that drive consumer demand. Out of this need to better understand how to improve the effectiveness of marketing investment dollars while maximizing supply chain efficiencies, multi-tiered causal analysis (MTCA) was born.

CONSUMER PACKAGED GOOD TERMINOLOGY

Historical point-of-sale (POS) data is the primary data set used to model and predict consumer demand in the CPG industry. POS data is collected by retailers through bar codes on the product packaging. For example, when you purchase a product at your local grocery store and the cashier scans the bar code, information on the product purchased is captured in a data warehouse and later sold to the ACNielsen and/or IRI companies who collect all purchases made for all products, channels and retail chains across all geographic areas.

The POS data is adjusted for data entry errors and other known aberrations, and then syndicated for repurchase by the CPG manufacturers who use this information to track their consumer sell-through or consumption. Because the data is syndicated, each CPG manufacturer can also buy (see) their corresponding competitors' consumer demand. ACNielsen and IRI combine the POS data with in-store audits, which determine merchandising actions and consumer promotional activities, such as displays, features, temporary price reductions and sales promotions. CPG manufacturers can acquire the raw POS data directly from the retailers. However, the retailers allow the CPG manufacturers to only access their individual consumer demand and price, not their competitors. The in-store audit information is not available because ACNielsen and IRI collect it separately.

The definitions of the terms that will appear throughout the rest of this article are:

- POS: Point-of-sale data collected by retailers and sold to the ACNielsen and IRI companies.
- Syndicated scanner data: ACNielsen and IRI syndicate the POS data by combining all products, stores, channels and geographies, as well as all competitors.
- In-store merchandising: Sales and marketing actions taken by CPG manufacturers and retailers to encourage consumers to purchase their products, including:
    - Displays: Nonpermanent floor displays showcase products on special, usually at a reduced price, in various locations around the store.
    - Features: Each week in the store circular, often found at the store entrance, certain products are featured as specials, usually at a reduced price.
    - Feature and displays: Products featured in the store circular have a corresponding display in the same week.
    - TPR: Temporary price reductions are found on shelves in stores where the price of the product is temporarily reduced, but the price reduction is not featured in the store circular or displayed on the floor in the aisle. Usually, a special colored tag is fixed to the shelf under the product indicating the temporary price reduction.
- Non-promoted retail price: Simply the everyday retail price of the product at the retailer.
- Distribution: The percentage of stores the product is being sold in.
- GRPs: Gross rating points are used to determine the effective weight of advertising. It is a measure of the number of households exposed (or reached) by the advertisement times the frequency of times the households actually see the advertisement. For example, 240 GRPs = 77 percent reach x 3.1 frequency.
- Consumer promotions: Sales and marketing tactics used by CPG manufacturers and retailers to get consumers to purchase their products, such as a buy-one-get-one-free special or a tie-in special with another product (for example, buy one tube of toothpaste and get a free toothbrush where the toothbrush is attached physically to the toothpaste package).
- DMA: Demographic market area is a designation set by ACNielsen for key markets that have similar marketing demographics. For example, Atlanta, New York, Chicago and other large cities would be considered DMAs.

WHAT IS MULTI-TIERED CAUSAL ANALYSIS

Multi-tiered causal analysis (MTCA) is a process or approach linking a series of multiple regression models together to measure the impact of marketing mix strategies on the supply chain. Manufacturers can have several tiers, depending on the sophistication of their supply chain. In the CPG industry, MTCA is used to model the push/pull effects of the supply chain by linking together a series of multiple regression models based on marketing investment strategies and replenishment policies to retailers.

The theoretical design applies in-depth causal analysis to measure the effects of the marketing mix on consumer demand at retail (pull—consumption/retail sell-through), then links it via consumer demand to shipments from the manufacturer (push—factory shipments) to the retailers. This situation is known as a two-tiered model. In the case of companies who have more sophisticated distribution networks, it could be a three-tiered (or more) model incorporating wholesalers (that is, consumer to retailer to wholesaler to manufacturing plant) and/or distributors.

MTCA integrates sell-in data, such as point-of-sale (POS) and syndicated scanner data (ACNielsen/IRI) into the forecasting process to determine the effects of consumer demand on factory shipments. A causal model is applied to predict POS data using all significant causal factors, such as retail price, media gross rating points, in-store merchandizing vehicles (i.e., displays, features and temporary price reductions) and sales promotions, as well as competitive retail activities. A second causal model is developed to forecast shipments using past POS data and the POS forecast as the main explanatory factor, taking the time lag between POS and shipments into account along with other causal factors, such as forward buys and trade promotions. Classical multiple linear regression methods are used to model marketing activities. They incorporate retail price, sales promotion, advertising, in-store merchandising (volume for displays, features, features and displays, and TPRs), store distribution, free-standing inserts (or coupons), product rebates, competitive activities and seasonality to predict consumer demand (retail sell-through).

Once the causal factors for consumer demand are determined and consumer demand is predicted, a second model is developed using consumer demand as the primary driver (explanatory variable), thus linking consumer demand to factory shipments. This model could include such factors as trade promotions, gross dealer price, factory dealer rebates, cash discounts (or off-invoice allowances), co-op advertising and seasonality to predict factory shipments. For example, if retail consumer demand (CD) of product A is:

(1) **CD** = β_0Constant + β_1Price + β_2Advertising + β_3Sales Promotion +
β_4ACV Feature + β_5FSI + β_6Store Distribution + β_7Seasonality + β_8 Competitive
Price + . . . β_{11} Competitive Variables,

Then factory shipments (FS) for product A could be:

(2) **FS** = β_0Constant + β_1CD (forward lag 1 period) +β_2 Gross Dealer Price +
β_3Factory Rebates + β_4Cash Discounts + β_5Co-op Advertising +
β_6Trade Promotions + β_7Seasonality.

In many cases, CD is lagged forward one or more periods to account for the buying patterns of retailers. For example, mass merchandisers, such as Walmart, buy in bulk prior to high periods of consumer demand, usually one or more periods (month or weeks) prior to the sales promotion. Other retailers, such as Publix, carry large varieties of product facings but small inventories, shortening their purchase cycle, which causes them to purchase products more frequently with virtually no lag on consumer demand when introduced into the factory shipment model. Other variables, such as advertising, also need to be lagged and transformed to account for the decaying effects and the cumulative aspects of consumer awareness.

The final step in the MTCA process is to conduct "what-if" simulations using the parameters of the models to determine future marketing strategies that ultimately become the short- and long-term forecasts used by the supply chain. The power of simulation stems from its ability to capture real-life scenarios. When the appropriate set of key business drivers is defined and their interactions using MTCA are determined, the result is an environment in which the inputs can be controlled to see what happens under different conditions.

The system also can be optimized based on individual constraints; for example, given X amount of marketing dollars, optimize the return on investment. Companies use simulation tools as the basis for the design of almost every complex situation that would cause someone to buy a product or service, including cars (styling, ergonomics, safety testing, fuel economy), medicine (drugs, medical procedures, prosthetics) and electronics (chips, computers, networks). As a result, simulation is expanding from product design to business processes in areas such as supply chains, project management and marketing.

In the case of MTCA, some of the business drivers (explanatory variables) are held static, while others are changed to simulate alternative marketing strategies and their corresponding effects on consumer demand, and ultimately on factory shipments. The goal is to:

- Simulate the impact of changes in those key business drivers that can be controlled, such as price, advertising, in-store merchandising and sales promotions (or events).
- Determine the outcomes.
- Choose the most optimal strategy that produces the highest volume and revenue.

The key assumption is that if all things hold true based on the model's parameter estimates, when the level of pressure on any one or group of key business drivers is changed it will have X impact on consumer demand, resulting in X change in factory shipments.

The most difficult key business drivers to simulate are those related to competitors and items that people have little control over, such as the weather, the economy and local events. The example in the next section will help clarify the practical application of what-if simulation tools.

CASE STUDY: THE BEVERAGE INDUSTRY

The following case study is a real-world application of multi-tiered causal analysis using data from the late 1990s. In this situation, a brand manager for a large soft drink bottling company wanted to evaluate the efficiency and productivity of their marketing efforts, take actions and gain competitive advantage by driving more profitable volume growth.

Three major questions (or concerns) were raised:

- What marketing tactics within the marketing mix are currently working to drive volume within the retail grocery channel?
- How could they put pressure on those key business indicators to drive more volume?
- What alternative scenarios could be identified to maximize their market investment?

The brand manager followed a process with four basic steps:

1. Identify all the pertinent data requirements for consumer demand and factory shipments.
2. Build the models using a subset of the data.
3. Test the predictive ability of the models using a holdout sample.
4. Refit the models using all the data to forecast the future.

This process was used to develop and link the Consumer Demand (CD) and Factory Shipment (FS) models. The by-product of this process was a more accurate forecast that reflected the company's marketing investment strategy.

THE PROCESS

(1) Identify all pertinent data requirements for consumer demand and factory shipments. The brand manager identified all of the pertinent data requirements for consumer demand and factory shipments. The brand manager then used ETL technology to extract, load and transform data from data repositories (data warehouses and/or data marts) from both internal and external technology architectures.

This particular task can be performed either automatically using business intelligence (BI) or reporting application/tools or by an internal IT Group. Usually, the information (data) is loaded into a central repository known as a data mart that resides on a server somewhere on the company's internal network. This step also includes any data transformations, for example, creating adstocks (half-life decay rates) using gross rating points (starting with one week half-life decays through 26 weeks).

Syndicated scanner data (153 weeks) was downloaded from the ACNielsen database at the brand/product level for the grocery channel for a particular retailer chain in the Dallas Demographic Market Area (DMA). The brand's weekly case volume, non-promoted price, in-store merchandising vehicles (displays, features, features and displays, and temporary price reductions), and distribution percentages by product were all downloaded along with major competitor information. The marketing events (sales promotions/events) calendar was loaded along with weekly gross rating points (past and future) managed by their advertising agency. Finally, weekly factory shipments were downloaded along with wholesale price, case volume discounts (off-invoice allowances), trade promotions/events and local retailer incentives.

(2) Build the models using a subset of the data. The brand manager began uncovering relationships and patterns using a subset of the data (149 weeks) by applying graphic tools, decision tree analysis and a basic correlation matrix using an advanced software application/tools package such as SAS®. The brand manager uncovered a strong correlation with consumer demand and factory shipments (R_2 =.4710, t-stat 11.59), as shown in Figure 1. (It is not uncommon in an environment where companies are moving from a push strategy to a pull strategy to see less pull-through by consumer demand.)

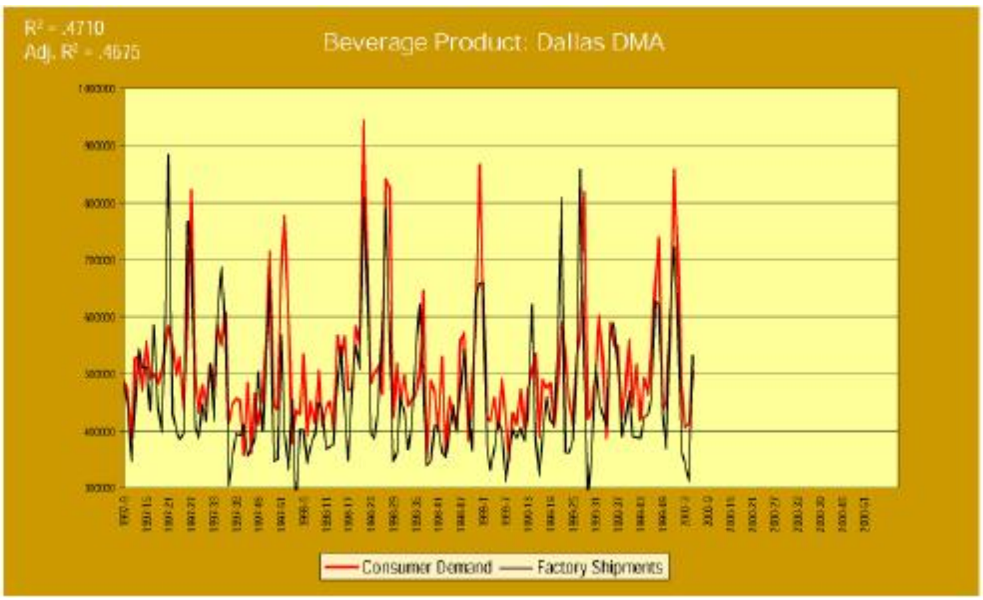

Figure 1. Consumer Demand vs. Factory Shipments

The bottler in this example was pulling the product through the retail channel but was still dependent on trade promotions and case volume discounts to push the product through the distribution network, as only 47 percent of their shipments were being explained by consumer demand. It should also be noted that there was no significant lag between consumer demand and factory shipments. This is not unusual for the grocery channel, as retailers carry small inventories with expanded offerings (product facings), making it difficult to purchase large quantities as can the mass merchandisers (e.g., Wal-Mart, Kmart). Grocery retailers tend to have shorter purchasing cycles at lower quantities, say one to two weeks, versus mass merchandisers who purchase larger quantities less frequently, say once a month.

Using this information, the brand manager developed a model for Consumer Demand (CD), also known as the first tier in the distribution network. It makes sense, as CD is driving factory shipments, rather than the reverse. Figure 2 shows the actual statistical output for CD. The model output demonstrates that 16 key business drivers (explanatory variables) were found to be significant, explaining 84 percent (Adj. R_2 = .8440) of the variation in CD. It is not unusual to have between 10 and 20 key business drivers explaining anywhere from 75 to 95 percent of the variation in CD. Keep in mind that it is more the norm when using time series data at this level of granularity.

CD Model Output					
Variables	Parameter Estimates (Elasticity)	Standard Error	t-Statistic	P-Value	R^2=.860 Adj. R^2= .844 Durbin-Watson=1975 MAPE=5.0%
Constant	13.973	0.587	23.798	0.000	
Product 1 Price	-5.735	0.571	-10.040	0.000	
Product 1 Feature	0.023	0.011	2.149	0.033	
Product 1 Feature & Display	0.062	0.017	3.569	0.000	
Product 1 Display Price	-1.862	0.400	-4.655	0.000	
Product 2 Feature	0.043	0.008	5.020	0.000	
Product 2 Display Price	-0.935	0.152	-6.135	0.000	
Competitor 1 Price	1.128	0.543	2.079	0.039	
Competitor 1 Feature	-0.014	0.008	-1.836	0.069	
Competitor 1 Distribution	-0.203	0.058	-3.534	0.001	
Competitor 2 Price	0.907	0.426	2.127	0.035	
Competitor 3 Display Price	0.254	0.131	1.930	0.056	
GRPs With 3 Week Half Life	0.065	0.024	2.696	0.008	
Memorial Day Sales Promo	0.249	0.069	3.616	0.000	
4th of July Sales Promo	0.276	0.063	4.386	0.000	
Thanksgiving Day Sales Promo	0.308	0.068	4.565	0.000	
Christmas Sales Promotion	0.180	0.062	2.927	0.004	

Figure 2. CD Model Output

As shown in the CD output in Figure 2, two member products of this brand were found to be significant in driving consumption through this channel of distribution. Three competitors were identified, with price being most significant as well as in-store merchandizing for competitor 1. Other key brand business drivers were price, in-store merchandising, advertising with a three-week half-life decay rate and several holiday sales promotions. The brand manager elected to use a Log-Log model, which tends to work much better at the key account level within a channel for a demographic market area. Semi-Log models also have been proven to work well using this level of data granularity. These methods tend to do a better job capturing saturation points associated with varying levels of marketing investment. Linear models assume the relationship goes into infinity. Each key business driver approaches a saturation point as additional pressure yields less and less incremental volume.

Finally, the CD model on average was able to predict consumer demand volume with a 95 percent accuracy (Fitted MAPE = 5.0 percent) using an in-sample holdout horizon of six periods.

(3) Test the predictive ability of the models using a holdout sample. It is very important to test the predictability of the model to determine how well the model forecasts into the future. Although it may fit the historical data well, it doesn't necessarily mean it will forecast the future accurately. The brand manager intentionally built the CD model using 149 weeks of data, rather than the entire data set of 153 weeks. Those additional six weeks became the holdout sample to test the predictability of the model.

In Figure 3, the results of the model projections are compared to the actual consumer demand. Overall, the predictability of the model is very good with a Mean Absolute Percentage Error (MAPE) of 4.94 percent. From a week-to-week perspective, the model is fairly good (well below the industry average of 25 to 35 percent error based on recent benchmarking surveys conducted by various organizations) with weeks three and five having a higher individual error (13.35 percent and 9.39 percent, respectively) in comparison to the overall MAPE.

CD Model Holdout Sample Results				
Weeks	Actual	Prediction	Error	Absolute % Error
Week 1	567905	573298	-5393	0.95%
Week 2	857890	857082	808	0.09%
Week 3	708809	614168	94641	13.35%
Week 4	483884	481088	2796	0.58%
Week 5	404960	366922	38038	9.39%
Week 6	413143	435025	-21882	5.30%
MAPE				4.94%

Figure 3. CD Model Holdout Sample Results

(4) Refit the models using all the data and forecast the future. After identifying and verifying the CD model parameters for the key business drivers and testing the model's predictive capabilities, the brand manager could elect to conduct simulations (what-if scenarios) around multiple marketing investment alternatives to test the volume and profit impact on the brand within this key market and channel. For example, by holding all other explanatory variables constant into the future and changing the amount (levels) of advertising (e.g., GRPs) and in-store merchandising execution (e.g., features, features and displays), the brand manager could determine the impact on CD, which also impacts shipments.

Upon completion of the simulations, the brand manager chose the most profitable scenario, which then became the CD forecast. Using the current model parameters for CD, the effects of changing each key business driver (explanatory variables) could be simulated into the future and the corresponding impact on consumer demand determined. One key business driver can be changed (holding the others constant) or multiple key business drivers can be changed simultaneously. For example, if advertising was increased by 5 percent, in-store merchandising (feature and display) was increased by 5 percent and retail price was lowered by 3 percent, consumer demand volume would increase by 2,959,466 units (from 28,817,025 to 31,776,492 or 10.27 percent), thus increasing sales profit by $1,923,653. If the increased profit outweighed the costs of those changes, then the brand manager would choose this scenario, which then becomes the CD forecast. The simulation is the easy part. Once chosen, then the company must execute the scenario (plan), otherwise the resulting forecast will be inaccurate.

The final step in the process was to create a forecast for CD based on the scenario that drives the most volume with the highest profit impact. In this case, the brand manager chose Scenario 1 (Figure 4).

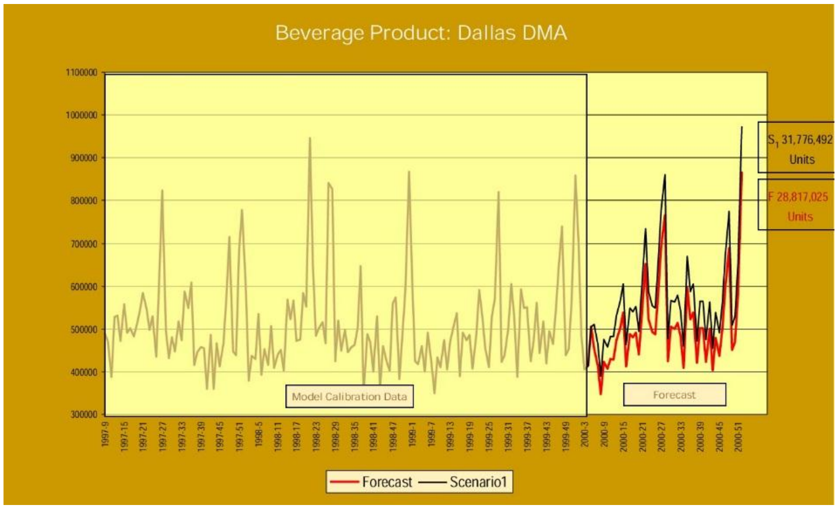

Figure 4. Consumer Demand: Forecast vs. Simulation

It is recommended that post-analysis assessments (comparisons of actuals to forecast for each key business driver) be conducted prior to updating the model and regenerating a forecast in order to identify opportunities and weaknesses in the marketing investment plan.

The process described above was then applied to develop a model for Factory Shipments (FS) using CD as the main key business driver along with its forecast based on the scenario chosen in the simulation phase. Hence, the brand manager linked the first tier to the second tier of distribution by incorporating CD as one of the key business drivers in the FS model.

As shown in the FS model output in Figure 3, seven key business drivers were found to be significant, explaining 79 percent (Adj. R^2 = .7863) of the variation in FS. CD is the main business driver with an elasticity of 0.432 (Parameter Estimate from Log-Log Model). In other words, as CD increases by 1 percent, FS increases by 0.432 percent, pulling brand volume through the retail outlets of this particular retailer in the Dallas DMA.

FS Model Output

Variables	Parameter Estimates (Elasticity)	Standard Error	t-Statistic	P-Value	R^2=.7992 Adj. R^2= .7863 Durbin-Watson=2.308 MAPE= 8.3%
Constant	10.259460	0.975	10.524	0.000	
CD	0.432497	0.056	7.762	0.000	
Product 1 Wholesale Price	-1.030453	0.018	-1.662	0.09	
Seasonal Indices	0.685532	0.058	11.880	0.066	
Labor Day Trade Promo	0.239063	0.101	2.360	0.000	
Off-Invoice Allowances	0.082738	0.043	1.942	0.052	
Product 2 Wholesale Price	-1.130739	0.035	-3.711	0.000	
Retailer Inventory	-0.018740	0.009	-2.127	0.033	
Product 3 Wholesale Price	-1.257774	0.117	-2.196	0.028	

Figure 5. FS Model Output

Other key business drivers impacting FS were product wholesale price, Labor Day trade promotion, off-invoice allowances, retailer inventory and seasonality. Additional simulations could be conducted at this level to determine the push effects on volume going into the retail outlet. Finally, the FS model on average was able to predict factory shipments volume with a 92 percent accuracy (Fitted MAPE = 8.3 percent). When testing for predictability of the FS

Model using a holdout horizon of six periods, the MAPE was 9.2 percent (six periods having an absolute error rate of 2.5, 9.5, 2.69, 18.9, 10.3 and 11.7 percent respectively).

FS Model Holdout Sample Results				
Weeks	Actual	Prediction	Error	Absolute % Error
Week 1	605204	620283	-15079	2.49%
Week 2	724120	792907	-68787	9.50%
Week 3	598349	614423	-16074	2.69%
Week 4	364271	433071	-68800	18.89%
Week 5	345055	380616	-35561	10.31%
Week 6	312645	349074	-36429	11.65%
MAPE				9.25%

Figure 6. FS Model Holdout Sample Results

Upon completion of the simulation process for FS, the brand manager selected the corresponding simulations for CD and FS, which then became the forecast for this brand. Multiple brands/products can be developed for each key customer by channel and demographic market area and summed up automatically using software technology such as SAS.

The next natural sequence in the MTCA process was to optimize the models based on marketing investment constraints, such as advertising expenditures, price and/or other key business drivers. Subsequently, by conducting financial assessments of each strategy, the brand manager could determine the optimal volume and profit impact on the brands.

CONCLUSION

Multi-tiered causal analysis is a simple process that links a series of causal models through a common element (retail consumer demand) to model the push/pull effects of the supply chain. It is truly a decision support system that is designed to integrate statistical analysis and POS (or syndicated) retail data to analyze the business from a supply chain perspective.

This process provides both brand and operations managers with the opportunity to make better and more useful decisions from multiple data sources (that is, retail syndicated, internal company and external market data). The objectives of the process are to provide a distinct opportunity to address supply chain optimization through causal models tiers and the simulation of alternative business strategies (sales/marketing scenarios).

The two basic objectives of multi-tiered causal analysis are to support and evaluate business strategies based on the effectiveness of marketing actions in both a competitive and holistic environment. By tying the performance of a brand, product and/or SKU at retail to shipments at a point in time, the outcome of making a change to the marketing mix can be simulated and evaluated to determine the full impact on shipments to retailers.

However, the true difficulties lie in the mental models of the marketing and operations communities and not in the availability of analytical approaches or computing resources within the decision support system framework. This is especially true for senior management at both the major retailers and at the manufacturers as they continue to view marketing strategies affecting consumer demand separate from replenishment (shipments). They continue to activate marketing mix models with suppliers, such as ACNielsen and Information Resources Inc. (IRI) without integrating factory shipments. The results are two separate forecasts that do not reflect the true push/pull effects of the manufacturer and retailers' marketing strategies on the entire supply chain. This methodology represents an extremely distorted view of the marketing environment, where the analyst implicitly assumes that consumer demand has no causality with factory shipments. This view has a tendency to exaggerate the impact of factory shipments from the manufacturer to the retailer, causing over- and/or under-replenishment of inventories.

The key benefit of multi-tiered causal analysis is that it captures the entire supply chain by focusing on marketing strategies and linking them, using a holistic process, to factory shipments. This process can be expanded to include category management initiatives by nesting the product or brand consumer demand model to a retail category demand model that capitalizes on each product's contribution to the expansion of the category. These relationships are what truly define the marketplace and all marketing elements within the supply chain.

Technology has caught up with the theories and mathematical approaches behind these concepts, which academics have offered to the market research community during the past several decades. Harnessing this technology has enabled researchers to leverage their data resources and analytics as a competitive advantage, offering a true, integrated supply-chain management perspective to optimize the value chain.

Sole reliance on a market-mix model is like taking a picture of marketing investment strategies through a telephoto lens. While one can see the impact at retail with precision, the foreground or background (impact on factory shipments) is either excluded or out of focus. As significant (or insignificant) as the picture may seem, far too much is ignored by this "telephoto" view. To capture the full potential of the supply chain, MTCA provides a "wide angle" approach to assure clear resolution of where a company is and where it wants to go.

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GLOSSARY

Consumer promotions. Sales and marketing tactics used by consumer packaged goods manufacturers and retailers to get consumers to purchase their products.

CPG. Consumer packaged goods.

Displays. An in-store merchandising tactic where nonpermanent floor displays showcase products on special, usually at a reduced price, in various locations around the store.

Distribution. The percentage of stores the product is being sold in.

DMA. Demographic market area is a designation set by ACNielsen for key markets that have similar marketing demographics.

Features. An in-store merchandising tactic where weekly store circulars, often found at the store entrance, feature certain products as specials, usually at a reduced price.

Feature and displays. An in-store merchandising tactic where products featured in the store circular have a corresponding display in the same week.

Gross rating points (GRPs). Used to determine the effective weight of advertising. It is a measure of the number of households exposed (or reached) by the advertisement times the frequency of times the households actually see the advertisement.

In-store merchandising. Sales and marketing actions taken by CPG manufacturers and retailers to encourage consumers to purchase their products, including displays, features, feature and displays, and temporary price reductions.

Multi-tiered causal analysis (MTCA). A process or approach linking a series of multiple regression models together to measure the impact of marketing mix strategies on the supply chain.

Non-promoted retail price. The everyday retail price of the product at the retailer.

POS. Point-of-sale data collected by retailers and sold to the ACNielsen and IRI companies.

SKU. Stock keeping unit.

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