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Modeling the Supply Chain Using Multi-tiered Causal Analysis

Charles W. Chase, Jr.

Multi-tiered causal analysis is not really a technique but rather a procedure or process that models the push/pull effects of the supply chain by linking a series of multiple regression models together, based on marketing investment strategies and trade investments to retailers. The conceptual design applies in-depth causal analysis to measure the effects of the marketing mix on consumer demand at retail (pull—consumption/retail sell-through) and links it, via consumer demand, to shipments from the manufacturer (push) to the retailers. This situation is known as a two-tiered model. In the case of more sophisticated distribution systems, a model of three tiers (or more) can be deployed—incorporating, for example, wholesalers (that is, consumer to retailer to wholesaler to manufacturing plant).

During the past 10 years, the consumer package goods (CPG) industry has been moving from a manufacturing "push" to a consumer demand "pull" strategy. Most 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 supply chain efficiencies. As a result, the sales forecasting function is slowly evolving into a more business analytical role, which is aligned with sales and marketing versus operations and logistics. Nevertheless, most are struggling with how to implement causal techniques like multiple linear regression (MLR) in order to model and predict consumer behavior along with short-term volume lifts associated with sales promotions. These key changes, which result from supply chain initiatives, are more focused on sales forecasting, as it has been cited as the primary driver of the integrated supply chain management process. Subsequently, current sales forecasting methods and applications are changing from simple time series extrapolations of past sales history to more sophisticated causal techniques like ordinary least squares regression (OLS).

Prior to the past decade, under the traditional push philosophy, simple time series techniques—like Winter's three-parameter exponential smoothing—could adequately predict sales demand. This was particularly the case in markets with little competition requiring little marketing efforts to stimulate consumer demand. In these situations, little 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, manufacturers' supply capabilities were roughly at full capacity. Keeping your product on 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, Coop Advertising). This process allowed 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 just increased the cash incentives to meet volume targets required to satisfy shareholders' volume and profit expectations.

As more competitive pressure entered the marketplace and consumers began to demand higher-quality products at lower prices, the retailers were forced to carry more alternatives (product facings) with lower margins. This situation created a proliferation of stock-keeping units (SKUs), forced onto the retailers' shelves along with pools of inventories stifling the manufacturer's capabilities to push inventories through the channels of distribution using cash incentives. In time, carrying 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 who sold products at regular prices, as consumers bought only during promotions, stockpiling products in their

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pantries for future consumption. Finally, manufacturers began shifting their marketing funds 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 versus pushing them through the system. This new focus on the consumer not only increased brand volumes at retail and expanded product categories but also increased margins for the manufacturers and profits for the retailers. As a result, sales forecasting has taken on a new role, requiring a more detailed business analysis approach, which takes advantage of 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 while maximizing supply chain efficiencies, multi-tiered causal analysis (MTCA) was born.

What is Multi-tiered Causal Analysis?

MTCA is not really a technique but rather a process linking (or nesting) a series of multiple regression models together to measure the impact of marketing mix strategies on the supply chain. You can have several tiers, depending on the sophistication of your supply chain. In the CPG industry, MTCA is used to model the push/pull effects of the supply chain by linking a series of multiple regression models together, based on marketing investment strategies and trade investments to retailers. The conceptual 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) to the retailers. This situation is known as a two-tiered model. In the case of companies who have more sophisticated distribution systems it could be a three-tiered (or more) model incorporating wholesalers (that is, consumer to retailer to wholesaler to manufacturing plant).

MTCA also integrates sell-in data, such as POS (Point-of-Sale) data, into the forecasting process of sell-through data, such as shipments. A causal model can be applied to forecast POS data, using all the significant causal factors, such as retail price, media gross rating points (GRPs), and sales promotions. A second causal model is used to forecast shipments. The shipment model uses past POS data and the POS forecast as the main causal factor, taking the time lag between POS and shipments into account along with other causal factors, such as forward buys and trade promotions. (See Figure 1.) Classical multiple linear regression methods are utilized to model marketing activities incorporating retail price, sales promotion, advertising, merchandising (%AVC—all commodity volume for features and displays), store distribution, free-standing inserts or coupons (FSIs), product rebates, competitive activities, and seasonality to predict consumer demand (retail sell-through).

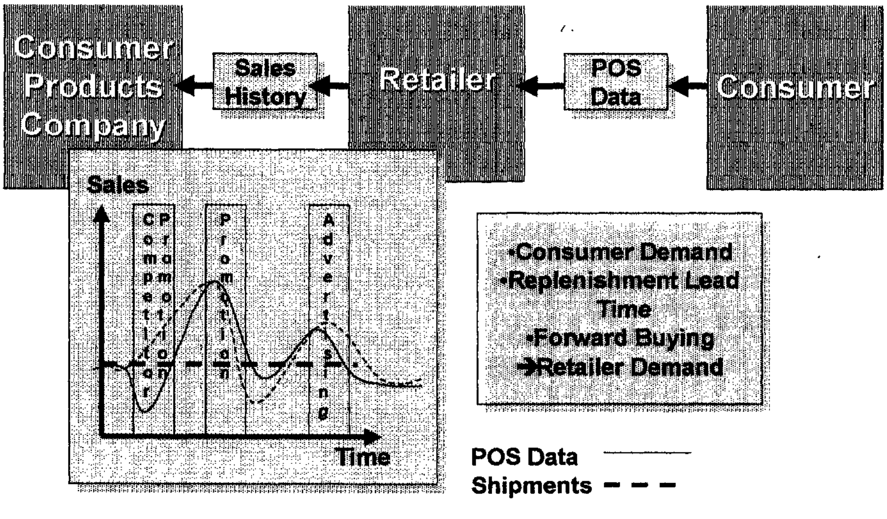

Figure 1. Multi-tiered Causal Analysis.

Once the causals for consumer demand are determined and consumer demand is predicted, a second model is developed using consumer demand as the primary driver, 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), coop advertising and seasonality to predict factory shipments. The basic equation can be written using the general notation:

$$(1) \qquad Y_i = \beta_o + \beta_1 X_1 + \beta_2 X_2 + \ldots \beta_n X_n + e_i\,.$$

In our example, we have elected to use an MLR technique—originally developed by Carl Friedrich Gauss, a German mathematician—known as OLS. It is a linear approach to multiple regression that eliminates the error term (e_i) by squaring the error terms, creating a best linear unbiased estimate (BLUE). This method has some very attractive statistical properties that have made it one of the most popular methods of regression analysis. OLS may be a linear modeling approach, but many times it works in situations in which you normally might not think it would. The general notion is:

$$(2) \qquad \acute{Y} = \beta_0 + \beta X_1 + \beta X_2 + \beta X_3 \ldots \beta X_n\,,$$

where

$\acute{Y}$ = dependent variable;
β_0 = constant;
β = coefficient for independent variable; and
X_i = independent variable.

The constant (β_0), also known as the intercept (a), simply states: If all the independent variables are equal to zero, then we will sell β_0 units of Product Y. This is easy to interpret if the constant is positive; however, it can also be negative. In such situations where it is negative, we simply say it is the anchor point for drawing our regression line. This does become somewhat difficult to explain. In these situations, we can restrict the constant to zero (Chase, 1997).

The following is a more practical example: If retail consumer demand (RCD) of Product A is

$$\begin{aligned}(3)\ \text{RCD} = {} & \beta_0\text{Constant} + \beta_1\text{Price} + \beta_2\text{Advertising} \\ & + \beta_3\text{Sales Promotion} + \beta_4\text{\%ACV Feature} \\ & + \beta_6\text{FSI} + \beta_7\text{Store Distribution} + \beta_8\text{Seasonality} \\ & + \beta_9\text{Competitive Price} + \ldots \beta_n\text{Competitive Variables,}\end{aligned}$$

then Product A's factory shipments (FS) could be

$$\begin{aligned}(4)\ \text{FS} = {} & \beta_0\text{Constant} + \beta_1\text{RCD (lag 1 period)} \\ & + \beta_2\text{Gross Dealer Price} + \beta_3\text{Factory Rebates} \\ & + \beta_4\text{Cash Discounts} + \beta_5\text{Coop Advertising} \\ & + \beta_6\text{Trade Promotions} + \beta_7\text{Seasonality.}\end{aligned}$$

In many cases, RCD is lagged one or more periods to account for the buying patterns of the retailers. For example, mass merchandisers—like Wal-Mart—buy in bulk prior to high periods of consumer demand, usually one or more periods (month, or four weeks) prior to the sales promotion. Other retailers, such as Publix, carry large varieties of product facings but small inventories, requiring 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.

Measuring FSI and Trade Promotion Lift Using Dummy Variables

Dummy variables can also be used to measure the unit lift associated with qualitative drivers, such as FSIs and factory trade promotions. For example, in the case of FSIs, we can use the circulation quantity (that is, 55 million FSIs) instead of ones in the period(s) they are dropped and zeros in the period(s) when they are not dropped. This does not only give us the ability to measure the average lift but also gives us the magnitude associated with each million dropped (or circulation). In the case of factory trade promotions, traditional methods of ones (turned on) and zeros (turned off) can be used. However, you need to create three separate dummy variables for each trade promotion to measure the lift associated with forward buy, sell through, and post-shipments when using monthly data. In other words, trade promotions require three separate lift variables to properly predict the quarterly spike associated with a trade promotion. In the case of using weekly data, most trade or consumer sales promotions last four to six weeks, requiring more dummy variables. For example, customers (that is, Wal-Mart, K-Mart, and Walgreens) will want product shipped one month prior to the trade promotion to pre-stock their shelves for the promotion; this is called forward buying. Then the promotion usually lasts four to six weeks, requiring a second variable to calculate the actual sell-through and restocking of the product. Finally, many manufacturers offer tiered trade promotions with multiple offerings, giving the channel distributors (that is, Wal-Mart, K-Mart, and Walgreens) opportunities to back-fill their inventories after the promotional period to bring inventories back to original levels. These activities usually occur in the third month, requiring a third variable (Chase, 1997).

Measuring the Lag Effect of Advertising

Most recently, polynomial distributed lags have been utilized to model the cumulative effects of advertising at retail over time (t). The general notion of a distributed lag model is that the dependent variable, Y_t, responds not only to changes in an input variable X at time t but also on the past history of the X_t series. If, for example, we stopped all advertising on Product A, its share of the market would not drop to its ultimate point overnight. Rather, we would expect a gradual erosion of its market share, as consumers' perception of the product dims as their memory fades. This technique is extremely effective in helping forecasters to better understand the dynamics of advertising awareness, which has helped marketing managers to maximize their advertising spend. The general linear distributed lag equation can be written as

$$(5) \quad Y_t = a + \beta_0 X_t + \beta X_{t-1} + \ldots \beta_n X_{t-n} + e_i .$$

(See Pindyck and Rubinfeld, 1991.)

A practical example for measuring the cumulative effects of advertising is

$$\begin{aligned}(6)\ \text{RCD} = {} & \beta_0\text{Constant} + \beta_1\text{Price} + \beta_2\text{Advertising} \\ & + \beta_{2a}\text{Advertising} + \beta_{2b}\text{Advertising} \\ & + \beta_{2c}\text{Advertising} + \beta_{2d}\text{Advertising} \\ & + \beta_{2e}\text{Advertising} + \beta_{2f}\text{Advertising} \\ & + \beta_{2g}\text{Advertising} + \beta_{2h}\text{Advertising} \\ & + \beta_3\text{Sales Promotion} + \beta_4\%\text{ACV Feature} \\ & + \beta_6\text{FSI} + \beta_7\text{Store Distribution} + \beta_8\text{Seasonality} \\ & + \beta_9\ \text{Competitive Price} + \ldots \beta_n\ \text{Competitive Variables.}\end{aligned}$$

In this particular example, the cumulative effects of advertising awareness span a nine-month period, building during the first four months, peaking at 3.4 months, and tailing off during the remaining 5.6 months (see Figure 2).

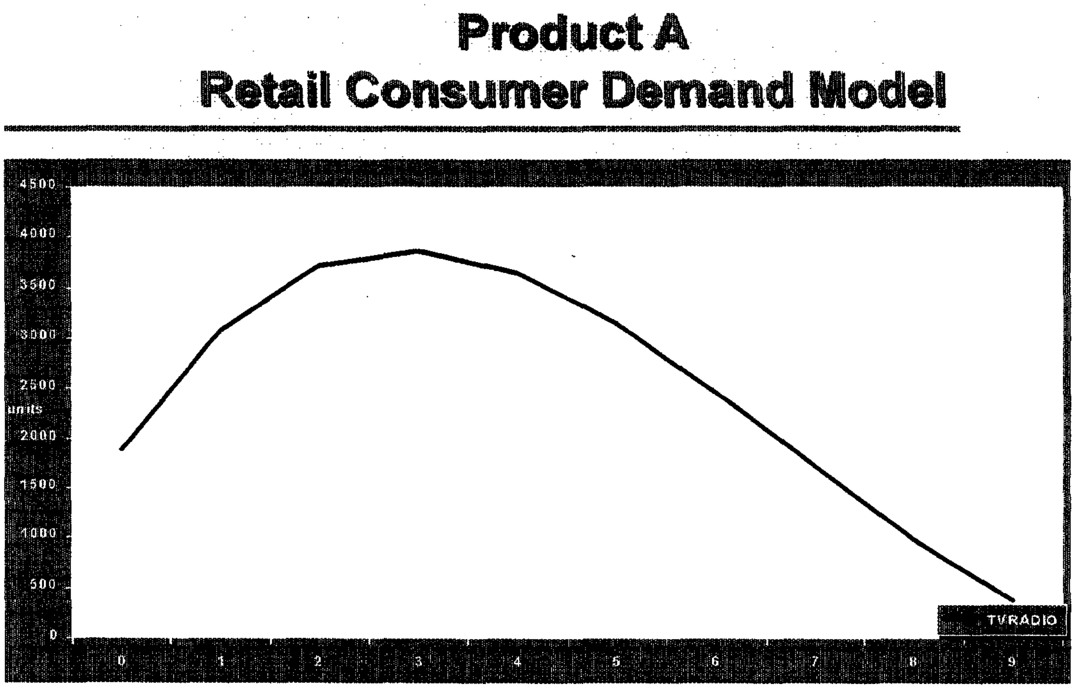

Figure 2. Polynomial Distributed Lag for TV Advertising.

Conclusion

MTCA is a simple process that links (or nests) a series of multiple regression models through a common element (retail consumer sales) 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 actionable 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 the tiering of regression models and the simulation of alternative business strategies (sales/marketing scenarios).

The two basic objectives of MTCA are (1) to support and (2) to 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 retail 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 retailer's marketing strategies on the entire supply chain. This methodology represents an extremely distorted view of the marketing environment, where the analyst implicitly assumes that retail 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 MTCA 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 retail 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 that academics have offered the market research community during the past several decades. Harnessing this technology has allowed researchers to leverage their thought leadership as a competitive advantage and to offer 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 view. To capture the full potential of the supply chain, MTCA provides a "wide angle" approach to assure clear resolution of where we are and where we want to go.

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