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HOW PROMOTIONS WORK: SCAN*PRO-BASED EVOLUTIONARY MODEL BUILDING

ABSTRACT

We provide a rationale for evolutionary model building. The basic idea is that to enhance user acceptance it is important that one begins with a relatively simple model. Simplicity is desired so that managers understand models. As a manager uses the model and builds up experience with this decision aid, she will realize its shortcomings. The model will then be expanded and will lead to the increase of complexity.

Evolutionary model building also stimulates the generalization of marketing knowledge. We illustrate this by discussing different extensions of the SCAN*PRO model. The purpose of published model extensions is to increase the knowledge about "how promotions work" and to provide support for more complex decisions. We summarize the generated knowledge about how promotions work, based on this process.

JEL-Classification: M31.

1 MODEL BUILDING IN MARKETING

In this paper we focus on econometric models applied to marketing problems. Model building in marketing, for example the specification, estimation and testing of equations that relate sales of a brand to variables partially controlled by managers, started about 50 years ago. At that time, researchers saw an opportunity to apply operations research and econometric methods to problems in a variety of business areas. The use of scientific methods was further stimulated in the US by the *Gordon/Howell* (1958) report that documented the dearth of discipline-based research training among faculty members at US business schools. The report stimulated various initiatives, partially supported by the Ford Foundation, which led to a dramatic shift in the nature and role of academic research in business schools.

Prior to the interest in econometric model building by a few academic researchers in marketing, *Art Nielsen* had introduced a commercial service based on bimonthly store audits. This audit covered a stratified random sample of grocery stores so that, for example, larger stores were covered disproportionally. *Nielsen*'s clients

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knew that the reports containing sales, market share, price and other data had a very high and known degree of accuracy. However, until the mid 1980's, *Nielsen* would only report the "scores" of brands. That is, *Nielsen* did not provide explanations of "score" magnitudes nor forecasts of future "scores".

Several reasons may account for *Nielsen*'s reluctance to explain or predict performances of brands. Perhaps the primary one is that brand managers did not ask for explanations. A typical brand manager devoted about a week to the interpretation of the bimonthly *Nielsen* report. Her interest would be in identifying and explaining changes in sales, market shares, prices, promotional activities, etc. For example, did the brand under her control experience an increase or decrease in absolute (sales) or relative (share) performance? What about other brands? And what might explain the observed changes (i.e. those not attributable to sampling error)? Brand managers would use their judgments to interpret changes and to attribute causes.

The bimonthly audits provided important market feedback to brand managers in a relatively stable market environment. The fact that the feedback from *Nielsen*'s audits was obtained, on average, a month past data collection did not appear to reduce brand managers' interests. Similarly, the limitation that the feedback represented a narrowly defined set of brands, sold in narrowly defined retail outlets, was apparently not a great hindrance either. However, in increasingly dynamic markets, characterized by, for example, changes in category sales, new entrants in a product category, new distribution channels and new media, such systems have great deficiencies.

An econometrician would suspect that managers must have experienced great difficulty isolating the correct reason(s) for changes in performance. A manager would somehow have to distinguish systematic from random variation in the various measures and properly relate (systematic) variation in multiple control variables to the (systematic) variation in performance variables. A manager's prior beliefs undoubtedly skew her interpretations. Yet, most managers lacked training in econometrics and statistics, so that any model-based output would be discounted. Related to this is the possibility that *Nielsen* believed that the bimonthly data were insufficient for econometric models. Thus, even if *Nielsen* agreed that econometric models have the potential to provide correct inferences, the highly aggregated nature of the data would make it a haphazard event, especially given the limited supply of econometricians at that time. Today, researchers in marketing have superior techniques at their disposal that are applied to much richer databases.

Academic researchers started publishing papers with econometric applications in the marketing literature in the 1960's. The early contributors include members of the Purdue school, associates of the MIT contingent, and several prominent European researchers. *Bass* and his students at Purdue pioneered simultaneous-equation applications[1], market share model estimation approaches[2], methods for pool-

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1 See *Bass* (1969), *Bass/Parsons* (1969), *Wildt* (1974).
2 See *Beckwith* (1972), *Clark* (1973).

ing cross-sectional and time series data[3], and time series analysis[4]. At MIT, *Little* contributed papers on adaptive control[5] and decision calculus[6], *Montgomery/ Silk* (1972) modelled dynamic communication effects, and *Montgomery/Urban* (1969) produced the first textbook on management science in marketing. In Belgium and Holland, pioneering contributions came from *Lambin* (1969) on advertising, and *Naert/Bultez* (1973) on logically consistent market share models, while *Naert/Leeflang* (1978) wrote a book on implementable marketing models. Importantly, a large body of work was produced at a time when the data sources were limited and subject to many weaknesses.

The academic interest in (econometric) model building largely predated commercial applications. Consistent with *Art Nielsen*'s reluctance to use bimonthly audit data for the estimation of marketing effects on performance variables, commercial interests in econometric applications grew only after superior data became available via scanner equipment in supermarkets. IRI introduced services based on household scanner panel data and field experimentation involving, among other things, the frequency and message of television commercials. The relevance of early academic research to commercial practice can be inferred from a few examples. *Eskin/Barron* (1977) published results from field experiments on the sensitivity of new-product sales to main- and interaction effects for price and advertising, and IRI's BehaviorScan service included improved experimental manipulation, measurement and analysis relative to *Eskin* and *Barron*. *Wittink* (1977) estimated an econometric model in which price elasticities, derived from time-series variation, were related to cross-sectional variation in advertising intensities. *Wittink*'s research was the impetus for *Nielsen*'s SCAN*PRO model in which scanner data on stores and weeks were pooled for the analysis of promotion effects[7]. Model results show that the promotional effects for a given item estimated with SCAN*PRO are similar across geographic areas. Demand is often quite elastic with respect to temporary price cuts. Interestingly, even in the absence of a price cut, a special display in an outlet or inclusion of a brand in a retailer's advertisement can easily double a product's sales. And on average, the joint use of a special display and feature advertising often produces a higher amount of additional sales than occurs when these activities are handled separately.

Ideally, model building is a systematic process in which the model builder interacts with the model user so as to create an implementable result. *Leeflang et al.* (2000) suggest eleven stages in the model-building process with an implementation focus[8]. They stress that a model should satisfy *Little*'s (1970) criteria of simplicity, completeness on important issues, adaptiveness and robustness. *Leeflang et al.* also identify direct and indirect benefits from model use that should exceed the associated costs. At a minimum, marketing decisions based on model outcomes must be closer to optimal than the corresponding decisions in the absence of a model. *Eskin* (1975) provides a useful illustration of the impact of economet-

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3 See *McCann* (1974), *Bass/Wittink* (1975), *Wittink* (1977).
4 See *Hanssens* (1980).
5 See *Little* (1966).
6 See *Little* (1970), *Little/Lodish* (1969).
7 See *Wittink et al.* (1988).
8 See *Leeflang et al.* (2000), p. 52.

ric analysis on the marketing program for a new product. In the absence of econometric model output, management would have selected either high advertising expenditures and a high price or low advertising and a low price based on the argument that a higher price provides a higher margin which allows for a larger advertising budget. This argument obviously ignores the demand magnitude. Indeed, management learned from the demand model, estimated from field experimental data, that high advertising and a low price actually offered the most attractive marketing mix.

Apart from the impact of marketing models on the quality of decisions by managers, model results also provide the basis for *empirical generalizations* which may improve our knowledge and understanding of marketing phenomena. For example, *Eskin/Barron* (1977) found that there is a high degree of similarity in the nature of interaction effects between advertising and price across multiple new consumer products in different categories. One interpretation of their interaction result (higher price sensitivity at higher levels of advertising) is that a higher frequency of advertising for a new consumer product attracts additional consumers who are more price sensitive than the consumers who contemplate the purchase more readily. In this case, aggregate demand for the new product shows a higher price sensitivity at higher advertising levels because the mix of consumers changes.

In this paper we provide a rationale for evolutionary model building. The basic idea is that researchers do not attempt to include all possible complexities in the initial specification. To enhance user acceptance it is important that one begins with a relatively simple model. Early applications may reveal some shortcomings, and the diagnostics can be used to guide further model development. Of course, the initial specification should be sufficiently informative for the quality of marketing decisions to be improved, while the simplicity of the initial model along with the evolutionary component can facilitate acceptance and use by marketing managers. Evolutionary model building also stimulates the generalization of marketing knowledge. We illustrate this by discussing different extensions of the SCAN*PRO model. The purpose of published model extensions is to increase the knowledge about "how promotions work" and to provide support for more complex decisions. The basic model, in its original form or its variants has been used in more than 3,000 commercial applications worldwide.

Sales promotion expenditures have grown substantially over the past 15 year in most U.S and Western European markets. The importance of sales promotion decisions has also grown in a relative sense: promotions account for an increasing percentage of the marketing budget of most packaged goods companies. The increased attention to promotion decisions and the increased availability of data, stimulates the development and application of sales promotion models. We discuss these developments in more detail in Section 2. After Section 3, on evolutionary model building, we present the published enhancements of SCAN*PRO model in Section 4. We summarize the generated knowledge about how promotions work, based on this process, in Section 5, and we provide conclusions in Section 6.

2 SALES PROMOTION AND SALES PROMOTION MODELS

During the past two decades, research on sales promotion has accelerated, and commercial use of sales promotion tools is now commonplace. Prior to the scanner data revolution, the ratio of expenditures in advertising in the U.S. to promotion was about 60:40. Today, in many consumer packaged goods companies, trade and consumer promotion accounts for about 70 percent of the marketing budget[9]. Of the $160 billion spent by packaged good manufacturers on promotions, 25 percent represents consumer promotions such as coupons and samples[10]. Trade promotion is the largest single category in the marketing mix budget of U.S. packaged good companies[11]. The theory and measurement of sales promotion effects has become an important research topic for both academics and practioners[12]. Sales promotion also plays a critical role in many (game-theoretic) models of vertical competition and cooperation between manufacturers and retailers[13].

Blattberg/Briesch/Fox (1995) provide empirical generalizations regarding both consumer promotions and trade promotions. They also identify six key issues with limited empirical results. Our research addresses several of these issues, specifically: 1. the shape of the deal effect curve; 2. interactions between display, feature advertising and price discount; and 3. the category expansion effect of deals. Other recent research has addressed the *long-term* effects of sales promotions on:

- brand choice[14];
- market structure[15];
- category sales[16];
- profit[17];
- brand equity[18].

The typical finding is that (long-term) effects of promotions on brand choice, category sales and profit are *not* persistent. The performance measures usually return to average values after a finite number of periods. Promotions may generate short-run surpluses. However, the long-run profitability of promotions requires *repeated* efforts[19].

It is critical that managers understand the source(s) of temporary sales increases. For example, it matters how much of the increase in sales for a promoted item is attributable to other items belonging to the same brand (cannibalization), to other brands, to stockpiling and to category expansion. The first decomposition of sales

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 9 See *Ailawadi/Neslin/Gedenk* (2001).
10 See *Zhang/Krishna/Dhar* (2000).
11 See *Silva-Risso/Bucklin/Morrison* (1999).
12 See, e.g., *Blattberg/Neslin* (1990), *Foekens* (1995), *van Heerde* (1999).
13 See, e.g., *Krishnan/Soni* (1997), *Kim/Staelin* (1999) and *Kumar/Rajiv/Jeuland* (2001).
14 See *Mela/Gupta/Lehmann* (1997).
15 See *Mela/Gupta/Jedidi* (1998).
16 See *Nijs/Dekimpe/Steenkamp/Hanssens* (2001).
17 See *Dekimpe/Hanssens* (1999).
18 See *Dekimpe/Hanssens/Silva-Risso* (1999).
19 See *Dekimpe/Hanssens* (1999), p. 410.

effects, based on models of household data, is provided by *Gupta* (1988) who shows that the sales elasticity of a promotion equals the category incidence elasticity plus the brand choice elasticity plus the quantity elasticity. *Chiang* (1991), *Chintagunta* (1993) and *Bucklin/Gupta/Siddarth* (1998) provide additional empirical results based on alternative or enhanced model formulations and estimation methods. *Bell/Chiang/Padmanabhan* (1999) show that on average about 75 percent of the sales elasticity is attributable to the brand choice elasticity. We return to the decomposition issue in Section 5 where we discuss related but different decomposition results based on models of store data that are part of the evolutionary model-building process.

Well-known models that are frequently used by consumer goods manufacturers are ACNielsen's SCAN*PRO and IRI's PROMOTER[20]. PROMOTER is a decision support system designed to provide evaluations of manufacturer trade promotions, so that brand managers can improve the allocation of promotion expenditures. It estimates the total promotion response, combining passthrough by retailers of trade promotions and the consumer response to promotions offered by retailers. To accomplish this, PROMOTER estimates baseline sales, the volume that represents an item's normal amount in the absence of promotions, after trend, seasonal and exception effects are accommodated. Promotion effects are estimated with reference to a dynamic baseline sales amount. PROMOTIONSCAN[21] represents enhancements of the PROMOTER model.

The SCAN*PRO model was ACNielsen's first attempt to show clients the estimated sales effects of promotions such as temporary price cuts, feature advertising and special displays for items in retail outlets. Since stores differ in the timing and nature of promotions, it is important to have store-specific data. And since promotional activities typically do not change within weeks, the use of weekly data maintains the exact variation over time. Thus data at the store-week level satisfy these desiderata. Before model results were provided to clients, the outcomes were tested and validated. Importantly, the model can be adapted to the specific needs of different clients. The initial model also proved to be a fruitful starting point for subsequent enhancements, some of which we review in Section 4. The enhancements allow academic researchers and managers to obtain a more complete understanding of promotion effects.

The original SCAN*PRO model is specified as follows for brand $j, j = 1, \ldots n$:

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

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

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

p_{krt} is the unit price for brand r in store k, week t,

20 See *Abraham/Lodish* (1987).
21 See *Abraham/Lodish* (1989).

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

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

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

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

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

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

The β_{rj} are the price discount (deal) elasticities (own-brand if $r = j$, cross-brand if $r \neq j$), the γ_{lrj} are the feature only-($l = 1$), display only-($l = 2$), feature & display-multipliers ($l = 3$), δ_{jt} is the (seasonal) multiplier for week t for brand j, λ_{kj} is store k's regular (base) unit sales for brand j if the actual price equals the regular price and there are no promotion activities for any of the brands $r, r = 1, \ldots, n$. The disturbance term is represented by u_{kjt}, n is the number of brands in the competitive set, K is the number of stores in the sample, and T is the number of weeks.

Equation (1) allows all brands to have unique own- and cross-brand effects for the marketing variables. The use of indicator variables as exponents allows for a simple interpretation of the parameters associated with feature and display variables. For example, a multiplier value of 2 for own-brand display means a doubling of brand unit sales when the brand is on display. Similarly, a cross-brand multiplier of 0.8 when brand r, $r \neq j$, is featured implies a 20 percent unit sales loss for brand j. Different modifications of (1) are discussed in Section 4.

3 EVOLUTIONARY MODEL BUILDING

We identified multiple criteria that models should satisfy based on *Little* (1970). These include *simplicity* and *completeness* on important issues. One might argue that it will be difficult for a model builder to satisfy both criteria at the same time. Simple models often provide reliable parameter estimates and this is an important determinant of (conditional) forecast accuracy. More complex models should provide valid parameter estimates, which are potentially less reliable (higher standard errors). Of course, validity (lack of bias) is also a determinant of forecasting accuracy, conditional on specific marketing activities. A marketing manager should prefer the model that maximizes the forecast accuracy, and it is in this sense that a model builder may have to make a trade-off between simplicity and completeness.

To expand on this idea, consider the following simplified representation. For a given econometric model, the expected forecast error is the sum of squared bias and variance. If the sample size available for parameter estimation is small, the variance matters greatly. As the sample size increases, bias becomes the dominant component in forecast error. Thus, it makes sense that we build more complete and complex models as the databases expand. Also, if one chooses between using aggregate and disaggregate data for decisions made at the aggregate level, it is easy to see why a model based on disaggregate data can provide superior forecasts. Specifically, if the disaggregate model is complete (no bias), then the variance component tends toward zero when the forecasts at the disaggregate level are combined to create a single forecast at the aggregate level.

For the SCAN*PRO model we compared the predictive validity of specifications based on aggregate and disaggregate data[22]. At the market level, we compared the forecast accuracy for a model estimated from market data with the accuracy of aggregated forecasts from models estimated from chain data and models based on store data. At the market level, the median relative absolute error[23] was lowest for a store-level model with chain-specific parameters. The worst performance obtained for the market-level model. The forecast accuracy at the chain level was also best for the store-level model with chain-specific parameters, while the chain-level model estimated separately for each chain was second worst out of six. Thus, even if we are not interested in exploring heterogeneity in parameters across disaggregate units, it is still advantageous to use disaggregate data. This also suggests that in an era with large databases, we expect that more complete models outperform simple models because complete models will have the smallest bias while variance tends to become irrelevant.

Should the criterion of simplicity, suggested by *Little* in 1970, be abandoned? No! The notion of evolutionary model building is that simplicity is especially desirable in the initial stage. This is so because a model user needs to have a basic understanding of what the model does and how it works. The simpler the model, the easier it is for a user to relate to its structure and its workings. Of course, a user may also object to a simple model's shortcomings, so the model builder must clarify that enhancements will be made over time. Ultimately, the bias component in forecast errors must be minimized. The greater the model builder's and the user's understanding of the phenomena to be modelled and the greater their allowance for surprising results (recall management's surprise about the interaction effect between advertising and price in *Eskin* (1975), discussed in Section 1 of this paper), the smaller the bias is expected to be.

Systematic weaknesses in a model can be identified by simulating forecasts under a wide variety of plausible market conditions. This corresponds to *Little*'s *robustness* criterion. It goes far beyond the idea of checking whether all parameter estimates have the expected signs. For example, a linear demand model may show the expected negative slope for own-brand price. But it will also predict negative demand for some prices, an implausible result. This should be seen not just as a

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22 See *Foekens/Leeflang/Wittink* (1994).
23 See *Armstrong/Collopy* (1992).

theoretical limitation (e.g. one might argue that the user will never set the price at the high levels for which the model predicts negative demand) because it also means that constraining the demand function to be linear over historically occurring prices is incorrect.
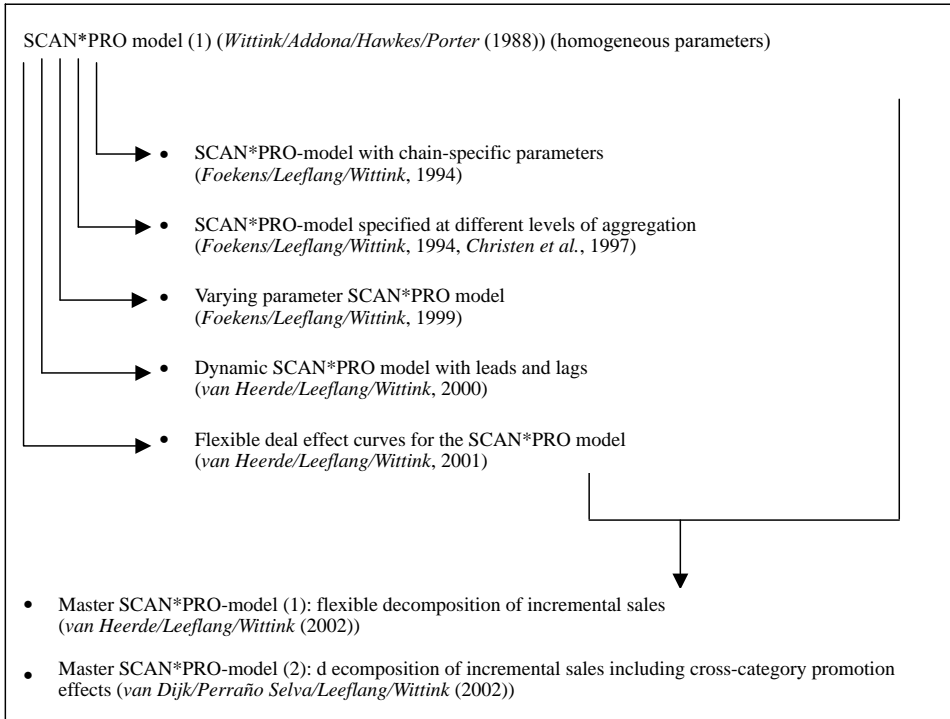
A model is robust if it is very unlikely to generate "bad" answers. Importantly, robustness is not necessarily easily observable. For example, a demand model can be fundamentally wrong and yet not show a severe discrepancy in its forecasts if the prices in the forecast period are within the range of prices in the estimation period. The observability of a bias due to model misspecification depends on the extent to which the user changes the nature of decisions from historical patterns. Thus, if a demand function is linear in price and this function fits the sample data ostensibly well, its limitation will not be observable unless future prices occur outside the historical range. Similarly, if the demand function misses a predictor variable that is highly correlated with an included one, the bias in the parameter estimate for the latter variable will be difficult to detect in the forecast error unless future decisions reflect a change in the association between the missing predictor and the included one(s).

The use of evolutionary model building to advance our knowledge about marketing phenomena implies that we build, refine and modify models in stages for any of the following reasons:

– the user needs to familiarize herself with the model, a process that is aided by simplicity;

– model use reveals that relying on the results improves decisions despite imperfections;

– continued model use and comparisons against actual outcomes reveal opportunities to enhance the specification;

– new data become available, and these data provide new opportunities;

– new methods become available, and these methods allow for greater flexibility in model structure;

– new results appear in the academic literature, and these results are relevant;

– new research questions appear.

We discuss the use of evolutionary model building for the SCAN*PRO model in Section 4.

Figure 1: Illustration of an evolutionary model-building process

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SCAN*PRO model (1) (Wittink/Addona/Hawkes/Porter (1988)) (homogeneous parameters)

              •   SCAN*PRO-model with chain-specific parameters
                  (Foekens/Leeflang/Wittink, 1994)

              •   SCAN*PRO-model specified at different levels of aggregation
                  (Foekens/Leeflang/Wittink, 1994, Christen et al., 1997)

              •   Varying parameter SCAN*PRO model
                  (Foekens/Leeflang/Wittink, 1999)

              •   Dynamic SCAN*PRO model with leads and lags
                  (van Heerde/Leeflang/Wittink, 2000)

              •   Flexible deal effect curves for the SCAN*PRO model
                  (van Heerde/Leeflang/Wittink, 2001)


      •   Master SCAN*PRO-model (1): flexible decomposition of incremental sales
          (van Heerde/Leeflang/Wittink (2002))

      •   Master SCAN*PRO-model (2): d ecomposition of incremental sales including cross-category promotion
          effects (van Dijk/Perraño Selva/Leeflang/Wittink (2002))
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4 THE EVOLUTIONARY SCAN*PRO-MODEL

We summarize the evolutionary model-building process for SCAN*PRO in *Figure 1.*

The SCAN*PRO model[24] is a store-level model developed to quantify the effects of promotional activities, implemented by retailers, on a brand's unit sales. The model accommodates temporary price cuts, displays, and feature advertising. In addition, it includes weekly indicator variables to account for seasonality and missing variables (such as manufacturer television advertising and coupon distributions) common to the stores in a metropolitan area, and store indicator variables. This model, and its variants, has been used in over 3,000 different commercial applications in North America, Europe, and elsewhere.

We return to the basic SCAN*PRO-model: equation (1). This assumes homogeneous parameters across stores belonging to different chains because of confidentiality agreements between ACNielsen and cooperating retailers. Its use also reflects a belief that aggregation of data over stores would create systematic prob-

24 See *Wittink/Addona/Hawkes/Porter* (1988).

lems. The appropriateness of this homogeneity assumption and aggregation issues was examined in *Foekens/Leeflang/Wittink* (1994) by estimating (1) and related expressions at: (i) the store level, (ii) the chain level, and (iii) the market level. For example, in a chain-level model we explain sales for brand *j*, chain *c*, week *t* as a function of such variables as the weighted average price for a brand (where the price is calculated as chain-level revenue divided by chain-level unit sales) and the proportion of (all) stores in the chain with promotion *l* for brand *j* in week *t*.

Comparisons of the forecast accuracy of variations of the SCAN*PRO-model at these three levels of aggregation [25] favor the most disaggregate (store) models (see also Section 3). However, the homogeneity assumption in equation (1) is implausible. The best model is a store model that accommodates heterogeneity in the parameters between chains. This *chain-specific store model* is obtained using the store data of each chain *c* separately. For example, if chain *c* has K_c stores, then its parameters are estimated on T x K_c observations. The parameters in this model refer to a specific chain, i.e. β_{rj}, γ_{lrj}, δ_{jt} and λ_{kj} in (1) are replaced by β_{crj}, γ_{clrj}, δ_{cjt} and λ_{ckj}, respectively.

Research questions about the relative performances of alternative models often have a practical basis. For example, managers tend to be interested in market-level models if they make marketing decisions at the market level, i.e. jointly for all stores and chains. *Christen et al.* (1997) demonstrate that there are substantial differences between the parameter estimates of a (nonlinear) model applied to linearly aggregated (summed) data and the corresponding estimates of the model applied to the original store data. The biases in the estimated effects from market-level data due to heterogeneity in the marketing activities across stores over which aggregation takes place can be very large. The source of the bias can be removed if the market-level aggregates represent geometric means (or geometric sums) of the appropriate store-level data so that mathematically consistent aggregation of data pertaining to equation (1) occurs.

We note that the model parameters in (1), as well as in the model with chain-specific parameters, are constant over time. Furthermore, the SCAN*PRO-model specified in (1) does not account for dynamic promotion effects. Dynamic effects occur if promotions such as temporary price cuts do not only increase sales at the time a brand's price is decreased but also displace future demand. Post-promotion dips in sales are expected to occur if consumers stockpile the promoted item.

We consider the estimation of dynamic promotion effects in two ways. First we discuss the SCAN*PRO-model in a form where the parameters vary while the structure of the model remains fixed[26]. This idea is based on findings by, for example, *Raju* (1992) who found that the frequency and recency of promotional activities affect a promotion's effectiveness on sales.

In a dynamic version of (1), functions are specified for the price parameters, the promotion multipliers and the store intercept. To illustrate, we show in equation

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25 See *Foekens/Leeflang/Wittink* (1994).
26 See *Foekens/Leeflang/Wittink* (1999).

(2) the price parameter *process function* for the *own-brand* price discount elasticity. In (2), the own-brand discount elasticity, that can vary by store and week, depends on the *magnitude* of and *time* since the previous discount for relevant brands. The expected signs are shown in parentheses below the equation.

$$\beta'_{kjt} = \beta'_{0j} + \beta'_{1j} \; Dsum_{kjt} + \beta'_{2j} \; CDsum_{kjt} + \beta'_{3j}d_\eta\left(\frac{1}{PTime_{kjt}}\right) + \beta'_{4j}d_\eta\left(\frac{1}{CPTime_{kjt}}\right) + u'_{kjt} \qquad (2)$$

$$(-) \quad (+) \qquad\qquad (+) \qquad\qquad\qquad (+) \qquad\qquad\qquad\qquad (+)$$

where: $Dsum_{kjt}$ is $\sum\limits_{s=1}^{\omega}\eta^{s-1} \times (discount_{kj,t-s})$ for brand j in store k, η is the

decline rate $(0 < \eta \le 1)$, ω is the number of weeks of history used for the discount variable in (2), and *discount* is the difference between regular and actual unit price,

$CDsum_{kjt}$ is $\sum\limits_{\substack{r=1 \\ r \ne j}}^{n} \sum\limits_{s=1}^{\omega}\eta^{s-1} \times (discount_{kr,t-s})$, and it represents the total,

discounted deal sum for brands other than brand j,

d_η is a dummy variable equal to 1 if $\eta = 1$ and 0 if $0 < \eta < 1$,

$PTime_{kjt}$ is the number of weeks since the last *own-brand price* promotion (within the last ω weeks preceding t) of brand j in store k,

$CPTime_{kjt}$ is the number of weeks since the last *other-brand price* promotion (within the last ω weeks) for brands other than brand j in store k, and

u'_{kjt} is a disturbance term.

In (2) we have separate discount magnitude and timing effects for both own- and other-brand promotions. The process function contains a decline rate parameter (η) in the definitions of *Dsum* and *CDsum* that allows more recent discounts to have a stronger effect on the own-brand price parameter if $\eta < 1$. In that case $d_\eta = 0$ which eliminates the "price timing" variables from (2), because a timing effect is then accommodated by the other predictors. For $\eta = 1$, the discounts in the preceding ω weeks are equally weighted. A grid search procedure is used for the determination of η.

The expected parameter signs for Equation (2) indicate that the own-brand price discount elasticity should move toward zero, the greater the magnitude of the most recent price promotion for own brand (*Dsum*) and for other brands (*CDsum*), and the fewer weeks since the previous price promotion for own brand (*Ptime*) and for other brands (*CPTime*). By substituting (2), and similar process functions for the multipliers and for the store/brand intercept (not specified here), in (1) we allow the parameters to vary across stores and over time as a function of

recent brand- and store-specific promotional activities. Estimation proceeds based on a generalized least squares procedure in two stages[27].

The empirical results indicate that baseline sales (sales under nonpromoted conditions) is dynamic. Consistent with expectations, an increase in sales due to a temporary price discount tends to reduce baseline sales in periods following the promotion. By allowing the store intercepts to vary based on the magnitude of a temporary price cut and based on the time since a promotion, we also accommodate the illusive post-promotion dip (discussed in the next paragraph). Effects on the own-brand discount elasticity show that the magnitude of and time since a previous discount change this elasticity as well.

We show in *Figure 2* fluctuations in the (estimated) intercept for one brand in one store over time. These fluctuations result from this brand's previous price discounts and the recency of non-price promotions by other brands. The dotted line in *Figure 2* represents the estimated intercept in a static model.

Figure 2: Graph of store 1 intercept for brand A (with a decline rate η = 0.67)

Min value = 96, Max value = 189, Fixed effect = 164
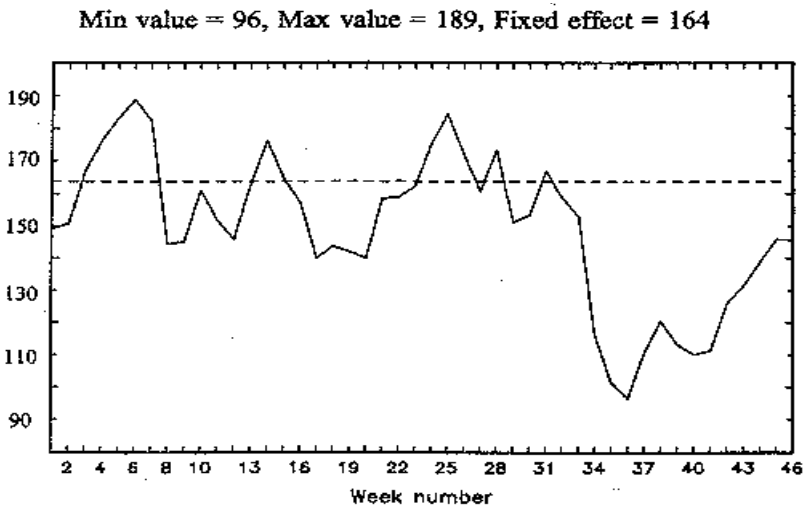
Source: *Foekens/Leeflang/Wittink* (1999), p. 264.

A second possibility to account for dynamic effects is to modify equation (1) by incorporating leads and lags for price promotion variables. *Van Heerde/Leeflang/Wittink* (2000) proposed such a model, prompted in part by a conundrum raised by *Neslin/Schneider-Stone* (1996). Researchers expect a pronounced dip in store-level sales in the weeks following a promotion. However, they rarely find such dips. Several arguments had been provided for the apparent absence of postpromotion dips in store-level scanner data. It turns out that the inclusion of

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27 See *Judge et al.* (1985), pp. 798–799.

extensive lead- and lagged variables resolves the dilemma. The model specifications we proposed can account for a multitude of factors that together cause complex *pre-* and *post*promotion dips.

Equation (1) includes four current promotional instruments as predictors. We modified this formulation with respect to the model specification and variable definitions. We now define own- and cross-brand discounts as separate variables for each of the four promotion conditions: without support, feature-only, display-only, and both feature and display. In addition, the model contains own-brand variables without price cuts for feature-only, display-only, and both feature and display, as well as lead- and lagged own-brand price discount variables. The use of separate discount variables for the promotion conditions has two advantages: (i) the set of own-brand variables is minimally correlated by definition, and (ii) this formulation allows for interaction effects between price cuts and the promotion conditions, akin to estimating a separate demand function for each support type. Thus this dynamic SCAN*PRO-model includes variables to capture dynamic price promotion effects separately for each of the promotion conditions.

We modeled lead- and lagged own-brand price discount effects for the four different conditions with three alternative *specifications* for dynamic effects:

- unrestricted dynamic effects;

- exponential decay dynamic effects;

- Almon dynamic effects.

The unrestricted dynamic SCAN*PRO-model has the following structure:

$$
\ln q_{kjt} = \sum_{r=1}^{n} \sum_{m=1}^{4} \beta_{rjm} \ln\left(\frac{p_{krmt}}{\bar{p}_{krm}}\right) + \sum_{u=1}^{s} \sum_{m=1}^{4} \beta_{jm} \ln\left(\frac{p_{kjm,t-u}}{\bar{p}_{kjm}}\right) +
$$

$$
\sum_{v=1}^{s'} \sum_{m=1}^{4} \beta_{jm,v} \ln\left(\frac{p_{kjm,t+v}}{\bar{p}_{kjm}}\right) \sum_{t=1}^{3} \gamma'_{lj} D_{lkjt} + \delta'_{jt} X_t + \lambda'_{kj} Z_k + u''_{kjt} \tag{3}
$$

where: $\ln\left(\dfrac{p_{kjmt}}{\bar{p}_{kjm}}\right)$ is the log price index (ratio of actual to regular price) of brand

j in store k in week t, $m = 1$ denotes that the observation is supported by neither feature nor display, $m = 2$ by feature only, $m = 3$ by display only, and $m = 4$ by feature and display; s is the number of lag weeks, s' is the number of lead weeks, and all other variables are as defined before.

This dynamic SCAN*PRO-model (3) includes flexible, multiple-week, pre- and post-price promotion *own-brand* variables and it incorporates *current cross-brand* price-promotional instruments. By having lead- and lagged variables for temporary price discounts with four types of support, it also accounts for dynamic effects for

features and displays, to the extent that these promotions were accompanied by price discounts. The unrestricted and Almon dynamic effect models provided the best fit to the data with similar dynamic effect magnitudes. The empirical results show that *own-brand* pre- and post-promotion effects together account for up to 25 percent of the sales increase. However, if stockpiling is estimated at the *category level* it accounts for about one third of the increase in own-brand sales[28].

The relationship between sales and temporary price discounts can be shown in a so-called deal effect curve. The literature suggests that several phenomena may produce complex nonlinearities and interactions in the deal effect curve: (i) threshold effects, (ii) saturation effects, (iii) interaction effects between deals of different items, and (iv) interaction effects between deals and promotion signals. We used a flexible semiparametric estimation method for the SCAN*PRO-model to allow the data to determine the shape of the deal effect curve[29]. Semiparametric regression models combine components of parametric and nonparametric regression models. Our implementation has the advantage of nonparametric regression (flexibility) for the deal effect variables and the advantage of parametric regression (efficiency) for all other predictor variables. Nonparametric modeling imposes few restrictions on the form of the joint distribution of the data which reduces the likelihood that estimated effects are biased. A potential disadvantage of the nonparametric approach is that it requires many observations. The sample size required explodes with the number of predictors because all interaction effects would have to be estimated without restrictions on any functional form. For these reasons, we restrict the nonparametric part to the estimation of the deal effect curve.

The model can be written as:

$$y_t = m\left(x_t^{(1)}\right) + x_t^{(2)}\beta + u_t, \qquad t = 1, \ldots, T \tag{4}$$

Here the vector of predictor variables x_t is split into two parts $x_t^{(1)}$ and $x_t^{(2)}$. The effect of $x_t^{(1)}$ is modeled nonparametrically, while the effect of $x_t^{(2)}$ is modeled parametrically. Since $x_t^{(1)}$ contains a subset of all predictor variables, the nonparametric function $m\,(.)$ operates on a vector of lower dimensionality than a fully nonparametric model would. This avoids the curse of dimensionality referred to above. The semiparametric SCAN*PRO-model in *van Heerde/Leeflang/Wittink* (2001) has the following specification:

$$\ln q_{kjt} = m(\ln(PI_{k1t}), \ln(PI_{k2t}), \ldots, \ln(PI_{knt}) + \sum_{l=1}^{3} \sum_{r=1}^{n} \gamma''_{lrj} D_{lkrt} + \delta''_{jt} X_t + \lambda''_{kj} Z_k + u'''_{kjt} \tag{5}$$

$$t = 1, \ldots, T \text{ and } k = 1, \ldots, K$$

where $m\,(.)$ is a nonparametric function, and PI_{krt} is a price index that defines the ratio of actual to regular price of brand r in store k in week t (see Equation (1)).

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28 See *van Heerde/Leeflang/Wittink* (2002).
29 See *van Heerde/Leeflang/Wittink* (2001).

Equation (5) is actually a fully flexible model as far as the main effects of the predictors are concerned because all continuous predictors (the price indices) are modeled nonparametrically. It also includes flexible interaction effects between the price index variables of the different brands (cross-brand effects). However, it does not allow for flexible interaction effects between the price index variables and the indicator variables (D_{lkrt}) of the parametric part, nor between these indicator variables themselves.

This flexible SCAN*PRO-model, estimated with the Kernel method[30], provides empirical support for threshold and saturation levels in the deal effect curve, and it outperforms alternative specifications on predictive validity criteria. Also, in one application with separate deal effect curves for the four different supports, a crossover interaction effect obtains between the deal effect curves for feature-only and display-only support. At zero discount, feature produces a higher sales effect than display. But the feature-only deal curve is relatively insensitive to price discounts. In the application, the display-only deal effect on sales exceeds the feature-only deal effect for discounts in excess of 20 percent.

Van Heerde/Leeflang/Wittink (2001) provide forecast error comparisons of parametric and semiparametric models. The parametric models include SCAN*PRO (equation 1), a model based on *Blattberg/Wisniewski* (1989, equation 5.1), and extensions of these models that accommodate additional interactions. The *Blattberg/Wisniewski* formulation differs from SCAN*PRO in the functional forms assumed for own- and cross-brand effects due to temporary price cuts. The additional interaction terms capture all first- and second-order interaction effects for the price indices through cross-products of the main-effect variables. The semiparametric specification is represented in Equation (5).

The forecast accuracy was calculated for data on three product categories. SCAN*PRO outperformed the *Blattberg/Wisniewski* formulation in two of the three categories. However, in all three cases, the parametric model with additional interaction terms outperformed the corresponding one without those terms. On average, across the three product categories, the Mean Squared Forecast Error decreased by 3,5 percent. However, the semiparametric model with flexible nonlinearity and flexible interaction effects between the price indices showed an average 12,7 percent improvement, varying from 8,9 to 17,0 percent. Thus, the allowance for more flexibility in nonlinear main effects and in interaction effects for the price index variables provides a substantial reduction in forecast error.

The flexible SCAN*PRO-model (5) and the dynamic SCAN*PRO-model (3) can be combined in Master SCAN*PRO-models to decompose promotion effects in store-level scanner data. The Master models are flexible, dynamic models to be estimated with semiparametric approaches. A standard Master model considers three sources for the own-brand sales increase resulting from a promotion: cross-brand effects, stockpiling effects, and category expansion effects. Cross-brand effects are the decreases in other brands' sales in the week of the promotion. Stockpiling effects are decreases in pre- and postpromotion category sales in an extended time period excluding the week of the promotion. Category expansion is the

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30 See the Appendix in *van Heerde/Leeflang/Wittink* (2001).

remaining increase in category sales in the extended time period (the volume due to the promotion that is not attributable to stockpiling or other brands).

Formally:

$$\sum_{r=1}^{n} \sum_{s=-T^*}^{s=T^*} q_{kr,t+s} = q_{kjt} + \sum_{\substack{r=1 \\ r \neq j}}^{n} q_{krt} + \sum_{\substack{s=-T^* \\ s \neq 0}}^{s=T^*} \sum_{r=1}^{n} q_{kr,t+s} \qquad or \qquad (6)$$

$$TC_{kt} = OB_{kjt} + CB_{kjt} + SP_{kt}$$

where TC_{kt} is total category sales in store k in the time window surrounding t $[t - T^*, t + T^*]$, OB_{kjt} is own-brand sales in week t, CB_{kjt} is cross-brand sales in week t, and SP_{kt} is category sales in the period surrounding t. An increase in OB_{kjt} resulting from a promotion in t can then be written as follows:

$$\Delta\,OB_{kjt} = \Delta\,TC_{kt} - \Delta\,CB_{kjt} - \Delta\,SP_{kt} \qquad (7)$$

This decomposition shows the change in sales in store k for brand j in week t to be equal to the change in total category sales over an extended time period minus the change in current cross-brand sales minus the change in category sales in the extended time period excluding week t.

Each of these four components (variables) in equation (6) is modelled as a function of promotional variables and covariates. For the decomposition to be exact, the model specification is identical across the four criterion variables. In *van Heerde/Leeflang/Wittink* (2002) the promotion effects are estimated for four product categories (two Dutch and two American data sets). On average, the three sources – cross brand, stockpiling and category expansion – account roughly for a third each of the unit sales effect for the focal brand. However, the flexible estimation shows that the percentage of the sales increase attributable to other brands decreases for larger price discounts while the percentage attributable to category expansion tends to increase. This percentage also depends on the support (feature and display, feature-only, display-only, neither). For example, under either of the supports with feature, about half of the sales effect is attributable to stockpiling. And in an extended decomposition where the category expansion effect is separated into a cross-store effect within the category and a remainder, the majority of the category expansion is accounted for by the cross-store effect when the support condition includes features. For the other two support conditions, the cross-store percent is quite modest. Thus, a temporary price cut for an item that is advertised by the retailer creates a very different pattern than a non-advertised price cut.

We note that this decomposition refers to unit sales effects, in contrast to the elasticity decomposition of household data discussed in Section 2. An appropriate question is why there is a dramatic difference between an elasticity decomposition of household data and a unit sales decomposition of store data. Possible reasons include: i) household versus store data; ii) elasticity versus unit sales effects; and iii) category differences between data sources. Several studies show that there are

systematic differences in effects between product categories. However, when both household- and store-data based results are available for the same category, the observed differences between elasticity and sales persist. A transformation of the elasticity result into a unit sales result shows that there is a fundamental difference between these two decompositions. *Van Heerde/Gupta/Wittink* (2001) show that the attribution of 75 percent on average to the secondary demand (brand choice) *elasticity* in *Bell/Chiang/Padmanabhan* (1999) corresponds to approximately 33 percent in *unit sales*.

Usually the available store-level data pertain to just one product category. With data on multiple product categories *in a given store*, we can also determine the effect of a promotion on the sales of products in other categories. Such product category interdependencies are the focus of a variation on the Master SCAN*PRO-model[31]. Daily observations on sales, prices and features for 5000 items sold by a Spanish hypermarket provide the basis for a further decomposition of the category expansion component in (7). *New data*, specifically multiple categories in one store, provide the impetus for this model enhancement.

5 FINDINGS: HOW SALES PROMOTIONS WORK

Empirical generalizations about the effects of promotions are provided in, for example, *Blattberg/Briesch/Fox* (1995), *Foekens* (1995), *van Heerde* (1999) and *Neslin* (2002). In this section we summarize the findings obtained from SCAN*PRO and its variants.

1. Temporary price cuts produce strong effects; price discount elasticities models are often greater than $|-2|$ (*Wittink et al.* (1988)).

2. Display- and feature multipliers show similar average magnitudes in parametric models; in the absence of a price cut sales often doubles with display or feature (*Wittink et al.* (1988)).

3. Multipliers are strongly biased upward in a nonlinear model applied to linearly aggregated (market-level) data; the magnitude of the bias depends upon the proportion of stores promoting the item (*Christen et al.* (1997)).

4. The effects of promotions are asymmetric; for example, a promotion for brand i may have an effect on brand j's sales while j's promotion does not affect brand i's sales (*Leeflang/Wittink* (1996), and *Foekens/Leeflang/Wittink* (1997)).

5. The higher the frequency of a promotion, the lower (toward zero) the price discount elasticity (*Foekens/Leeflang/Wittink,* (1999)).

6. The deeper the most recent price discount, the lower (toward zero), the price discount elasticity (*Foekens/Leeflang/Wittink* (1999)).

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31 See *van Dijk/Parreño Selva/Leeflang/Wittink* (2002).

7. Promotions create both lagged and lead effects, consistent with the idea that consumers engage in stockpiling and anticipate future promotions (*van Heerde/Leeflang/Wittink* (2000)).

8. The dynamic effects of promotions are substantial: shifts in the timing of purchases of the promoted brand account for up to 25 percent of the current sales effect (*van Heerde/Leeflang/Wittink* (2000)).

9. There is a threshold effect: discounts below 10 percent often generate sales levels that differ little from baseline sales (*van Heerde/Leeflang/Wittink* (2001)).

10. There is a saturation effect: discounts above 25 percent often provide minimal sales increases relative to sales obtained at a 25 percent discount (*van Heerde/Leeflang/Wittink* (2001)).

11. The shape of the deal effect curve for a brand depends on associated promotion signals (*van Heerde/Leeflang/Wittink* (2001)).

12. Deal effect curves for different supports may intersect; for example, the feature-only deal curve may show less discount sensitivity than the display-only curve (*van Heerde/Leeflang/Wittink* (2001)).

13. The unit sales effect of a promotion for a brand can be decomposed into different effects: one attributable to other brands, another attributable to stockpiling, and a third attributable to category expansion; on average, each source accounts for about one third of the unit sales increase; however, the nature of the decomposition depends on the magnitude of a price discount and on the promotion signal (*van Heerde/Leeflang/Wittink* (2002)).

14. A promotion for one SKU may reduce sales of other SKU's belonging to the same brand (*Foekens/Leeflang/Wittink* (1997), and *van Heerde/Leeflang/Wittink* (2002)).

15. The category expansion effect in a store or chain can be decomposed into a store-switching effect and a within-store effect attributable to other categories (*van Heerde/Leeflang/Wittink* (2002)).

6 CONCLUSION

Econometric model building has become an important part of academic research and commercial applications in marketing[32]. The SCAN*PRO model, developed in the 80's for commercial use, has been used extensively to support promotion decisions for brands. Model extensions published in the academic literature show how an evolutionary model-building process may proceed. Models evolve for many reasons, including the availability of new estimation methods, access to better data, and the identification of opportunities to improve the specification. The latter

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32 See *Leeflang et al.* (2000).

may occur when validation results reveal specific model shortcomings or related research provides new marketing insights that are relevant.

In this paper, we reviewed published extensions of the SCAN*PRO model. The initial work focused on parameter heterogeneity issues – across stores and chains – and on aggregation biases. Subsequent research focused on models with varying parameters to reflect how promotions cause fluctuations not only in sales but also in the marginal effects. The varying parameter specification was precipitated by other academic research on promotions.

The dynamic model with leads and lags resolved a conundrum that plagued marketing scientists for quite some time. Why did researchers obtain lagged effects in household models when those effects were rarely observed in models of store data? After considering possible explanations of this phenomenon, we concluded that lagged effects could be captured if more complex model specifications were used.

The availability of advanced estimation methods provided the impetus for the estimation of flexible deal effects. The application of nonparametric estimation methods provided new insights into the shapes of deal effect curves.

We are currently completing work on the decomposition of incremental sales due to promotions. The decomposition idea was stimulated by research on household data. With household data, the decomposition distinguishes between category incidence, brand choice (conditional on category incidence), and quantity (conditional on brand choice). Both category incidence and quantity capture category expansion and/or stockpiling effects so that neither of these variables have a unique interpretation. However, with store data the insights are more compelling: it is actually possible to separate these two sources of sales increases for a brand.

The state of the art (science) of econometric modelling now allows an increase in a brand's unit sales due to a promotion to be decomposed in great detail. The basic model separates cross-brand effects, stockpiling effects and category expansion effects. It accomplishes this separately for the different supports for temporary price cuts (display and /or feature), and it allows the decomposition to depend on the magnitude of the discount. Furthermore, for SKU data the cross-item effects can isolate cannibalization by distinguishing within- and between-brand effects. If the data represent multiple chains, the category expansion effect can be decomposed into cross-store effects within the category and cross-category (or other) effects within the store.

Traditionally, much research in marketing model building focused on brand competition within categories. One of the attractive properties of the decomposition approach is that it shows the component of sales increases for a brand due to a promotion that is attributable to brand competition. However, the decomposition approach also facilitates the identification of competition between categories. These model-building enhancements, developed in an evolutionary approach, attest to the potential that econometric applications have both for academic research and for industry use.

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