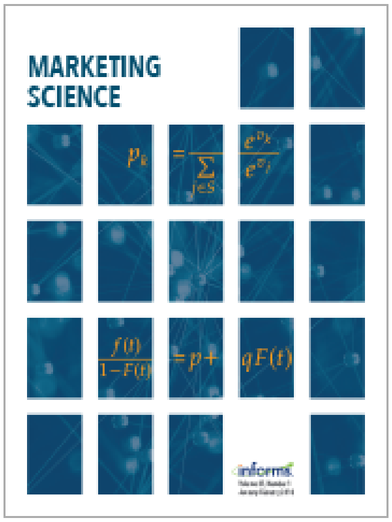

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How Dynamic Consumer Response, Competitor Response, Company Support, and Company Inertia Shape Long-Term Marketing Effectiveness

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Long-term marketing effectiveness is a high-priority research topic for managers, and emerges from the complex interplay among dynamic reactions of several market players. This paper introduces restricted policy simulations to distinguish four dynamic forces: consumer response, competitor response, company inertia, and company support. A rich marketing dataset allows the analysis of price, display, feature, advertising, and product-line extensions.

The first finding is that consumer response differs significantly from the net effectiveness of product-line extensions, price, feature, and advertising. In particular, net sales effects are *up to five times* stronger and longer-lasting than consumer response. Second, this difference is not due to competitor response, but to company action. For tactical actions (price and feature), it takes the form of *inertia*, as promotions last for several weeks. For strategic actions (advertising and product-line extensions), *support* by other marketing instruments greatly enhances dynamic consumer response. This company action negates the postpromotion dip in consumer response, and enhances the long-term sales benefits of product-line extensions, feature, and advertising. Therefore, managers are urged to evaluate company decision rules for inertia and support when assessing long-term marketing effectiveness.

Key words: long-term marketing effectiveness; dynamic consumer and competitor response; company inertia and support; vector autoregressive (VAR) models; impulse-response functions; policy simulation restrictions; postpromotion dip
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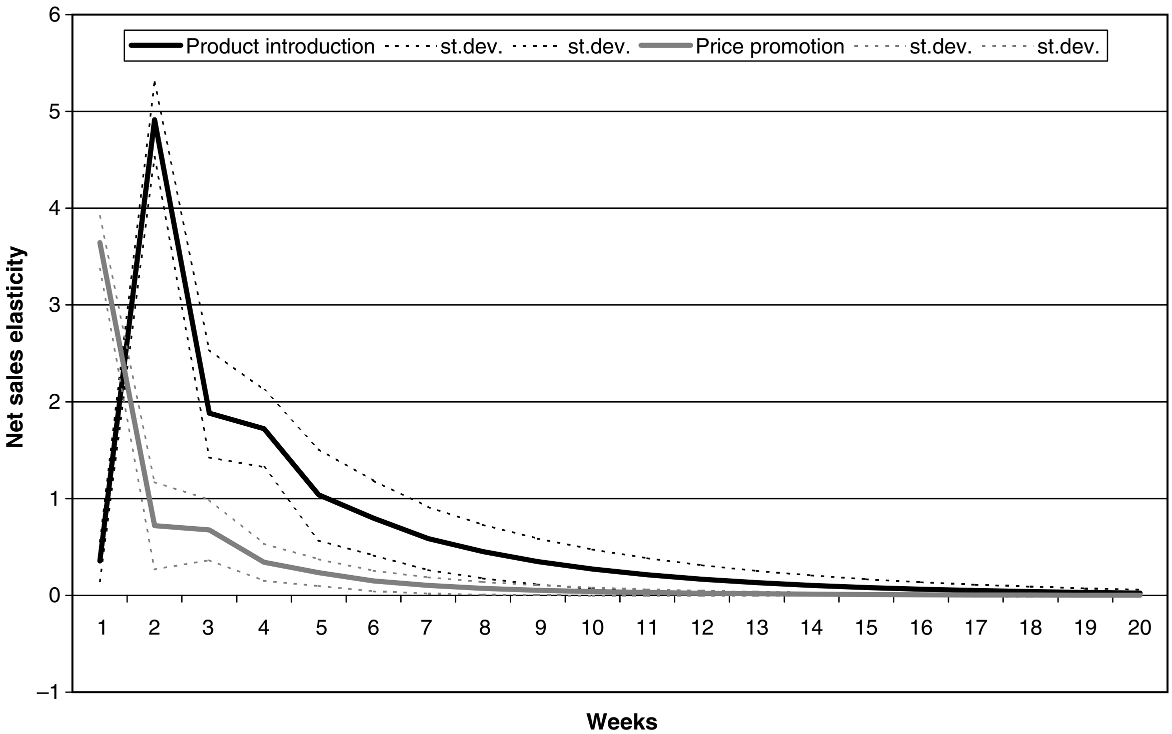
1. Introduction

Besides consumer demand, current marketing decisions often influence future company and competitor marketing activity. The 0% financing deals initiated by General Motors as an emergency measure after September 11, 2001 were quickly copied by competitors and continued a year later, even on the new 2003 models (*Wall Street Journal*, 2002). Likewise, escalation of advertising expenditures has been demonstrated in many industries (Metwally 1978). As a result, marketing managers are urged to consider the net long-term impact of their decisions, which includes dynamic consumer and competitor response, as well as associated future company actions (Chen 1996, Dekimpe and Hanssens 1999, Jedidi et al. 1999, Krishna et al. 2000).

Recent econometric studies compute this net long-run marketing impact by means of impulse-response functions derived from vector autoregressive (VAR) models (Bronnenberg et al. 2000; Dekimpe et al. 1999; Nijs et al. 2001; Pauwels et al. 2002; Srinivasan et al. 2000, 2004). In essence, an impulse-response function is the outcome of a "conceptual experiment" that tracks the full chain of events set in motion by a change to the marketing variable (Pesaran and Shin 1998). These events include consumer reactions such as promotion-induced stockpiling (Neslin 2002), competitor reactions such as retaliation (Leeflang and Wittink 1996), and company decision rules that back the initial marketing action by (1) prolonging it over time ("inertia"), such as keeping prices low for several weeks after a price promotion (Krishna et al. 2000, Srinivasan et al. 2004), or (2) supporting it with other actions, such as backing a product-line extension with advertising (Keller 1998). The over-time result of this chain of events is estimated as the net effect of the marketing action on sales. Figure 1 presents two typical examples of such impulse-response functions, showing the net sales elasticity of a price promotion and a product-line extension. While only the product-line extension effect shows "wear-in," i.e. it takes a number of weeks before the peak sales impact is reached, both impulse-response functions show "wear-out," i.e., it takes several

Figure 1 Net Sales Elasticity for Product-Line Extensions and Price Promotion of the Market Leader



weeks after the peak impact before sales effects die out.

Even though the net performance effect of a marketing action has strong managerial relevance, it remains unclear which part of it is due to dynamic consumer response, to dynamic competitor response, to company inertia, or to company support. As a result, it is often hard to understand sign and magnitude of the net dynamic impact, and to reconcile it with marketing theory and managerial intuition. Two examples serve as an illustration for tactical as well as strategic marketing actions. First, the absence of a significant postpromotion sales dip in several empirical studies (Blattberg et al. 1995) may be due to the fact that prices do not return to their regular levels for several weeks (Srinivasan et al. 2004). A plausible reason for such prolonged company action, as confirmed in recent experiments, is the managerial tendency to weigh past prices when setting future prices (Krishna et al. 2000). When confronted with evidence of price inertia, managers often want to find out to what extent it contributes to performance impact.

Second, advertising may fail to affect sales due to its inability to generate consumer response for established brands (Abraham and Lodish 1990), or due to competitive retaliation campaigns that cancel any demand gain (Bass and Pilon 1980). The distinction between these explanations is crucial, especially if managers obtain information that competitors will not respond as they have in the past. Indeed, in both examples, managers typically have little reason to believe that dynamic consumer response will deviate from historically observed patterns, but may have good reason to expect changes to company actions and/or competitor response. Moreover, several authors have demonstrated the relevance of combining the output of quantitative models with managerial judgment (Blattberg and Hoch 1990, van Bruggen et al. 1998). Finally, while recent research appropriately models marketing-sales endogeneity (e.g., Dekimpe and Hanssens 1999, Swait and Andrews 2003), Lodish (1980) and Shugan (2004) point out that marketing decision makers may face exogenous constraints and prior commitments that are unrelated to the context of the model. Therefore, it appears useful to combine the flexibility of vector autoregressive models that allow estimation of these dynamic forces, with policy simulations that allow their restriction and separation in conceptual forecasting experiments.

In this study, we introduce such restricted policy simulations to answer three related research questions. First, what is the dynamic response of consumers (demand) to marketing actions? Second, to what extent do dynamic competitor response, company inertia, and company support add to consumer response in order to form net marketing effectiveness? Finally, do these dynamic forces play a different role for tactical actions, such as (price) promotions, versus more strategic actions, such as advertising and product-line extensions?

The following section introduces our methodological framework. Section 3 introduces a rich marketing dataset, while §4 reports on the empirical findings. Finally, §5 provides conclusions, implications, and areas for future research.

2. Framework

All of the above dynamic forces are captured in the time-series modeling framework presented in Table 1. First, we examine the time-series properties for all sales and marketing variables (as extensively discussed in Dekimpe and Hanssens 1995). Based on these properties, we formulate models of the dynamic interactions among sales, marketing, and competitive marketing. Next, we use the estimated coefficients to simulate the net impact of a marketing action on sales, known as the impulse-response function. Finally, we extend the methodology by restricting endogenous variables to their steady-state baseline, which allows separation of consumer response, competitor response, company inertia, and company support. Calculation of the standard errors of these restricted policy simulations allows their formal comparison.

2.1. Vector Autoregressive (VAR) Model

In the absence of cointegration, which is rarely found among sales and marketing actions in consumer packaged goods (e.g., Nijs et al. 2001, Srinivasan et al. 2004), vector autoregressive (VAR) models are estimated with the stationary variables in levels and the evolving variables in differences. Equation (1) displays the basic form of our model:

$$\begin{bmatrix} S_t \\ FM_t \\ OM_t \\ CM_t \end{bmatrix} = \begin{bmatrix} \alpha_S + \delta_S t + \sum \lambda_S SD_t \\ \alpha_{FM} + \delta_{FM} t + \sum \lambda_{FM} SD_t \\ \alpha_{OM} + \delta_{OM} t + \sum \lambda_{OM} SD_t \\ \alpha_{CM} + \delta_{CM} t + \sum \lambda_{CM} SD_t \end{bmatrix} + \begin{bmatrix} 0 & \beta_{12}^0 & \beta_{13}^0 & \beta_{14}^0 \\ 0 & 0 & 0 & 0 \\ 0 & \beta_{32}^0 & 0 & 0 \\ 0 & \beta_{42}^0 & 0 & 0 \end{bmatrix} * \begin{bmatrix} S_t \\ FM_t \\ OM_t \\ CM_t \end{bmatrix} + \sum_{k=1}^{K} \begin{bmatrix} \beta_{11}^k & \beta_{12}^k & \beta_{13}^k & \beta_{14}^k \\ \beta_{21}^k & \beta_{22}^k & \beta_{23}^k & \beta_{24}^k \\ \beta_{31}^k & \beta_{32}^k & \beta_{33}^k & \beta_{34}^k \\ \beta_{41}^k & \beta_{42}^k & \beta_{43}^k & \beta_{44}^k \end{bmatrix} * \begin{bmatrix} S_{t-k} \\ FM_{t-k} \\ OM_{t-k} \\ CM_{t-k} \end{bmatrix} + \begin{bmatrix} u_{S,t} \\ u_{FM,t} \\ u_{OM,t} \\ u_{CM,t} \end{bmatrix} \quad (1)$$

with $[u_{S,t}, u_{FM,t}, u_{OM,t}, u_{CM,t}]' \sim N(0, \Sigma_u)$ and lag number K also known as the order of the model.

First, the vector of endogenous variables log of sales (S), log of focal marketing action (*FM*), log of own other marketing actions (*OM*), and log of competitive marketing actions (*CM*) is related to its own past, allowing complex dynamic interactions among

Table 1 Overview of Methodological Steps

Methodological step	Relevant literature	Research question
1. *Unit root and cointegration tests*		
Augmented Dickey-Fuller Test	Enders (1995)	Are variables stationary or evolving?
Zivot-Andrews test	Zivot and Andrews (1992)	Are unit root results robust to unknown breaks?
Cointegration analysis	Johansen et al. (2000)	Are evolving variables in long-run equilibrium?
2. *Model of dynamic interactions*		
Vector Autoregressive model	Dekimpe and Hanssens (1999)	How do sales and marketing variables interact in the long run and the short run, accounting for the unit root and cointegration results?
VAR in differences	Bronnenberg et al. (2000)	
Vector Error Correction model	Franses (1998)	
3. *Policy simulation analysis*		
Unrestricted impulse response	Sims (1980); Hamilton (1994)	What is the dynamic impact of a marketing change on sales, assuming all the historically observed interaction patterns apply?
Cumulative marketing elasticity	Pauwels et al. (2002)	
Restricted policy simulation	This paper	How do dynamic consumer response, competitor response and company action contribute to long-term marketing effectiveness?
4. *Validation analysis*		
VAR specification	Sims (1980), Faust (1998)	Are the results robust to the endogenous variables?
Information criterion	Pesaran and Smith (1998)	Are the results robust to the lag selection criterion?
IRF Comparison criterion	This paper	Are the results robust to the comparison criterion?

these variables. Second, the vector of exogenous variables typically includes (i) an intercept α, (ii) a deterministic-trend variable t, to capture the impact of omitted, gradually changing variables, and (iii) seasonal dummy variables SD (Nijs et al. 2001). Finally, Equation (1) explicitly displays the modeling of immediate (same-week) interactions among the endogenous variables. First, sales may be affected immediately by all company and competitive marketing actions through coefficients β^0_{12}–β^0_{14}. Second, the model assigns causal priority to the focal marketing action, which can immediately affect sales (β^0_{12}), own other marketing actions (β^0_{32}), and competitive marketing actions (β^0_{42}), but not vice versa. In other words, this causal ordering assumes that companies cannot change their focal marketing activity, observe immediate reaction, *and* adapt their actions again within the same time period, which makes sense for weekly data of retail-distributed consumer packaged goods (Leeflang and Wittink 1992, Dekimpe et al. 1999). Our explicit treatment of restrictions on the immediate reactions reflects a structural VAR approach to identification (Bernanke 1986), which is more appropriate[1] for subsequent policy restrictions than weak (implicit) identifying assumptions in the form of either the Choleski decomposition (e.g., Sims 1980, Dekimpe et al. 1999) or of the generalized impulse-response analysis (e.g., Pesaran and Shin 1998, Nijs et al. 2001). Moreover, we choose to obtain the coefficient estimates and residual covariance matrix by seemingly unrelated regression (SUR). Instead, we could estimate these parameters through maximum likelihood estimation by imposing policy restrictions on the residual covariance matrix. In that case, however, any misspecification of a single model equation could have pervasive effects on all the parameters of the system.

Compared to alternative specifications, VAR models are especially well suited to measure dynamic interactions between sales and marketing variables and to estimate dynamic market response (Dekimpe and Hanssens 1999, Montgomery et al. 2004, Pauwels et al. 2002). First, the endogenous treatment of own and competitive marketing implies that they too are explained by their own past and the past of the sales variables. In other words, this dynamic system model estimates the baseline of each endogenous variable and forecasts its future values based on the dynamic interactions of all jointly endogenous variables. Specifically, the VAR model accounts for dynamic consumer response through coefficients β^k_{11}–β^k_{14}, for prolonged company action through coefficients β^k_{21}–β^k_{24}, for cross-marketing company support through coefficients β^k_{31}–β^k_{34}, and for dynamic competitor response through coefficients β^k_{41}–β^k_{44}.

Second, dynamic effects are not a priori restricted in time, sign, or magnitude. As for the former, permanent effects are possible for evolving performance variables, and statistical criteria such as the Schwarz Bayesian criterion (SBC) or Akaike information criterion (AIC) suggest lag lengths K that balance model fit and complexity (Lutkepohl 1993). As for sign and magnitude, all coefficients are separately estimated and need not adhere to fixed patterns of wear-in and wear-out assumptions. In recent years, VAR models have been used to assess the long-run effects of marketing activity such as advertising, distribution, price promotions, and new product introductions (Bronnenberg et al. 2000; Dekimpe and Hanssens 1999; Horváth et al. 2001; Nijs et al. 2001; Pauwels et al. 2002, 2004; Pauwels and Srinivasan 2005; Srinivasan and Bass 2000; Srinivasan et al. 2004).

2.2. How to Distinguish Dynamic Forces in a Vector Autoregressive System?

After estimation of the above VAR model, the researcher could consider several alternative approaches to examine which dynamic forces drive long-term marketing effectiveness. First, one could impose restrictions directly on the estimated coefficients, whose number exceeds ($N^2 \times K$), with N the number of endogenous variables and K the number of lags. Wald tests on joint exclusion restrictions allow us to investigate which (sets of) variables contribute significantly to the explanatory power of the model. Unfortunately, several issues may explain the absence of exclusion restriction tests in empirical literature. First, the high degree of multicollinearity among the estimated coefficients complicates the exclusion assessment (Ramos 1996). Second, if we follow the test results, the reestimation of the (appropriately restricted) VAR models may still induce omitted-variable bias to the other parameter estimates (Sims 1980, Faust 1998). One approach to overcome this issue is to estimate several restricted VAR models and to compare their results (Horváth et al. 2001). Such procedure quickly becomes very elaborate, however, and no statistical significance criteria exist to compare the effect of estimates across different models. As a general strategy, econometric researchers prefer instead to impose restrictions on the long-run, structural impulse responses (Enders 1995).

An alternative approach to capture the dynamic behavior based on the VAR model is forecast error variance decomposition (FEVD). While impulse-response functions trace the effects of a shock in one variable on other variables, the FEVD separates the variation in one variable into component shocks to the

[1] Because this paper focuses on dynamic marketing effects, not on same-week interactions, please see Pauwels and Wolfson (2003) for a detailed discussion of structural identification options in this context.

system (Hamilton 1994). In our context, FEVD may help assess the contribution of past sales, marketing, and competitive marketing to current sales, marketing activity, and competitive marketing activity. Specifically, we can apply FEVD for sales to demonstrate the drivers of sales variation, and for marketing activity to demonstrate its dependence on past sales, on past marketing actions, and on past competitive marketing actions. Unfortunately, FEVD does not answer our research question: How do these dynamic forces influence*the net effectiveness of a marketing action*? For instance, the fact that competitive marketing activity contributes to the variation in our brand's sales does not necessarily mean that competitive *reaction* to a specific marketing action is important. In other words, FEVD can at most demonstrate the necessary conditions for the existence of dynamic response. More importantly, FEVD does not give the researcher control to exclude certain response patterns.[2]

For these reasons, we prefer a third approach that maintains the flexible and complete nature of the unrestricted VAR model and imposes restrictions only on the associated policy simulations. In particular, we choose to extend the impulse-response function framework to separate the dynamic results of a marketing action.

2.3. Impulse Response Functions and Their Interpretation

Because of their sheer number and multicollinearity, it is infeasible to interpret the estimated VAR coefficients directly (Ramos 1996, Sims 1980). The main interest of VAR modelers, therefore, lies in the net result of all the modeled actions and reactions over time, which can be derived from the estimated coefficients through the associated impulse-response functions. These impulse-response functions simulate the over-time impact of a change (over its baseline) to one variable on the full dynamic system[3] (Litterman 1984, Bronnenberg et al. 2000).

The impulse-response function's ability to track the full chain of events set in motion by a marketing action, sometimes appears a liability in practical applications. Specifically, unrestricted impulse-response analysis implies a scenario in which historically observed reaction patterns are assumed to persist in the future. Managers often feel uncomfortable with this scenario, as they may have good reason to believe that competitor response and/or company action will differ in the future (Blattberg and Hoch 1990). In other words, managers like to know to what extent the predicted net impact of a contemplated marketing action is a result of consumer and competitor response, which are largely outside their control, versus company inertia and support. Therefore, we may specify restricted policy simulations that allow dynamic response only by a subset of the endogenous variables that are expected to behave as they did in the estimation period.[4] To the extent that such restrictions do not change the data-generating process (Lucas 1976), restricted policy simulation analysis combines the high flexibility of VAR models to pick up historical reaction patterns and translate them into a net impact, with the researcher's desire to disentangle this net impact and the managerial desire to predict long-term marketing effects under different competitor reaction and company action scenarios.

2.4. Restricted Policy Simulations

We estimate separate policy simulations by restricting different endogenous variables to their VAR-predicted baseline, i.e., unaffected by the marketing change. In the typical case of stationary variables, this amounts to restricting endogenous variables to remain in their steady state. After checking the stability conditions (Hamilton 1994), we may write our model in terms of deviations from the steady-state means, summarizing the variables for ease of exposition:

$$(s, fm, om, cm)'_t = \sum_{k=0}^{K} \Phi_k (S-\mu_S, FM-\mu_{FM}, OM-\mu_{OM}, CM-\mu_{CM})'_{t-k} + (u_S, u_{FM}, u_{OM}, u_{CM})'_t. \quad (2)$$

The unconditional forecasts for the steady-state deviations for sales (s), the focal marketing action (fm), other marketing actions (om), and competitor marketing actions (cm) are zero for any forecast period. However, what is the forecast for the sales deviation conditional on the knowledge that a focal marketing variable changes by one unit ($u_{FM,\,t} = 1$)? The answer depends on the endogenous variables that we allow to be affected. Focusing on the sales

[2] The same two issues apply to approaches such as Granger causality tests, which may be used before VAR estimation to decide whether certain marketing variables should be included in the model (Hamilton 1994).

[3] Besides the sign and magnitude of the individual impulse-response coefficients, recent research has also considered their total dynamic impact, operationalized as the sum of all significant dynamic response coefficients (Pauwels et al. 2002). Based on the log-log formulation of the model and the unit-change calculations, this total dynamic impact corresponds to the dynamic sales change relative to its sample mean and can be expressed as the dynamic elasticity, making the results comparable across settings (e.g., Baumol 1977, Nijs et al. 2001, Ramos 1996).

[4] Restricted policy simulations may also be used for scenario analysis under specified patterns of company and competitor response (e.g., twice as strong as in the past). The usefulness of these specific conceptual experiments depends on the strength of the (qualitative) evidence for such scenario.

equation of the VAR system in (2), the conditional sales forecast for p periods ahead is:

$$\hat{s}_{t+p} = \beta_{12}^{0} fm_{t+p} + \beta_{13}^{0} om_{t+p} + \beta_{14}^{0} cm_{t+p} + \beta_{11}^{1} s_{t+p-1} + \beta_{12}^{1} fm_{t+p-1} + \cdots. \quad (3)$$

Starting from the steady state, the first two updated forecasts for the sales deviation become:

$$\begin{aligned}
\hat{s}_t &= \beta_{12}^0 fm_t + \beta_{13}^0 om_t + \beta_{14}^0 cm_t = \beta_{12}^0 + \beta_{13}^0\beta_{32}^0 + \beta_{14}^0\beta_{42}^0 \\
\hat{s}_{t+1} &= \beta_{12}^0 fm_{t+1} + \beta_{13}^0 om_{t+1} + \beta_{14}^0 cm_{t+1} + \beta_{11}^1 s_t + \beta_{12}^1 fm_t \\
&\quad + \beta_{13}^1 om_t + \beta_{14}^1 cm_t \\
&= (\beta_{12}^0 + \beta_{13}^0\beta_{32}^0 + \beta_{14}^0\beta_{42}^0) \\
&\quad \cdot (\beta_{21}^1\beta_{12}^0 + \beta_{21}^1\beta_{13}^0\beta_{32}^0 + \beta_{21}^1\beta_{24}^0\beta_{42}^0 + \beta_{23}^1\beta_{32}^0 + \beta_{24}^1\beta_{42}^0) \\
&\quad + \beta_{13}^0(\beta_{31}^1\beta_{12}^0 + \beta_{31}^1\beta_{13}^0\beta_{32}^0 + \beta_{31}^1\beta_{14}^0\beta_{42}^0 + \beta_{32}^1 \\
&\qquad + \beta_{33}^1\beta_{32}^0 + \beta_{34}^1\beta_{42}^0) \\
&\quad + \beta_{14}^0(\beta_{41}^1\beta_{12}^0 + \beta_{41}^1\beta_{13}^0\beta_{32}^0 + \beta_{41}^1\beta_{14}^0\beta_{42}^0 + \beta_{42}^1 \\
&\qquad + \beta_{43}^1\beta_{32}^0 + \beta_{44}^1\beta_{42}^0). \quad (4)
\end{aligned}$$

A plot of these forecasts against time yields the unrestricted impulse-response function, allowing all endogenous variables to respond according to the historically observed reaction patterns, as captured by all estimated VAR coefficients. If instead we allow only consumer (sales) response, we restrict future own and competitive marketing actions to remain in steady state, i.e., to have zero deviations. In that case, the forecast expressions in (4) greatly simplify to:

$$\begin{aligned}
\hat{s}_t &= \beta_{12}^0 \\
\hat{s}_{t+1} &= \beta_{11}^1\beta_{12}^0 + \beta_{12}^1.
\end{aligned} \quad (5)$$

These updated forecasts, plotted as a function of forecast period p, represent the restricted policy simulation of sales to the marketing change, allowing only for consumer response (restricted Simulation 1). Similarly, we add competitor response by allowing deviations from the steady state of the competitor marketing actions (Simulation 2), resulting in the forecasts:

$$\begin{aligned}
\hat{s}_t &= \beta_{12}^0 + \beta_{14}^0\beta_{42}^0 \\
\hat{s}_t + 1 &= \beta_{14}^0(\beta_{41}^1\beta_{12}^0 + \beta_{41}^1\beta_{14}^0\beta_{42}^0 + \beta_{42}^1 + \beta_{44}^1\beta_{42}^0).
\end{aligned} \quad (6)$$

In a similar fashion, company inertia is added to consumer response by allowing sales as well as the focal marketing action to change over time (Simulation 3). Simulation 4 instead adds company support to consumer response. Finally, Simulation 5 combines Simulations 3 and 4 by allowing for both types of company action.[5]

Standard errors for all impulse-response experiments are computed sequentially for each forecast period by applying the delta method to the estimated autoregressive coefficients and the estimated variance-covariance matrix (see appendix for a detailed discussion).

3. Data Description

Extensive marketing-mix data are available for the product category of frozen dinners and entrees. This category is the largest within the frozen food market, with more than \$5.9 billion in annual sales (American Frozen Food Institute 2003). In the early 1990s, six national brands competed for the lion's share of the market: Stouffer, Swanson, Healthy Choice, Budget Gourmet, Lean Cuisine, and Weight Watchers. Therefore, we estimate the VAR model in Equation (1) with 30 endogenous variables: sales and five marketing actions for each of these six brands. Table 2 summarizes their sales and marketing activity.

The data set combines 156 weeks of ACNielsen Sales and Causal data with advertising exposure (gross rating points) in the period February 1991–January 1994. For the total U.S. market, we obtain brand[6] sales, price (average price per serving), display (percentage of All Commodity Volume displayed), feature[7] (percentage of All Commodity Volume featured), and advertising (gross rating points). Moreover, we compute product-line extensions as the number of SKUs that are added to the brand's assortment in a given week.[8] Because the advertising data are collected for Monday–Sunday periods, we align them with the ACNielsen Saturday–Friday periods (assuming equal

[5] Note that our restricted simulation analysis differs from, e.g., the decomposition of price elasticity in Gupta (1988). The complex interaction and feedback effects in VAR models imply that the sales effect of sequentially restricting, e.g., competitor and company action, will not add up to the total sales effect of allowing changes in both variables.

[6] Because advertising data are only available at the brand level, we aggregate the ACNielsen data from the SKU level to the brand level by using the full-period SKU market shares as constant weights, in line with previous applications such as Pauwels et al. 2002 (Footnote 2). For our complex dynamic model, this choice preserves degrees of freedom that would be lost by setting aside an initialization period to compute these shares. We thank an anonymous reviewer for pointing out that, while this procedure strictly speaking puts sales at both sides of the equation, this fact is unlikely to affect the results much, as verified by the author for a 399-week dataset (Pauwels 2004).

[7] For error normality purposes, we transform the limited dependent variables feature and display by the transformation $(x/1-x)$, which expands their [0, 1] range into [0, ∞[.

[8] Because smaller temporary fluctuations of the product-line variable may be due to a lack of availability or lack of sales, we only count SKU additions that are substantial and persist in the product line for several months. We do not study product deletions, as they did not occur for the six major brands as they did for smaller brands (e.g., Le Menu).

Table 2 Average U.S. Sales and Marketing Actions for Frozen Food Brands 2/1991–1/1994

	Share (%)	Unit sales	Price	Display (%)	Feature (%)	Advertising	PLE*
Stouffer	15.1	2,091,549	\$2.36	6	15	58.29	5
Swanson	10.9	1,685,501	\$2.05	5	17	16.35	6
Healthy Choice	10.8	1,338,506	\$2.64	4	20	34.76	18
Budget Gourmet	10.4	1,897,238	\$1.78	5	23	28.88	9
Lean Cuisine	10.0	1,496,902	\$2.24	4	11	40.09	17
Weight Watchers	7.8	1,132,408	\$2.27	3	13	21.61	18

*Product line extensions: number of new product (SKU) introductions over the data period.

distribution of advertising over the days of the week). The aligned dataset covers the period 2/2/1991–12/18/93 for all variables. Based on the deterministic seasonality in category sales (Miron 1996), eight weeks with exceptionally high or low demand are identified.[9] Demand peaks in mid-January and March reflect consumers' New Year's and spring resolutions for low-calorie entrees, whereas family get-togethers around Thanksgiving, Christmas, and New Year greatly reduce the demand for frozen food (Bender 2000).

4. Results

4.1. Unit Root Tests

First, the unit root tests show that all variables are trend stationary.[10] Therefore, all marketing effects wear out without leaving a permanent sales impact, and the sum of all significant immediate and dynamic effects represents the cumulative sales impact (Pauwels et al. 2002).

4.2. Vector Autoregressive Models

SUR estimation of the VAR model yields the coefficient estimates and their variance-covariance matrix Σ_p.[11] For illustration purposes, we apply Wald exclusion restriction tests and forecast variance error decomposition (FEVD). First, the Wald tests[12] fail to exclude sets of dynamic coefficients in virtually all cases. The major exception is that cross-marketing competitive response does not significantly add to model fit for any brand (p-values vary between 0.13 and 0.47). Moreover, marketing actions by Swanson and Budget Gourmet do not evoke significant competitive response. None of the other exclusion sets hold.

Second, forecast variance error decomposition shows that, for each brand, sales (consumer response) are driven by its own marketing actions and at least one competitive marketing action. Moreover, marketing actions are driven by their own past (inertia), other own-marketing actions (support), and some competitive actions (typically the same marketing instrument).

In summary, both exclusion restriction tests and the forecast error variance decomposition indicate the presence of most dynamic interactions in our elaborate VAR model. The one exception is the cross-marketing competitor response. These results are in line with previous literature that reports many same-marketing (simple) competitive effects, but few cross-marketing (multiple) competitive effects (Hanssens 1980b, Steenkamp et al. 2002). Still, we need to analyze the restricted policy simulations for an answer to our research questions.

4.3. Policy Simulations for Dynamic Consumer Response and the Net Sales Impact

Our first research question focuses on the difference between consumer response and net sales impact. Table 3 compares the estimated consumer response, based on the first restricted policy simulation, with the net sales impact based on the unrestricted policy simulation.

First, immediate consumer response is significantly positive for all marketing actions. In line with previous literature, price promotions have the largest immediate elasticity, followed by product-line extensions, display, feature, and advertising (Tellis 1988, Hanssens et al. 2001). Second, dynamic consumer response is negative for price promotions, indicating a postpromotion dip (Blattberg et al. 1995). In contrast, display and feature show no significant dynamic consumer response (Mela et al. 1998), while the more strategic actions, advertising and product-line extensions, enjoy positive dynamic response. Finally, permanent effects are absent for all actions. The average length of the wear-in period is zero for price and nonprice promotions. Indeed, the goal of these tactical

[9] Detailed results are available upon request.

[10] Detailed results available upon request.

[11] Given the sheer number of estimates, detailed results available upon request.

[12] We exclude coefficients corresponding to respectively, (1) cross-marketing competitor response; (2) same-marketing competitor response; (3) cross-marketing company response; (4) same-marketing company response to (a) past company sales, (b) past company's actions, (c) past competitor marketing actions, and all combinations of the above.

Table 3 Average Estimates of Consumer Response and Net Sales Impact

	Immediate	Dynamic	Permanent	Wear-in	Wear-out
Consumer response					
Price	2.866	*−0.253*	*0*	*0*	*1*
(standard error)	(0.271)	(*0.142*)			
Display	0.102	*0.017*	*0*	*0*	*1*
	(0.028)	(*0.035*)			
Feature	0.031	*−0.002*	*0*	*0*	*1.2*
	(0.009)	(*0.004*)			
Advertising	0.001	*0.003*	*0*	*1.2*	*1.8*
	(0.001)	(*0.001*)			
Product	0.548	*2.264*	*0*	*1.2*	*3.0*
	(0.224)	(*0.435*)			
Net impact					
Price	2.866	**6.395****	0	0	5.2
	(0.271)	(2.404)			
Display	0.102	0.014	0	0	2.2
	(0.028)	(0.117)			
Feature	0.031	**0.111****	0	0	2.0
	(0.009)	(0.035)			
Advertising	0.001	**0.018****	0	2.0	4.2
	(0.001)	(0.005)			
Product	0.548	**6.822***	0	1.2	4.3
	(0.224)	(2.064)			

* Significantly different from dynamic consumer response at the 10% level.
** Significantly different from dynamic consumer response at the 5% level.

actions is to stimulate immediate action (Neslin 2002). In contrast, both advertising and product-line extensions experience an average wear-in of about one week. As for wear-out, the effects of tactical actions die out in about a week, while advertising and product-line extension effects take, respectively, two and three weeks to die out. The lengths of the estimated advertising wear-in and wear-out times may appear short, but are in line with the few previous studies on weekly data,[13] reporting a 90% duration interval of advertising effects of one to two months (Little 1979, Nakanashi 1973, Sexton 1970, Simon 1982, Steenkamp et al. 2002).

The difference of dynamic consumer response with the net sales impact is significant at the 5% level for price, feature, and advertising, and at the 10% level for product-line extensions. First, the net dynamic effects are higher for all marketing actions, except for display. For the tactical actions, price and feature, negative dynamic consumer response transforms into a positive net sales impact. As a result, the cumulative net impact (immediate + dynamic) is, respectively, 354% and 395% of cumulative consumer response. For the strategic actions, advertising and product-line extensions, positive consumer response is significantly enhanced. The cumulative net impact of advertising is five times higher than its cumulative consumer response, while product-line extensions obtain a cumulative net impact that is 262% higher than consumer response only. The size of this difference suggests that either competitor response or company action, or both, greatly contribute to the net dynamic marketing impact.

Second, the wear-out periods of the net sales impact are typically longer than those for consumer response. Especially noteworthy is the five-week wear-out period for price promotions versus the one-week wear-out of consumer response. Figure 2 illustrates this scenario for market leader Stouffer. The one-week postpromotion dip in consumer response transforms into several weeks of net sales benefits. Validation analyses (available upon request) show that the above findings are robust to the specification of smaller VAR models and to different choices of lag length and policy simulation comparison criteria (see appendix).

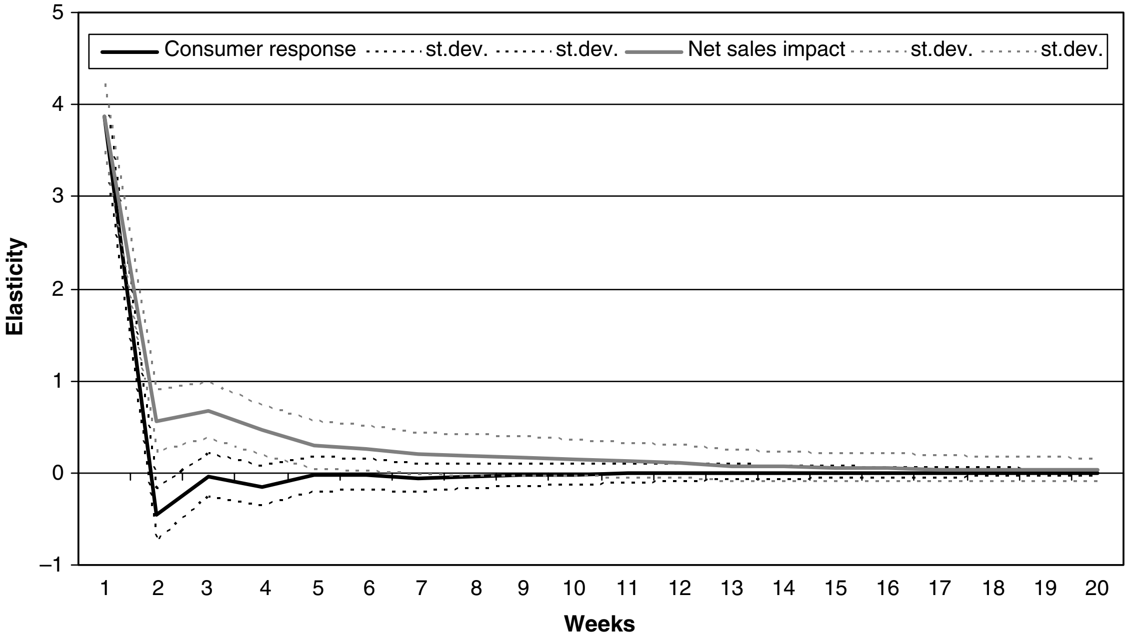
In summary, we consistently find that the net dynamic impact of marketing actions significantly differs from dynamic consumer response, with display being the only exception. This finding indicates that either competitor response or company action, or both, are very important. We turn to this issue next.

4.4. Policy Simulations Including Dynamic Competitor Response and Company Action

Table 4 presents the cumulative elasticity for all policy simulation experiments. For price, feature, advertising, and product-line extensions, adding competitor response to consumer response (*numbers in*

[13] Estimated wear-in and wear-out times depend on the time interval used (Clarke 1976, Leone 1995).

Figure 2 Consumer Response and Net Impact of Price Promotion by Market Leader Stouffer



italics) does not significantly change the dynamic elasticity. In contrast, adding company action to consumer response produces elasticity estimates similar to the net sales impact (numbers in bold). This finding is consistent with Horváth et al. (2001), who obtain larger net promotional effects in models that allow for company feedback because "internal decision rules dominate (competitive reactions)" (p. 26). Do we observe this phenomenon because competitors are unaware or unable to react (Chen 1996)? Not exactly: Additional analysis reveals few instances of passive response; competitors either react in an aggressive (Steenkamp et al. 2004) or an accommodating way (Sudhir 2001). In other words, at least some competitors react in ways that might reduce the net impact of the initiating marketing action. The observation that competitive response does not do so indicates that competitor actions might both decrease and increase company sales (Brandenburger and Naalebuff 1996). For advertising, Bender (2000) notes the simultaneous presence of "confusion" effects and "share of voice" effects and urges researchers to allow for both positive and negative cross effects of advertising. Likewise, promotions for one brand may increase shopper attention to the category and enhance competitor sales (Dekimpe et al. 1999, Pauwels et al. 2002). Specifically, the frozen food industry in the early nineties showed great potential for category expansion, as the household penetration rate was still low (American Demographics 1999), despite major technological innovations in the eighties, specific product improvements in the nineties, and the growing

Table 4 Dynamic Sales Elasticity of Marketing Actions (Standard Error in Parentheses)

	Price	Feature	Advertising	Product
Consumer response	*−0.253*	*−0.002*	*0.003*	*2.264*
	(0.142)	(0.004)	(0.001)	(0.435)
Competitor response	*−0.159*	*−0.004*	*0.003*	*2.311*
	(0.191)	(0.007)	(0.001)	(0.463)
Company inertia	**4.360****	**0.061****	*0.004*	*2.557*
	(1.485)	(0.016)	(0.002)	(0.540)
Company support	*0.846*	*0.010*	**0.016****	**6.074***
	(0.558)	(0.009)	(0.006)	(1.428)
Company action	**5.502****	**0.112****	**0.018****	**6.219***
	(1.814)	(0.036)	(0.006)	(1.607)
Net sales impact	**6.395****	**0.111****	**0.018****	**6.822***
	(2.404)	(0.037)	(0.005)	(2.064)

* Significantly different from dynamic consumer response at the 10% level.
** Significantly different from dynamic consumer response at the 5% level.

Figure 3 Feature Inertia for Market Leader Stouffer

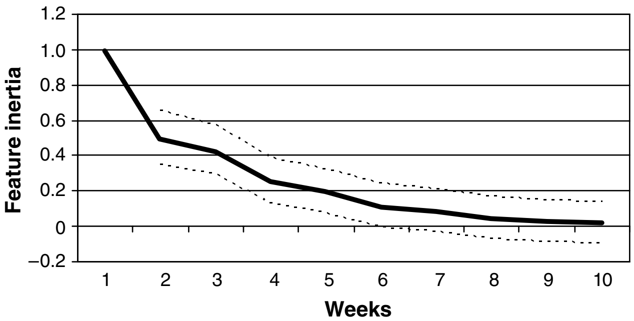
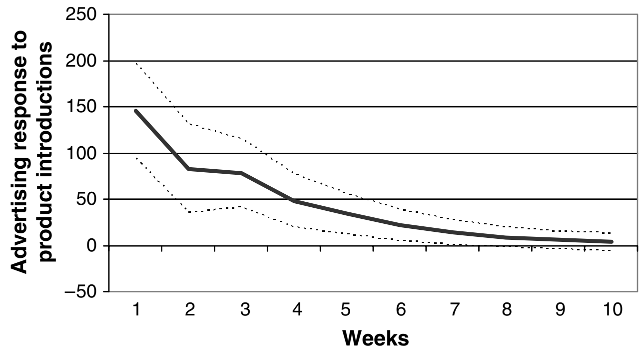


Figure 4 Advertising Support for Product: Advertising Response to One-Unit Line Extension



household demand for convenience foods (American Frozen Food Institute 2003).[14]

While company action is the main driver of the net sales impact, the importance of inertia versus support depends on the marketing action. First, for both price promotions and feature, company inertia is the main contributor to the higher net sales impact. Figure 3 illustrates feature inertia for market leader Stouffer by showing the dynamic response of percent of ACV featured to an immediate 1% increase in ACV featured. Similar to price decisions, feature activity takes several weeks to revert to its baseline level. The importance of company inertia reflects convergent results in experiments (Tversky and Kahneman 1974, Krishna et al. 2000) and econometric studies (Pesendorfer 2001, Srinivasan et al. 2004), that managers anchor current price decisions on past pricing decisions.

In contrast, company support, not inertia, bridges the gap between consumer response and the net sales impact for the more strategic actions, advertising and product-line extensions. Figure 4 illustrates how a product-line extension is supported by increased advertising activity for about two months. Similar support is provided by price reductions and promotional activity. Likewise, advertising obtains a higher sales impact when accompanied by price and/or product changes (i.e., when it has something new to say about the value proposition) and when it is supported at the point of purchase (Alba et al. 1991). Such integrated marketing support, exploring synergies across marketing actions, has been advocated in marketing for decades (Kotler 2001) and formalized in the "Integrated Marketing Communications" framework (Schultz et al. 1993). Moreover, observed marketing action dependencies may also result from the reactions of different decision makers (Ehrenberg et al. 2000), both within the company (different departments, different managers within one department) and among companies in the supply chain, such as manufacturers and retailers, which may be formalized into an efficient consumer response initiative (Kurt Salmon Associates 1993, Sansolo 1993).

In summary, we find that, in this dataset, dynamic competitor response does not contribute to the net impact for any considered marketing action. Instead, company action bridges the gap between consumer response and the net sales impact of a marketing action. In particular, company inertia contributes to the net sales impact for the tactical actions of price and feature, while company support is important for the strategic actions of advertising and product-line extensions.

5. Conclusions

Three main conclusions follow from the empirical separation of consumer response, competitor response, company inertia, and company support. First, *consumer response* to a marketing action differs from the net effect, as measured by the unrestricted policy simulation. Whereas dynamic consumer response to a marketing action conforms to marketing theory and managerial intuition, its net sales impact often does not. Therefore, managers and researchers should include supply effects in the net impact analysis of marketing decisions. Second, *company action* appears to be an important factor over and above consumer response. In other words, company decision dependencies are responsible for a large part of the net impact of a marketing action. Finally, *competitive response* does not change the net marketing impact in our dataset.

For tactical marketing actions, company action mostly takes the form of inertia. For instance, the well-known "postpromotion" dip, observed in consumer response, disappears for the net impact because prices stay low for several weeks. This finding confirms previous suggestions that extended

[14] An alternative explanation for the lack of competitor response effect is that our data are at the retail level, where one tends to find more evidence of cooperative behavior (Sudhir 2001). We thank the reviewers for this insight.

promotional activity may be responsible for masking postpromotion dips (Blattberg and Neslin 1990; van Heerde et al. 2000, 2001). In general, inertia or decision anchoring appears "extremely robust" across experts and across important decisions (Plous 1993, p. 151). For strategic marketing actions, company support succeeds in enhancing the positive consumer impact of the initial advertising and product-line changes. Indeed, it makes managerial sense to support important strategic decisions such as product-line extensions with all other marketing actions (Schultz et al. 1993, Cooper 1993). The response separation in our analysis allows assessment of which part of the net product impact is due to the line extension itself versus the supporting marketing actions.

Managerial implications flow from the expected competitor response and company action to a contemplated marketing action. First, the net effectiveness of typical marketing actions may not depend as universally and strongly on competitive response as previously thought (e.g., Bass and Pilon 1980, Chen 1996). This finding is in line with several recent studies reporting that aggressive competitive reaction is not an important factor in the market behavior of the analyzed categories (Horváth et al. 2001, Steenkamp et al. 2002). Interestingly, Sudhir (2001) also reaches this conclusion with a structural model of strategic interactions among manufacturers and retailers, and retailer pricing rules. While our model is not structural (it is reduced form), it addresses Sudhir's stated limitation that "we have not modeled any kind of dynamics that affect demand or supply.... That can have intertemporal demand effects, which in turn can affect supply-side behavior" (p. 262). Indeed, the feedback loops in our VAR model allow for both intertemporal demand and supply effects. The fact that two fundamentally different (but complementary) models reach a similar conclusion indicates a more generalizable insight. Moreover, while Sudhir's (2001) empirical analysis investigates categories with high concentration, which facilitates tacit collusion (Besanko et al. 1996), this study investigates a non-concentrated category. Still, boundary conditions for the lack of competitive response impact may include the competitive intensity in, and characteristics of, the product category. Therefore, a large-scale replication is needed to investigate the brand and category conditions under which competitor response affects the net long-term impact of a marketing action.

Second, it appears worthwhile to take a closer look at the nature and profitability of own company decision rules. While the present analysis establishes the presence of company inertia and support and their sales impact, it cannot determine whether this action is deliberate, and whether it is profitable. In case of profitable company action, managers may consider marketing actions whose consumer response by itself is unimpressive. Advertising is a good example; as several studies fail to find significant consumer response for established brands (e.g., Abraham and Lodish 1990, Hanssens 1980a). However, advertising may increase the benefits of promotions and product introductions, as it induces retailer and salesforce support (Ehrenberg et al. 2000) and draws consumer attention to the improved product value (Hanssens et al. 2001).

In case of unprofitable company action, managers should consider the possibility of changing the dynamic dependencies between marketing actions. Some experimentation is typically needed to determine whether such changes leave the estimated dynamic interactions between consumers, company, and competitors intact (Lucas 1976). For instance, managers can return to regular prices faster than usual after a promotion to investigate whether the intended prevention of consumer sticker shock really justifies lost margins (Kopalle et al. 1996). Decision support systems are helpful tools in this respect, as managers who use such systems are less inclined to anchor their decisions on earlier decisions (van Bruggen et al. 1998). Evidently, the restricted policy simulations may also be used for scenario analysis under specified company and competitor response. Instead of restricting all competitor responses to zero, we could omit competitor response up to or after a certain time period, specify that it will be twice as strong as in the past, or set the response to any value. In each case, we can calculate the dynamic impact of the contemplated marketing action. The usefulness of these simulations depends on the strength of the (qualitative) evidence for such scenarios, which was not available in the analyzed dataset.

For *marketing researchers*, our findings on the prominence of expanded company action contribute to growing empirical evidence of, and call for more analysis on, marketing decision dependencies (Steenkamp et al. 2002, van Bruggen and Wierenga 2000). Far from being a new idea, these dependencies reflect Forrester's (1961) forceful argument in favor of feedback loops as the basic constituencies of economic and social systems.

This study has several limitations that offer useful avenues for future research. First, the dataset is at the aggregate retail level, and thus does not allow modeling of cross-store heterogeneity and strategic retailer behavior (Sudhir 2001). The fact that the dataset is at the national level renders these issues less germane, but adds potential aggregation bias, including the averaging of product-line extensions over U.S. stores. Second, the data did not provide the information on profit margins and costs necessary to perform marketing profitability analyses. Third, the findings are based on data from well-established, mature product categories. If promotions and advertising induce trial for new products (Abraham and Lodish 1990), their sales effects could be permanent. Moreover, the minor importance of the dynamic competitor response may depend on the competitive environment that companies face. Therefore, future research should expand the restricted policy simulation analysis to different market and competitive conditions and examine whether the current results generalize. Other unanswered research questions include whether competitors react to the marketing action itself or to its impact on their sales (investigation of the direct and indirect effect paths in the VAR model) and whether net sales effectiveness depends on the timing of the marketing action (development of state-dependent models of dynamic interactions). Finally, we strongly encourage future research to find ways to increase VAR-estimation efficiency and reduce the typically high standard errors.

As a first step towards separation of dynamic marketing forces, this paper yields three major implications. First, dynamic consumer response largely follows marketing theory predictions for tactical as well as strategic marketing actions. Second, the net dynamic impact differs significantly and substantially from consumer response, except for marketing action display. Third, the major contributor to this difference is not competitor response, but company action in the form of inertia for tactical actions, and of support for strategic marketing actions. Therefore, managers are urged to look beyond dynamic consumer and competitor response and to evaluate company decision rules for inertia and support when assessing long-term marketing effectiveness.

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Appendix. Standard Error Calculation for Restricted Policy Simulations

We start from Equation (2), as the deterministic components determine the value of the steady-state variables, but have no effect on deviations from it, so both they and derivatives with respect to them are set to zero (Lütkepohl 1990). First calculate the derivatives of each endogenous variable with respect to all the parameters, period by period, starting in the period of the impulse. Consider the derivative of sales with respect to β_{11}^1, the coefficient of lagged sales, when the impulse response function is left unrestricted:

$$\begin{aligned}\frac{\partial s_t}{\partial \beta_{11}^1} &= s_{t-1} + \beta_{11}^1 \frac{\partial s_{t-1}}{\partial \beta_{11}^1} + \cdots + \beta_{11}^k \frac{\partial s_{t-k}}{\partial \beta_{11}^1} + \beta_{12}^0 \frac{\partial fm_t}{\partial \beta_{11}^1} \\ &\quad + \beta_{12}^1 \frac{\partial fm_{t-1}}{\partial \beta_{11}^1} + \cdots + \beta_{12}^k \frac{\partial fm_{t-k}}{\partial \beta_{11}^1} + \beta_{13}^0 \frac{\partial om_t}{\partial \beta_{11}^1} \\ &\quad + \beta_{13}^1 \frac{\partial om_{t-1}}{\partial \beta_{11}^1} + \cdots + \beta_{13}^k \frac{\partial om_{t-k}}{\partial \beta_{11}^1} + \beta_{14}^0 \frac{\partial cm_t}{\partial \beta_{11}^1} \\ &\quad + \beta_{14}^1 \frac{\partial cm_{t-1}}{\partial \beta_{11}^1} + \cdots + \beta_{14}^k \frac{\partial cm_{t-k}}{\partial \beta_{11}^1}. \end{aligned} \tag{A.1}$$

Again, these expressions are in deviations from steady state, which simplifies the calculations. Because s, m, and cm are zero in all periods prior to the impulse, irrespective of the value of β_{11}^1, the derivative in (A.1) equals zero in all these periods. Having calculated the derivatives of all variables with respect to all parameters, stack the values of the sales derivatives into a vector D_s and calculate the quadratic form $D_s' \Sigma_p D_s$, where Σ_p is the variance-covariance matrix of the parameters. At the time of the impulse, all terms in D_s equal zero except for the derivative of sales with respect to the β^0 coefficients. As the focal marketing action is set to one at that time, the standard error of s will equal the square root of the expression:

$$\begin{aligned} &v_{12} + (\beta_{32}^0)^2 v_{13} + (\beta_{42}^0)^2 v_{14} + (\beta_{13}^0)^2 v_{32} + (\beta_{14}^0)^2 v_{42} \\ &\quad + 2(\beta_{32}^0 c_{12,13} + \beta_{42}^0 c_{12,14} + \beta_{13}^0 c_{12,32} + \beta_{14}^0 c_{12,42} + \beta_{13}^0 \beta_{14}^0 c_{32,42} \\ &\qquad + \beta_{13}^0 \beta_{32}^0 c_{13,32} + \beta_{13}^0 \beta_{42}^0 c_{14,32} + \beta_{14}^0 \beta_{32}^0 c_{13,42} \\ &\qquad + \beta_{14}^0 \beta_{42}^0 c_{14,42} + \beta_{32}^0 \beta_{42}^0 c_{13,14}) \end{aligned} \tag{A.2}$$

with $v_i = \mathrm{var}(i)$, $i \in \{\beta_{12}^0, \beta_{13}^0, \beta_{14}^0, \beta_{32}^0, \beta_{42}^0\}$, and $c_{i,j} = \mathrm{cov}(i, j)$, $i, j \in \{\beta_{12}^0, \beta_{13}^0, \beta_{14}^0, \beta_{32}^0, \beta_{42}^0\}$.

In the period following the impulse, these calculated derivatives become the derivatives of the lagged variables, s_{t-1}, m_{t-1}, and cm_{t-1}. The derivatives for the current period can then be calculated and the delta method applied to generate standard errors for the current response to last period's impulse. We repeat this procedure until the end of the response horizon.

To make this calculation when the impulse-response function is restricted, zero out the parameters, variances and covariances corresponding to the restriction. In Equation (5), we are permitting only consumer response, so β_{32}^0 and β_{42}^0 are all set to zero, as are their variances (v_{32} and v_{42}) and all covariances involving these parameters ($c_{12,32}$, $c_{12,42}$, $c_{13,32}$, $c_{13,42}$, and $c_{14,32}$, $c_{14,42}$, and $c_{32,42}$.) The standard error of sales in the period of the impulse is just $\sqrt{v_{12}}$, the standard error of β_{12}^0. In Equation (6), we also permit competitor response; and the standard error becomes:

$$\sqrt{v_{12} + (\beta_{42}^0)^2 v_{14} + (\beta_{14}^0)^2 v_{42} + 2(\beta_{42}^0 c_{12,14} + \beta_{14}^0 c_{12,42} + \beta_{14}^0 \beta_{42}^0 c_{14,42})}. \tag{A.3}$$

Calculation of the standard errors for each forecast experiment allows a formal comparison of the unrestricted and restricted policy simulations, as they are all based on the same estimated coefficients and residual covariance matrix from the same VAR model. To the best of our knowledge though, guidelines have yet to be developed for such comparison. We distinguish two criteria for comparing the output of policy simulations; the first focusing on the individual impulse-response coefficients, the second on their cumulative impact. Formally, the first criterion states that two policy simulations are significantly different if they yield significantly different coefficients in *any* period. The second criterion states that two policy simulations are significantly different if their *total dynamic* impact (i.e., over all dynamic periods) significantly differs. This criterion is more stringent (as significant differences in specific periods may negate each other), and has strong managerial relevance. For instance, suppose we find that the dynamic impact of a price promotion does not change significantly when we add competitor response. This result implies that managers need not incorporate such response in the benefit analysis of the contemplated price promotion, provided it does not alter historically observed reaction patterns. Therefore, we report the standard errors for the latter criterion and validate with the findings for the former criterion. As for the significance level, one may either apply the t-test significance levels of 10% and 5% or maintain comparability with previous marketing research by applying the one-standard error bands that are used to judge significant differences from zero and from the long-run convergence value (e.g., Nijs et al. 2001), as motivated in Pesaran et al. (1993) and Sims and Zha (1995, Footnote 15).

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