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Competitive Reactions to Advertising and Promotion Attacks

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How do competitors react to each other's price-promotion and advertising attacks? What are the reasons for the observed reaction behavior? We answer these questions by performing a large-scale empirical study on the short-run and long-run reactions to promotion and advertising shocks in over 400 consumer product categories over a four-year time span.

Our results clearly show that the most predominant form of competitive response is passive in nature. When a reaction does occur, it is usually retaliatory in the same instrument, i.e., promotion attacks are countered with promotions, and advertising attacks are countered with advertising. There are very few long-run consequences of any type of reaction behavior. By linking reaction behavior to both cross- and own-effectiveness, we further demonstrate that passive behavior is often a sound strategy, while firms that do opt to retaliate often use ineffective instruments, resulting in "spoiled arms." Accommodating behavior is observed in only a minority of cases, and often results in a missed sales opportunity when promotional support is reduced. The ultimate impact of most promotion and advertising campaigns depends primarily on the nature of consumer response, not the vigilance of competitors.

Key words: empirical generalizations; advertising and price-promotion effects; competitive strategy; time-series analysis
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1. Introduction

In consumer and business markets alike, we observe a never-ending sequence of marketing actions and competitive reactions that eventually shape both the structure of a market and the performance of its participants. New products are launched, distribution is developed, advertising campaigns are initiated, prices adjusted, etc. The market-response literature has made substantial progress in quantifying the typical short-run performance effects of such marketing actions and reactions, and we have begun to understand some of their long-run consequences as well (e.g., Hanssens et al. 2001, Leeflang et al. 2000).

In this repetitive marketing game, managers need to know whether or not marketing reactions are necessary (i.e., essential to the long-run survival of their brands), or discretionary, i.e., they may have desirable short-run outcomes, but are inconsequential to the brand's long-run competitive position. This is a difficult task, as it entails knowledge about the direction of a competitive effect (beneficial, harmful or neutral), its duration, as well as the effectiveness of competitive response for both retaliating and accommodating behavior. Absent such knowledge, it is not surprising that empirical studies find systematic deviations between actual versus Nash-optimal marketing-spending levels in competitive markets. For example, some competitors may behave suboptimally, while others are supraoptimal, i.e., they fare better than they should (e.g., Carpenter et al. 1988; Leeflang et al. 2000, Ch. 11).

Our paper begins this process by examining the way in which competitors react to two of the most prevailing forms of marketing activity, viz., price promotions and advertising. We examine the competitive reaction elasticities due to price promotion or advertising attacks, both in the short and the long run, and quantify the moderating impact of a variety of brand and category factors influencing the magnitude of these elasticities. We also study the implications of reaction behavior on the sales levels of the defending brands.

Our study is based on all major participants in 442 consumer product categories in The Netherlands, sampled weekly over a four-year period. We focus on the top three brands in each category, and measure promotion and advertising reaction behavior while controlling for the rest of the marketing mix, i.e., distribution coverage, new-product introductions, and feature and display support. We employ time-series models that measure the short- and long-run differential impact of promotion and advertising attacks in terms of competitive as well as sales response. The breadth (number of product categories and brands) and detail (full marketing mix) of our dataset leads to a first major contribution of the study: A rich set of empirical generalizations on the intensity and duration of different competitive reactions ("How do brands react?"). As a second contribution, we explain why they react as they do: We link a set of reaction elasticities to a number of theory-based brand and category characteristics to test under what circumstances competitive reactions are most likely to be incurred ("What are the drivers of reaction?"). Finally, we link our findings on competitive reaction behavior with the corresponding cross- and own-effectiveness for, respectively, the attacking and defending brand, and assess the soundness of passive, retaliatory, and accommodating behavior ("Is their reaction behavior justified?").

The present study can be positioned vis-à-vis two research streams. The first is a series of studies based on vector-autoregressive models with exogenous variables (VARX models) (Bronnenberg et al. 2000, Dekimpe and Hanssens 1999, Nijs et al. 2001, Pauwels et al. 2002, Srinivasan et al. 2002). While these papers all share an estimation methodology, their substantive topics differ. Bronnenberg et al. (2000) study how market share and retailer distribution jointly determine the market structure in new repeat-purchase categories. Dekimpe and Hanssens (1999) examine the short- and long-run profit implications of marketing actions. Pauwels et al. (2002) focus on the short- and long-run decomposition of the promotional sales bump in terms of category incidence, brand choice, and purchase quantity, while Srinivasan et al. (2002) study the financial implications of price promotions for manufacturers and retailers. Hence, all previous studies focus on capturing differences in performance rather than reactivity. This performance focus is also present in Nijs et al. (2001), who study the primary-demand effects of price promotions, while reporting some relevant summary statistics on competitive reactivity. Our paper contributes over and above Nijs et al. (2001) in several important respects. First, Nijs et al. use the extent of reactivity as a potential driver of primary-demand expansion, while we study *conditions* under which competitive reactions are more or less aggressive. Second, through an explicit link with own- and cross-sales elasticities, we examine whether the observed competitive reactions are *justified* or not. Third, we extend Nijs et al.'s summary table on the extent of competitive reactivity (Table 5) by explicitly comparing the *strength of reaction* to, respectively, price-promotion and advertising attacks. This enables a further comparison of *simple* versus *multiple* reaction patterns. In addition, we simulate and compare *retailer-driven* versus *manufacturer-dominated* price-promotion reactions.

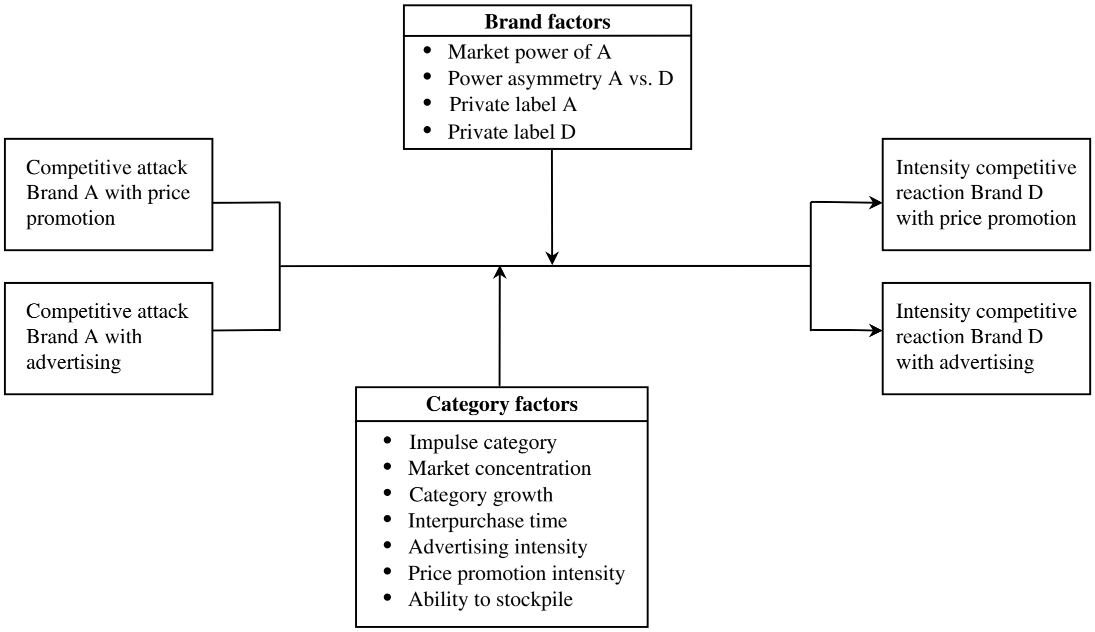
The second stream of research to which our paper can be compared consists of a series of studies by Leeflang and Wittink (1992, 1996, 2001; see also Brodie et al. 1996). They study the extent of competitive reactivity to price promotions, a number of brand-related factors moderating this competitive reactivity, and whether the observed reaction behavior is justified. Our study differs from their work along several key dimensions as well. We examine the *simple* and *multiple* reactions to both *price promotions* and *advertising*. We also study *short-run* as well as *long-run* effects. In addition, our work provides a basis for deriving *empirical generalizations*. While Leeflang and Wittink study a single category and seven brands, our dataset covers 442 categories and over 1,200 brands. Moreover, this extensive dataset allows us to examine the moderating impact of both *brand-* and *category-*related characteristics on competitive reaction elasticities. Finally, Leeflang and Wittink distinguish between reactions and no reactions. However, reactions can be of two types, with different implications, viz. accommodation and retaliation (Gatignon and Reibstein 1997). We study both types of reactions.

The remainder of the paper is organized as follows. In the next section, we lay out the conceptual framework guiding our research. Using this framework, we develop predictions concerning main effects of price promotions and advertising on reactions of competing brands, as well as the role of factors that can increase or reduce these effects. Next, we describe the data set and the methodology, and we report the statistical results. Our findings are validated through the administration of a management survey. Then we assess the managerial soundness of passive, retaliatory, and accommodating behavior on the part of the defending brand. The final section summarizes the findings, draws conclusions, and provides suggestions for future research.

2. Drivers of Competitive Reactions

Figure 1 depicts the conceptual framework that guided our research. We examine the effect of a shock

Figure 1 **Conceptual Framework**



in price (i.e., a price promotion) and advertising by Brand A (the Attacker) on the intensity of the competitive reaction by rival Brand D (the Defender). In this study, price promotions are temporary price reductions offered to the consumer, while advertising refers to mass-media advertising. The effects of a price promotion or an advertising shock by Brand A on Brand D's competitive reaction are allowed to be moderated by brand and category characteristics.

2.1. Effect of Price Promotion and Advertising on Reactions of Competing Brands

When a competing brand initiates a price or advertising shock, how do other brands respond? Key issues in this respect include whether the defender uses the same instrument as the attacker (simple reaction) or a different instrument (multiple reaction), and how intense the competitive reaction by the defending brand will be. The intensity of response can range from very accommodating (e.g., substantially decreasing advertising in response to an advertising shock), to passive (no reaction), to strong retaliation (e.g., substantially increasing advertising in response to an advertising shock).

We expect that absence of reaction to a competitive attack is most common (Leeflang and Wittink 1996), while accommodating reactions are least common (Nijs et al. 2001). Further, we propose that competitive *actions* with price promotions generate more frequent, as well as stronger, competitive *retaliations* than competitive actions using advertising. Indeed, managers have a limited span of attention and time (Zaltman and Moorman 1989), so they will attend only to certain competitive actions. More visible actions generate higher levels of awareness and are more likely to attract competitors' response, and price actions are especially visible (Chen and Miller 1994, Leeflang and Wittink 2001). In addition, price actions can directly affect profit margins and the business' bottom line, their effect materializes quickly, their impact is relatively easily determined, and they tend to be more provocative (Chen and MacMillan 1992).

Third, we propose that competitive *retaliation* with price promotions is more prevalent than retaliation with advertising. It is plausible that, if managers notice a competitive attack and intend to respond, they will be inclined to use an instrument that typically yields fast results. From their previous experience, they will have noticed that price promotions usually yield faster results than advertising (cf. Lodish et al. 1995, Neslin 2002). When we combine this proposition with the previous one, it suggests that if the manager reacts, price-promotion *retaliation* to price-promotion attacks should be more prevalent than any other action-reaction combination. Finally, given managers' short time horizon (Keil et al. 2001) and consistent with Nijs et al. (2001), we expect that reactions are stronger in the short run than in the long run.

2.2. Factors Affecting the Intensity of Competitive Reactions

The strategy literature suggests that three underlying behavioral drivers of competitive reaction are *awareness* of the competitive attack, *motivation* to react, and *ability* to react (Chen 1996, Chen et al. 1992). These three drivers are implicated in the specific factors affecting the intensity of competitive reactions to price promotions and advertising discussed below, and provide a rationale for why certain reaction patterns are observed. More specifically, we submit that intensity of competitive reaction is influenced by the characteristics of the attacking and the defending brand, including the market power of the attacking brand, the power asymmetry between attacker and defender, and whether attacker/defender are a private label or a national brand. We also hypothesize effects of category characteristics such as the extent to which purchases of the category are based on impulse, market concentration, category growth, interpurchase time, advertising intensity, price-promotion intensity, and stockpilability.

2.2.1. Brand Factors

Market Power of the Attacking Brand. More powerful brands typically have larger marketing budgets, a wider distribution (Reibstein and Farris 1995), and more and better shelf space (at least in the packaged-goods industry; cf. Corstjens and Corstjens 1995). Consequently, their competitive actions are noticed more often (e.g., through heavier feature and display support or actions in more stores due to wider coverage). Awareness of competitive moves is a necessary condition for a reaction to occur (Chen et al. 1992). Further, due to their greater market power, competitive attacks by these brands are perceived to be more threatening to the defender (Gatignon and Reibstein 1997). Social conflict theory posits that the greater the perceived threat posed by an actor, the greater the motivation of other actors to react in kind (Deutsch 1969). Similarly, in strategy research, Dutton and Jackson (1987) proposed that competitors are motivated to take stronger retaliatory action if they view the action as threatening. Thus, we expect that the intensity of retaliation to a competitive attack increases with the market power of the attacking brand.

Power Asymmetry. Consistent with work in sociology (e.g., Bacharach and Lawler 1981, Molm 1990), we argue that the intensity of retaliation depends on the *power asymmetry* between the attacking and defending brand. Whereas the large threat posed by a powerful attacking brand constitutes a strong *motivation* to react (see above), the power of the defending brand relative to the attacking brand is a crucial component of the defender's *ability* to react. We expect that the greater the power asymmetry in favor of the attacker, the smaller the likelihood of retaliation. First, from an economic perspective, weak brands often do not have sufficient resources to respond to price promotion or advertising attacks by strong brands. Second, relative power theory (Cook and Emerson 1978, Kumar et al. 1998) argues that weaker defenders retaliate less because they want to avoid the risk of incurring overwhelming retaliation in turn. On the other hand, relatively powerful defenders have less reason for restraint and fear retaliation less, and hence are more likely to retaliate if attacked.

Private Label vs. National Brand. We argue that, in general, there is less competitive reaction associated with private labels, both when the private label is the attacker and when it is the defender. Indeed, the motivation to react is lower in the case of private labels. A competitive move by a private label may be seen as less threatening by other private labels, compared to a competitive move by a national brand. Within-store purchase influences are typically very strong (Kahn and McAlister 1997), and hence private labels may compete less directly with each other than with national brands. National brands are less likely to retaliate to private labels than to other national brands because they have much to gain from a collaborative relation with retailers (Steenkamp and Dekimpe 1997). Moreover, in case of a reaction with price promotions, both the national brand's motivation and its ability to react to an attack by a private label are restricted. Indeed, price promotions require retailer cooperation, which is less likely to be forthcoming when it concerns a response to a competitive move by the retailer's own brand.

It is also plausible that private labels react less to competitive attacks than national brands do. If the attacker is a national brand, then that brand as well as the retailer selling it may benefit from the additional sales generated from the increased marketing effort. Moreover, given the retailer's considerable control over the marketing activities (especially pricing and price promotion) of the national brands, it may feel less threatened. Similarly, when the attacking brand is a private label, the defending private label may feel less threatened as argued above.

2.2.2. Category Factors

Category Impulse Buying. Impulse categories are typically bought on a whim when the urge strikes the consumer (Steenkamp and Gielens 2003). Price promotions work directly on purchase behavior in the store rather than on cognitive processes preceding purchase (Blattberg and Neslin 1990), and stimulate the impulse-buying urge (Bell et al. 1999). Hence, in impulse categories, the defending brand may expect to lose more sales to price-promotion attacks than in categories where consumers plan their purchases ahead, and therefore, will be more motivated to retaliate in kind to counter price-promotion attacks.

Market Concentration. Economic theory suggests that in concentrated markets, profit margins are higher. Companies may be less motivated to engage in a price war in such markets because it dissipates attractive high margins (Ramaswamy et al. 1994). This encourages firms to substitute nonprice forms of competition such as advertising for price competition (Lipczynski and Wilson 2001). Consistent with this expectation, Ramaswamy et al. (1994) found that in industrial markets, market concentration had a negative impact on the likelihood of price retaliation and a positive impact on the likelihood of retaliation with marketing communication (i.c., salesforce), while Putsis and Dhar (1998) found that, in consumer product categories, noncooperative response to price promotions is more likely in less concentrated markets.

Category Growth. If category sales are flat, competitive actions quickly become a zero-sum game in which the attacking brand's sales gains are the defending brand's sales losses. In such low-growth markets, the defender will be highly motivated to respond aggressively to protect sales volume (Aaker and Day 1986). On the other hand, market growth is a critical structural indicator of future potential profits, hence brands in high-growth categories should be more motivated to retaliate in order to defend their position (Gatignon et al. 1990).

The empirical evidence is mixed as well. In consumer markets, Robinson (1988) found that competitive retaliation to new-product introductions was stronger in growing markets, while a study of industrial firms by Ramaswamy et al. (1994) found that retaliation with salesforce (price) was more (less) common in high-growth markets. Given these two contradictory theoretical views and inconclusive empirical evidence, we examine the effect of category growth on reaction intensity in an exploratory fashion.

Interpurchase Time. Bell et al. (1999) found that consumers are more responsive to price promotions in categories characterized by longer interpurchase times. Consequently, other brands will be more motivated to retaliate to a price promotion attack with their own price promotion. Advertising is often posited to affect behavior through its effect on the cognitive process preceding purchases (Assael 1998). This is one of the reasons why advertising effects typically take longer to materialize. Given that managers often have a short-term time perspective and need to produce results relatively fast (Zaltman and Moorman 1989), this reduces, in general, the ability of the firm to use advertising in reaction to attacks by other brands. The exception, though, is when (i) the attack is made using advertising, which typically will not show strong short-term effects on competitive sales (see, e.g., Lodish et al. 1995) that would stimulate the manager to react fast, *and* (ii) consumers purchase the category infrequently. In the latter case, interpurchase times are longer and hence, there is more time to affect consumer cognitions using advertising before the consumer reenters the market. Hence, we expect that the intensity of advertising retaliation to an advertising attack is higher in categories characterized by a long interpurchase time.

Advertising Intensity. Economic theory indicates that the marginal gain from advertising is greater the more sensitive the demand curve is to advertising expenditures: "if the advertising elasticity of demand is high, advertising is highly effective, so it pays the firm to advertise" (Lipczynski and Wilson 2001, p. 209). As a result, we would expect higher advertising intensity in categories where the advertising elasticity of demand is greater (Cabral 2000). In these categories, managers will be more motivated to react in kind to advertising attacks, given the effectiveness of advertising. Such reaction behavior might further be motivated by managers' desire to reduce their personal risks. By reacting with advertising to competitive advertising attacks, the manager reacts in conformance with category behavior, and hence can hardly be blamed when it does not work (Saunders et al. 2000; see also Keil et al. 2001).

Price-Promotion Intensity. Heavy use of price promotions in a category is likely to increase consumers' price sensitivity (Boulding et al. 1994). Hence, in these categories, managers will be more motivated to react with their own price promotion to a price promotion attack. Herd behavior also works in the same direction.

Ability to Stockpile. In a category that is easy to stockpile, the incentive to respond quickly in kind to an attack causing a substantial and immediate sales loss is great, as consumers will not be shopping in that category for a long time. This, together with the short time horizon of most managers' performance evaluations, suggests that the defending brand has a strong motivation to retaliate in kind to price-promotion attacks with an instrument that is expected to produce strong effects fast, i.e., with price promotions, while deemphasizing competitive retaliation with an instrument typically yielding less strong results in the short run, i.e., advertising (cf. Keil et al. 2001, who link managers' short time horizon to the need to maintain their brands' position in the short run). We expect that this is especially the case for simple reactions. Price promotions are particularly effective in easy-to-stockpile categories (Narasimhan et al. 1996), and their strong effect on brand switching (Bell et al. 1999) requires a response that is also expected to produce fast results. On the other hand, advertising attacks produce less-strong sales effects, and competitive retaliation with advertising is less necessary in these categories.

Table 1 gives an overview of our predictions concerning factors affecting the intensity of retaliation by the defending brand to a competitive price-promotion/advertising shock. Although for some variables we expect a null effect on particular competitive reaction behaviors (see Table 1), we include

Table 1 Expected Effect of Key Determinants of Competitive Reaction by Defender

	Reaction to price promotion		Reaction to advertising	
Determinant	…with price promotion	…with advertising	…with price promotion	…with advertising
Brand factors				
Market power attacker[a]	+	+	+	+
Power asymmetry attacker vs. defender	−	−	−	−
Attacker: Private label	−	−	−	−
Defender: Private label	−	−	−	−
Category factors				
Impulse category	+			
Market concentration	−	+	−	+
Category growth	?	?	?	?
Interpurchase time	+			+
Advertising intensity				+
Price promotion intensity	+			
Ability to stockpile	+			−

[a] Read as: the higher the market power of the attacker, the more aggressive (less accommodative) the competitive reaction by the defender.

them as covariates in our analyses. Controlling for these effects provides a stronger test of our predictions and produces more accurate estimates for our focal constructs.

3. Data and Methodology

3.1. Data Description

Data are available on 442 frequently purchased consumer-good categories in The Netherlands.[1] These categories correspond to IRI's classification in different product types, and give a quasi-complete coverage of the goods offered in a typical supermarket. IRI provided us with data on volume sales, price, distribution coverage, new-product introduction, and feature and/or display information. Advertising data were purchased from the BBC research agency. These data, covering four years of weekly scanner data, are described in more detail in Nijs et al. (2001). For each of these categories, the top three brands are considered, provided they obtain an average share of at least 5% over the sampling period. Europanel supplied data on the average interpurchase time in a category, while category stockpilability and impulse buying were collected in a separate questionnaire on the Europanel household panel. The breadth, as well as the detail, of the data at hand allow us to not only derive extensive empirical generalizations on the nature of competitive reactivity, but also to test the framework outlined in §2.

Table 2 compares our focal market, The Netherlands, with the United States and four major European countries on a number of key marketing statistics. On the various measures The Netherlands is broadly similar to other European countries, and comparable to the United States on inflation rate, private-label share, private-label price gap, and grocery store density. Retail concentration in the United States is lower, while advertising and promotion intensity (and GDP/capita) are higher. However, in many individual states of the United States, the concentration level is comparable to that of individual European Union countries (Steenkamp and Dekimpe 1997).

The Netherlands has been used repeatedly in recent studies on promotional effectiveness. Despite the difference in promotion intensity, the results from these studies were comparable to U.S. results. van Heerde et al. (2001, 2004) had both Dutch and U.S. categories in their sample, and reported comparable deal-effect curves (2001) and comparable decompositions of the sales-promotion effect into its constituent sources (2004, Table 4) across the two countries. Nijs et al. (2001, pp. 15–16) compared the contemporaneous effect of price promotions on primary demand for 10 Dutch categories with the corresponding estimates derived from U.S. data by Bell et al. (1999). The results were very similar, with an average elasticity of 1.01 for the Dutch data, compared to 0.91 for the American data. Finally, the average short-run own-sales elasticity of price promotions computed on our sample was highly similar to the results reported in the study by Srinivasan et al. (2002), involving 75 U.S. brands: 3.94 versus 4.08.

3.2. Derivation of Reaction Elasticities

Time-series techniques are used to derive our focal constructs, i.e., the simple and multiple reaction elasticities after an initial price-promotion or advertising shock, as well as the own- and cross-sales elasticities of both marketing-mix instruments. Each elasticity is estimated for both the short and the long run, and for the different brand combinations in each of the categories. In a second step, the estimated reaction elasticities become the dependent variables in a model that links them to the set of covariates described in our conceptual framework (see Figure 1).

A six-equation VARX model with the logarithm of advertising expenditures, price, and sales of two brands (i and j) as endogenous variables; and their distribution coverage, feature and display, feature activity only, and display activity only as exogenous variables; is used to link performance and control

[1] These 442 categories are selected from a broader database of 560 categories, using the following criteria: The top three brands have a combined market share in excess of 15% and each brand has nonzero weekly sales throughout the period.

Table 2 Comparison of The Netherlands with Major Western Countries on a Number of Marketing Statistics

	Netherlands	Germany	United Kingdom	France	Spain	United States
GDP/capita (1999,$)	24,472	25,476	24,235	23,987	15,051	32,523
Annual inflation rate (1990–1999)	2%	2%	3%	2%	4%	2%
Ad spend (2000, % of GDP)	1.11%	0.98%	1.14%	0.75%	1.01%	1.62%
Ad spend/capita (2000, $)	272	250	276	180	152	527
% sold on any promotion (2001)	24%	15%	25%	15%	20%	38%
Private-label share (2000)	18%	23%	33%	23%	14%	19%
Private-label price index vs. national brands (1997)	70	57	70	71	63	67
Grocery stores per '000 population (1997)	0.4	0.9	0.6	0.6	2.0	0.6
Market share top-five retail chains (2000)	53%	25%	57%	59%	36%	31%

Notes. Figures on GDP and annual inflation are from World Bank reports. Figures on advertising are from AdAgeGlobal, with the exception of The Netherlands, which are based on BBC/VEA. Percentage sold on any promotion are from IRI and refer to consumer packaged goods. Private-label shares are obtained from Europanel except for the last figure (19%), which is from ACNielsen and applies to the United States and Canada combined. Private-label price indices and number of grocery stores per '000 population are from ACNielsen. Market share of the top five retail chains are from M + M Planet Retail, with the exception of the United States, which is based on *Supermarket News*.

variables.[2] VARX models are specified in levels, differences, or error-correction form, depending on preliminary unit-root and cointegration tests.[3] The most general VARX model thus obtained is given in Equation (1):

$$\begin{bmatrix} \Delta\ln ADV_{i,t} \\ \Delta\ln P_{i,t} \\ \Delta\ln S_{i,t} \\ \Delta\ln ADV_{j,t} \\ \Delta\ln P_{j,t} \\ \Delta\ln S_{j,t} \end{bmatrix} = \begin{bmatrix} c_{0,ADV_i} + \sum_{s=2}^{13} c_{s,ADV_i} SD_{st} + \delta_{ADV_i} t \\ \quad + \xi_{ADV_i} NPI_t \\ c_{0,P_i} + \sum_{s=2}^{13} c_{s,P_i} SD_{st} + \delta_{P_i} t + \xi_{P_i} NPI_t \\ c_{0,S_i} + \sum_{s=2}^{13} c_{s,S_i} SD_{st} + \delta_{S_i} t + \xi_{S_i} NPI_t \\ c_{0,ADV_j} + \sum_{s=2}^{13} c_{s,ADV_j} SD_{st} + \delta_{ADV_j} t \\ + \xi_{ADV_j} NPI_t \\ c_{0,P_j} + \sum_{s=2}^{13} c_{s,P_j} SD_{st} + \delta_{P_j} t + \xi_{P_j} NPI_t \\ c_{0,S_j} + \sum_{s=2}^{13} c_{s,S_j} SD_{st} + \delta_{S_j} t + \xi_{S_j} NPI_t \end{bmatrix}$$

$$+ \sum_{l=1}^{8} \begin{bmatrix} \phi_{11}^{l} & \cdots & \phi_{16}^{l} \\ \vdots & \ddots & \vdots \\ \phi_{61}^{l} & \cdots & \phi_{66}^{l} \end{bmatrix} \begin{bmatrix} \Delta\ln ADV_{i,t-l} \\ \Delta\ln P_{i,t-l} \\ \Delta\ln S_{i,t-l} \\ \Delta\ln ADV_{j,t-l} \\ \Delta\ln P_{j,t-l} \\ \Delta\ln S_{j,t-l} \end{bmatrix}$$

$$+ \begin{bmatrix} \alpha_{ADV_i} & 0 & 0 & 0 & 0 & 0 \\ 0 & \alpha_{P_i} & 0 & 0 & 0 & 0 \\ 0 & 0 & \alpha_{S_i} & 0 & 0 & 0 \\ 0 & 0 & 0 & \alpha_{ADV_j} & 0 & 0 \\ 0 & 0 & 0 & 0 & \alpha_{P_j} & 0 \\ 0 & 0 & 0 & 0 & 0 & \alpha_{S_j} \end{bmatrix}$$

$$\cdot \begin{bmatrix} e_{ADV_i,t-1} \\ e_{P_i,t-1} \\ e_{S_i,t-1} \\ e_{ADV_j,t-1} \\ e_{P_j,t-1} \\ e_{S_j,t-1} \end{bmatrix} + \begin{bmatrix} \gamma_{11} & \cdots & \gamma_{18} \\ \vdots & \ddots & \vdots \\ \gamma_{61} & \cdots & \gamma_{68} \end{bmatrix}$$

$$\cdot \begin{bmatrix} \Delta\ln Dist_{i,t} \\ \Delta\ln F_{i,t} \\ \Delta\ln D_{i,t} \\ \Delta\ln FD_{i,t} \\ \Delta\ln Dist_{j,t} \\ \Delta\ln F_{j,t} \\ \Delta\ln D_{j,t} \\ \Delta\ln FD_{j,t} \end{bmatrix} + \begin{bmatrix} \mu_{ADV_i,t} \\ \mu_{P_i,t} \\ \mu_{S_i,t} \\ \mu_{ADV_j,t} \\ \mu_{P_j,t} \\ \mu_{S_j,t} \end{bmatrix} \tag{1}$$

[2] To avoid overparameterization, we do not estimate a nine-equation model with the sales, advertising, and price series of the top three brands as endogenous variables. In that case, every additional autoregressive lag would result in the estimation of 81 additional parameters. Instead, we estimate three six-equation models, covering, respectively, brands (1, 2), (1, 3), and (2, 3)—see Nijs et al. (2001) or Srinivasan et al. (2002) for a similar practice. Two robustness checks were implemented: (i) To further reduce the dimensionality of the VARX model, we also estimated all promotional reaction patterns in a four-equation model with advertising expenditures as exogenous variables, and (ii) a six-equation model with the three major brands' sales and price series as endogenous variables (and advertising again as exogenous). Our classification into aggressive, passive, and accommodating reactions was very robust.

[3] For implementation details, see Nijs et al. (2001). A table providing a detailed overview of the options taken can be obtained from the authors.

where the subscripts i and j refer to the two brands under consideration, ADV denotes advertising expenditures, P is price, S is volume sales, $DIST$ is distribution coverage, FD is feature and display activity, F is feature activity only, D indicates display activity only, and NPI denotes a new-product introduction. Deterministic components include an intercept (c_0), trend (t), and seasonal dummy variables (SD_{st}), while $[\mu_{ADV_{i,t}} \mu_{P_{i,t}} \mu_{S_{i,t}} \mu_{ADV_{j,t}} \mu_{P_{j,t}} \mu_{S_{j,t}}]' \sim \mathrm{N}(\vec{\mathbf{0}}, \Sigma)$. In this equation, it is assumed that all variables have a unit root and that an equilibrium or cointegrating relationship exists between the different variables. If no such relationship is found, all α-parameters (which measure the speed of adjustment to the long-run equilibrium) are restricted to zero. If some of the variables are found to be stationary, they are specified in levels rather than in first differences. For mixed models in levels and differences, we test for cointegration among the latter, and restrict the α-parameters of the former to zero. If an endogenous variable is found not to have a deterministic trend in the data-generating process (based on the procedure described in Enders 1995), the corresponding δ-parameter is set to zero, as are all the ξ-parameters when the category did not witness a major new-product introduction. The new-product introduction is captured through a step dummy variable when dealing with stationary series, and as a pulse dummy variable in case of unit-root series.

From these VARX models, impulse-response functions (IRFs) are derived that trace the over-time incremental effect of a competitive action (see Bronnenberg et al. 2000 or Dekimpe and Hanssens 1999 for a detailed exposition). Previous literature has defined marketing actions in two ways:[4] (i) in absolute, nominal numbers (e.g., 10% off, $1,000 increase) or (ii) relative to a benchmark or baseline. This second approach is reflected in popular models such as SCAN*PRO (see e.g., Foekens et al. 1999), and in recent VARX-based studies such as Bronnenberg et al. (2000), Nijs et al. (2001), and Pauwels et al. (2002). In line with this research tradition, we define competitive actions as one-unit deviations from the attacker's expected (log-transformed) price or spending level.[5] These expected levels are derived as unconditional VARX-based forecasts (i.e., in the absence of a price/advertising shock). Similarly, we derive an expected (log-transformed) sales level as performance benchmark, measured as the unconditional sales forecast from the VARX model. Given a competitive shock in period t^* (i.e., an unexpected price promotion or advertising increase), a new set of marketing-mix and performance forecasts is derived based on the extended information set at hand, explicitly taking into account that the competitor's price or advertising deviated from its expected level. The difference between two corresponding forecasts then gives the incremental impact in period t^*+i $(i = 0, 1, 2, \ldots)$ on an endogenous variable in the system, and constitutes the corresponding IRF.[6]

Given that we work in log-log space, impulse-response estimates have been shown to be elasticities at the unit-shock level, enabling cross-category comparisons (Nijs et al. 2001). IRFs that track the incremental impact of a competitive action by brand i on the price or advertising of brand j (P_j and ADV_j) give the *reaction elasticities* (η), while the IRFs tracing the incremental effect on S_j give the corresponding *cross-sales elasticities*. This procedure resulted in 2,124 pairwise cross-sales elasticity estimates and corresponding reaction elasticities, from which 270 outlying cases were removed due to extreme elasticity values. These elasticities form the basic unit of analysis for both our empirical generalizations and our second-stage analyses. The unit of analysis is thus *not* an individual price promotion or advertising change of brand i to which brand j may or may not have reacted. Instead, and in line with previous research (e.g., Leeflang and Wittink 1992), our elasticity estimates indicate whether, *on average*, brand j reacts to an attack by brand i.

IRFs contain many estimates, viz., one difference or incremental impact per future period. To make a comparison across multiple categories more manageable, we follow Nijs et al. (2001), and derive two summary statistics from each impulse-response function: (i) the asymptotic value, which measures the persistent or long-run effect, and (ii) the net effect over the dust-settling period (capturing the short-run impact), which is the time needed for the IRF to stabilize.[7]

[4] See Pauwels et al. (2002) for an extensive discussion of this distinction.

[5] This explains why the *price* variable is included as an endogenous variable, as it enables us to (i) derive a benchmark (expected) price level, and (ii) to operationalize *price promotions* as temporary deviations from this benchmark level.

[6] A critical issue in the derivation of impulse-response functions is the temporal (causal) ordering between the different endogenous variables of the VARX model, as this determines which current-period responses are allowed for. We adopt the approach developed in Evans and Wells (1983), and used in recent marketing applications by Dekimpe and Hanssens (1999) and Nijs et al. (2001). The information in the residual variance-covariance matrix is used to derive, based on the residuals' multivariate normality property, a vector of expected instantaneous shock values following a one-unit shock to $\ln(P_i)$ or $\ln(Adv_i)$ of the attacking brand. In so doing, the only assumption imposed is that the shocked variable (the price or advertising series of the attacking brand) is ordered first in the sequence. This is conceptually appealing in that we allow (but do not impose) that the initiating brand elicits an instantaneous reaction in all other endogenous variables.

[7] Formally, the persistent effect can be seen as IRF_∞. The short-run effect, in contrast, is defined as $\sum_{t=0}^{k} IRF_t$, with k the number

In case of very infrequent advertisers (in our case, defined as having fewer than 25 weeks of advertising), there is insufficient variability to reliably estimate all the ϕ parameters associated with that endogenous variable. In those instances, advertising for that brand is treated as an exogenous variable (unless no advertising at all was used over the considered time span, in which case the variable is completely omitted from the model specification), whose over-time impact is subsequently derived in IRF format using the procedure described in Pesaran and Shin (1998). Hence, depending on whether or not the attacking and defending brand are infrequent advertisers, a six-, five-, or four-equation model is estimated. In this way, even if the attacking brand is an infrequent advertiser, one can still derive the defending brand's reaction and cross-sales elasticity to the advertising attack. No reaction elasticity is derived only when the infrequent advertiser is the defending brand. We refer to Table 3 for a detailed discussion of the different cases and their implications for sample size.[8]

3.3. Explaining Reaction Elasticities

To explain the variability in competitive intensity, we stack the corresponding elasticities and link them to the covariates corresponding to the expectations developed in §2. Four models are considered, which differ in time dimension, in short run (SR) versus long run (LR), and in competitive shock instrument, price or advertising. Each model consists of two equations, corresponding to the following endogenous variables: (i) a reaction elasticity describing the intensity of reaction by means of price promotions ($\eta_{P,P}$ for a reaction to a competitive price promotion or $\eta_{P,ADV}$ for a reaction to a competitive advertising shock), and (ii) a reaction elasticity for the intensity of reaction by means of advertising changes ($\eta_{ADV,P}$ or $\eta_{ADV,ADV}$).

Table 3 Impact of Advertising Frequency on Parameter Estimation

	Issue	Implications for sample size
Regular advertisers		
Attacker	No problem	Included in all moderator analyses
Defender	No problem	Included in all moderator analyses
Infrequent advertisers		
Attacker	No problem*	Included in all moderator analyses
Defender	Not estimable	Excluded from all equations that include *reactions* with advertising
Zero advertisers		
Attacker	Not applicable	Excluded from all equations that include *attacks* with advertising
Defender	No problem (reaction elasticity = 0)**	Included in all moderator analyses

* Derived using the Pesaran and Shin (1998) procedure.
** In these instances, we use the median standard error to derive the weights in our second-stage WLS estimation.

The predictors in these equations are the constructs shown in Table 4.[9]

The models are estimated using weighted least squares to account for the fact that the endogenous variables are estimated quantities. Weights are the inverse of the standard error of an equation's dependent variable.[10] Advertising and price reaction

of weeks in the dust-settling period. The chosen value for k is determined empirically by a search for four consecutive IRF estimates that are not significantly different from the IRF's convergence value (cf. Nijs et al. 2001). We do not use $\sum_{t=0}^{\infty} IRF_t$ as our measure of long-run effectiveness, as this measure would diverge towards infinity in case of persistent effects.

[8] The maximum number of observations is obtained for price-promotion reactions to price-promotion attacks ($n = 1{,}779$). For three reasons, this number of observations is smaller than $3*2*442$. First, 528 observations were lost because in some categories the top three brands do not each achieve an average market share of at least 5% over the sampling period. Second, 270 outlying cases were removed due to extreme elasticity values. Finally, 75 cases were lost due to missing information on one or more covariates. The number of reaction elasticities involving advertising (either by the attacker or the defender) is smaller than 1,779 and depends on the specific situation as detailed in the text.

[9] Note that we explain the first-stage variability in the *reaction* elasticities based on a set of brand- and category-specific factors. No structural model is specified to simultaneously explain reaction and response elasticities because of (i) space limitations, (ii) the focus of the special issue on competitive reaction behavior, and (iii) because the correlation between reaction and response elasticities may be somewhat inflated, as some VARX parameters may appear in both underlying IRFs. However, in §6 we will nevertheless be able to make various substantive inferences on the appropriateness of a defender's strategy through a sequence of cross-tabulations (decision trees). By focusing on instances where, e.g., no reaction occurred (zero reaction elasticity), or where the response elasticities are zero, this inflated correlation issue will be considerably mitigated.

[10] Our moderator analysis is conducted in two separate stages. As discussed in Bolton (1989, p. 159), a one-stage approach becomes prohibitively complex when there are a large number of brands/categories and/or independent variables. This is indeed the case in our analysis. First, this operation would result in a giant data matrix with time series of over 200 observations stacked across 442 categories (over 1,200 brands). Moreover, a six-equation VAR model with eight lags involves the estimation of 288 autoregressive parameters. Estimating the model in one stage would require the addition of a process function on each one of these parameters. Apart from some efficiency loss (Bolton 1989), the differing accuracy of the estimated dependent variables yields biased estimates of the second-stage standard errors if the model residuals exhibit heteroscedasticity. This bias is avoided, however, through our use of WLS (see Narasimhan et al. 1996 or Nijs et al. 2001 for a similar approach).

Table 4 Measurement of Moderators

Moderators	Measurement
Brand factors	
Market power attacker	Average market share (based on volume, expressed as proportion) of the attacking brand (Gatignon et al. 1990).
Power asymmetry attacker vs. defender	Difference in market share between attacker and defender (cf. Molm 1990).
Attacker: Private label	Dummy variable; 1 = if the attacker is a private label, 0 = otherwise.
Defender: Private label	Dummy variable; 1 = if the attacker is a private label, 0 = otherwise.
Category factors	
Impulse category	Measured on Europanel's Dutch household panel ($n = 3{,}675$) using items and procedures developed by Narasimhan et al. (1996). Classification as high or low impulse category based on a median split of the factor scores.
Market concentration	Number of brands with a market share > 1% over a period of at least three months (Bell et al. 1999).
Category growth	Mean of the first difference of the log-transformed category, volume sales (Franses 1998).
Interpurchase time	Average number of weeks between two purchases in a category, based on averaging the interpurchase time across 3,675 Europanel panel members. Classified as high or low interpurchase time based on a median split.
Advertising intensity	Proportion of sales spent on advertising (both expressed in euros) at the category level (Lipczynski and Wilson 2001).
Price-promotion intensity	Number of weeks in which ≥ 1 of the top five brands in a category was at least two std. deviations below its average price level (Nijs et al. 2001).
Ability to stockpile	Measured on Europanel household panel using items and procedures developed by Narasimhan et al. (1996). Categories were classified as high or low ability to stockpile based on a median split of the factor scores.

elasticities are coded in such a way that an increase in their value is associated with a more intense retaliation.

4. How Do Brands React to a Competitive Attack?

The first-stage empirical results are shown in Table 5. In each case, we classify various types of reaction behaviors as retaliatory, accommodating, or simply absent. When relevant, we also report separate results for the subgroup of frequent (>25 weeks) advertisers. We derive generalizations on intensity and duration of reaction, and choice of marketing instrument, and compare them to the expectations developed in §2.

The Dominant Short-Run Reaction Form Is No Reaction. Consistent with our expectation, the predominant form of short-run reaction to advertising and price-promotion attacks is no reaction at all. Indeed, for 54% of the brands under price-promotion attack, the average short-run promotion reaction is not significantly different from zero, and 85% of these brands do not, on average, react with advertising changes. By the same token, for 82% of the brands under advertising attack, the average short-run advertising reaction is not significantly different from zero, and 68% do not react with promotion. These findings replicate earlier results by Nijs et al. (2001). When we focus on advertising reactions for brands that are "regular" advertisers—defined as at least 25 weeks of advertising spending over the four-year period—a passive reaction remains the most common one. Among regular advertisers, price promotion (advertising) attacks result in advertising reactions, on average, in only 41% (46%) of the cases.[11]

Price promotions may be induced by both retailers and manufacturers, and the timing and extent of manufacturer reactions may depend on negotiations with the retailer (Leeflang and Wittink 1992). Our data measure the actual prices observed on the retail floor, which are the prices that can trigger consumer response (reflected in cross- and own-sales elasticities) and competitive response (reaction elasticities). Leeflang and Wittink (1992, 1996) have argued that quick reactions tend to be retailer driven, while manufacturer-directed reactions tend to occur only after a few weeks. The speed of reaction can vary across manufacturers (e.g., due to the speed of internal decision making and the adaptive capacity

[11] One could argue that our procedure of always placing the attacking instrument first in the temporal ordering for the IRF derivation might, in some instances, result in a double counting of instantaneous effects. However, this is less likely to be an issue given the (weekly) temporal aggregation level of our data (Hanssens et al. 2001). In addition, when considering only the instantaneous effects (rather than the combined effect over the dust-settling period reported in Table 5), a comparable predominance of no reaction was observed. Moreover, if double counting of the instantaneous effects were indeed an issue, the observed frequency of no instantaneous reactions should be considered a conservative estimate. Finally, given the weekly nature of our data, double counting is most likely to be an issue when looking at *within*-brand reactions (we thank the area editor for pointing this out). When working with a four-equation model in which advertising is treated as an exogenous variable (cf. Footnote 2), one explicitly *excludes* any instantaneous within-brand advertising effect in the shock vector. Still, very comparable results were obtained, as in our focal six-equation model, suggesting that double counting is not a major issue in the latter.

Table 5 A. Percentage Significant Reactions Following an Attack with Price Promotions

	Not significant (%)	Retaliation (%)	Accommodation (%)
Short-run reaction with price promotion	54	30	16
Short-run reaction with advertising (all)*	85	8	7
Short-run reaction with advertising (regular advertisers)	59	21	20
Long-run reaction with price promotion	92	5	3
Long-run reaction with advertising (all)*	100	0	0
Long-run reaction with advertising (regular advertisers)	100	0	0

B. Percentage Significant Reactions Following an Attack with Advertising

	Not significant (%)	Retaliation (%)	Accommodation (%)
Short-run reaction with price promotion	68	17	14
Short-run reaction with advertising (all)*	82	14	4
Short-run reaction with advertising (regular advertisers)	54	37	9
Long-run reaction with price promotion	96	2	2
Long-run reaction with advertising (all)*	100	0	0
Long-run reaction with advertising (regular advertisers)	100	0	0

* Cases with no advertising at all during the sample period and brands with very infrequent advertising (i.e., less than 25 weeks) are counted in the nonsignificant category.

of the organization; see e.g., Gatignon and Reibstein 1997) and across categories. Leeflang and Wittink (1992, 1996) allow manufacturer-dominated reactions to show from Week 5 onwards. We assessed the robustness of our classification of observed reaction behavior to varying time windows (viz., zero weeks [i.e., contemporaneous, as in our model], 3, 4, 5 [i.e., the decision rule proposed by Leeflang and Wittink], 6, and 7 weeks). The percentage of non-significant manufacturer-dominated short-run reactions with price promotions following an attack with price promotions (advertising) varied across the time windows considered between 58% and 64% (between 71% and 78%).[12] Thus, our results exhibited a high degree of stability to when we allowed manufacturer-dominated reactions to materialize first, and the key conclusion that the dominant short-run reaction form is no reaction remains the same.

Simple-Reaction Patterns Tend to Be Retaliatory, But Multiple Reactions Are as Often Retaliatory as Accommodating. Significant short-run promotion reactions to promotion attacks are twice as likely to be retaliatory than accommodating (30% versus 16%). Advertising reactions to advertising attacks are four times more likely to be retaliatory (14% versus 4% overall, and 37% versus 9% for regular advertisers). In contrast, advertising reactions to price promotions are about equally often retaliatory as accommodating (8% versus 7% overall, and 21% versus 20% for regular advertisers). Similarly, promotion reactions to advertising attacks are only slightly more retaliatory (17% versus 14%). In conclusion, while managers tend to react in the same direction with the same instrument, there is little consensus on how to react with a different marketing instrument. These results further support our expectation that (i) retaliation with price promotions is more prevalent than retaliation with advertising, and (ii) if a reaction is observed, retaliation with price promotion to price-promotion attacks is more prevalent than any other action-reaction combination.

Retaliations to Price-Promotion Attacks Are Stronger Than Those to Advertising Attacks. Consistent with our expectations, the average short-run promotion retaliation elasticities are 1.49 for promotion attacks versus 0.00 for advertising attacks by regular advertisers. By the same token, the mean advertising retaliation elasticities are 79.6 for promotion attacks versus 0.59 for advertising shocks by regular advertisers.[13]

Reactions Are Stronger in the Short Run Than in the Long Run. Consistent with Nijs et al. (2001), we find that long-run reactions occur very rarely. In over 90% of the instances, price promotion attacks do not elicit a persistent or long-run price-promotion reaction on the part of the defending brand. Following an advertising attack, this number increases to over 96%. Long-run advertising adjustments are almost never observed, irrespective of whether the attack was initiated through a price promotion or through an advertising change: Nonsignificant long-run effects

[12] In this validation, we (i) focus solely on manufacturer-dominated reactions, and therefore do not include private labels, and (ii) use a common maximum length (26 weeks) for the dust-settling period, which is more in line with the procedure used by Leeflang and Wittink (1996). A detailed overview of the results may be obtained from the authors.

[13] The unusually high advertising reaction elasticity in response to price shocks comes from the possibility of high spending jumps or cuts, for example, from $10,000 to $200,000—a 1,900% increase.

are observed in over 99% of the cases. Thus, managers in competitive settings are typically short-run oriented, and their initial reactions, if any, have little effect on their long-run marketing-spending behavior.

In this section, we have examined the competitive reactions following an attack using price promotion or advertising. We observe considerable variation in the *short-run* elasticities. In the next section, we will investigate key brand and category sources of this variation. However, Table 5 also reveals that *long-run* competitive-reaction effects occur only in a small minority of cases. Thus, there is not enough variation to meaningfully estimate a model of long-term effects moderators. Indeed, only one out of 40 parameter estimates has a p-value below 0.10 in the models involving long-run reaction elasticities, a result that can be expected by chance.

5. When Are Competitive Reactions More Aggressive?

Table 6 reports the results of the moderator analysis on the short-run promotion and advertising reaction elasticities in response to both a price-promotion shock and an advertising shock.

5.1. Competitive Reaction to Price Promotions

The moderator effects for reactions with price promotions are summarized in Column 2 of Table 6. We do not report the corresponding estimates for reactions with advertising, as none of the moderating effects turned out to be significant.

Consistent with expectations, the more powerful the attacker, the greater is the price-promotion reaction elasticity ($b = 0.20, p < 0.05$). This indicates that, relative to a weaker brand, a powerful brand initiating a price promotion should count on more aggressive promotion retaliation by other brands in the category. However, as predicted, power asymmetry also matters. Controlling for the market power of the attacker, the greater the power disadvantage of the defender vis-à-vis the attacker, the less likely that the defender will retaliate ($b = -0.09, p < 0.05$). Contrary to expectations, there is insufficient evidence to support the claim that a price promotion initiated by a private label evokes less retaliation than a promotion attack by a national brand, nor is it evident that a private label reacts less aggressively to a price promotion than a national brand.

We find that defenders are more prone to react aggressively toward a price promotion attack with their own price promotion in categories that are high on impulse buying ($b = 0.04, p < 0.01$) and in categories that are characterized by a high interpurchase time ($b = 0.02, p < 0.05$). This is consistent with our theorizing. Support is also found for our expectation that in concentrated markets, reactions with price promotions are less aggressive ($b = -0.01, p < 0.01$). However, we do not find support for our expectation that price-promotion reaction elasticities are higher in categories characterized by high price-promotion intensity. One possible explanation for this result is that managers' tendency to use price promotions to conform to "normal" category behavior is reduced by the fear of initiating a price war in a category already characterized by heavy use of price tactics. This would immediately affect the company's bottom line (Chen and MacMillan 1992). Finally, the direction of the effect for ability to stockpile is as expected, but does not reach statistical significance.

The residual correlation between price-promotion and advertising reaction elasticities is 0.08. This indicates that the intensities of promotion and advertising reactions to promotion attacks are, for all practical purposes, independent of each other.

5.2. Competitive Reaction to Advertising

Column 4 in Table 6 shows the results of the moderator analyses of advertising reactions to advertising attacks. We do not report the corresponding estimates for reactions with price promotions in Table 6, as only one of the moderating effects (market concentration) turned out to be significant (see below).

Table 6 **Effects of Key Moderators on Intensity of Competitive Reaction***

	Reaction to price promotion		Reaction to advertising	
	...with price promotion ($N = 1779$)		...with advertising ($N = 770$)	
Moderator	Parameter	t-value	Parameter	t-value
Market power attacker	0.20^{b}	2.28	0.63^{a}	2.73
Power asymmetry attacker vs. defender	-0.09^{b}	−1.71	-0.24^{b}	−1.79
Attacker: Private label	−0.02	−0.99		
Defender: Private label	−0.01	−0.40		
Impulse buying	0.04^{a}	2.41	−0.04	−1.22
Market concentration	-0.01^{a}	−6.99	-0.03^{d}	−6.07
Category growth	−1.07	−0.35	-56.37^{d}	−5.50
Interpurchase time	0.02^{b}	1.84	0.08^{a}	2.33
Category advertising intensity	−0.00	−0.11	0.13^{a}	5.09
Category price promotion intensity	−0.17	−1.08	0.43	1.15
Ability to stockpile	0.01	0.88	-0.07^{b}	−2.18

*We do not report parameter estimates (t-values) for multiple reactions, as in both cases, the moderating effects were insignificant as a set.
[a] $= p < 0.01$ (one-sided).
[b] $= p < 0.05$ (one-sided).
[c] $= p < 0.10$ (one-sided).
[d] $= p < 0.01$ (two-sided).

As predicted, the more powerful the attacker, the more aggressive the reaction to an advertising shock with advertising ($b = 0.63$, $p < 0.01$). Furthermore, the more powerful the attacker vis-à-vis the defender, the less aggressive the competitive reaction to an advertising attack with advertising ($b = -0.24$, $p < 0.05$). Contrary to expectations, we find that competitive reactions with advertising are *less* aggressive in more concentrated markets ($b = -0.03$, $p < 0.01$; two-sided). In growing categories, we observe less aggressive reactions with advertising in response to an advertising attack ($b = -56.37$, $p < 0.01$; two-sided).

Consistent with expectations, reactions with advertising to advertising attacks are more aggressive in categories characterized by a long interpurchase time ($b = 0.08$, $p < 0.01$) and in categories characterized by high advertising intensity ($b = 0.13$, $p < 0.01$), while they are less aggressive in categories that are easy to stockpile ($b = -0.07$, $p < 0.05$).

Finally, as expected, we find that competitive reactions with *price promotions* are less aggressive in more concentrated markets ($b = -0.00$, $p < 0.05$; not reported in Table 6). The residual correlation between price-promotion and advertising reaction elasticities is a negligible 0.01.

5.3. Managerial Validation of Econometric Results

We performed a validation of our econometric results by surveying managers who face business environments and marketing decisions similar to those in our database. External validation is especially pertinent in the context of competitive decision making and reactivity (Montgomery et al. 2005). This survey information is not intended to replace our econometrically derived insights, but rather to enhance confidence in our statistical findings.

We collected data on the competitive reaction behavior of Dutch account, brand, and trade managers, using a brief questionnaire. We contacted some 140 managers, and received 52 completed questionnaires, for a response rate of 37%. This is a high response rate for mail surveys (Dillon et al. 1994, p. 144). The survey instructions made it clear that the responses were anonymous, and that there were no right or wrong responses. In our questions we explicitly asked for potential reactions to *unexpected* promotions and advertising changes to ensure a maximal fit with our shock operationalization. The results are reported in Table 7.

Overall, managers report that absence of reaction to a competitive attack is more common than reac-

Table 7 Managers' Survey Results

	Response ($n = 52$)	
Question	Yes	No
If I notice that a competing brand unexpectedly spends more on price promotions, I will also increase price promotions for my brand.	36%	64%
If I notice that a competing brand unexpectedly spends more on price promotions, I will increase advertising expenditure for my brand.	10%	90%
If I notice that a competing brand unexpectedly spends more on advertising, I will increase price promotions for my brand.	31%	69%
If I notice that a competing brand unexpectedly spends more on advertising, I will also increase advertising expenditure for my brand.	6%	94%
	Advertising	Price promotion
Suppose a competing brand unexpectedly increases its advertising expenditure or unexpectedly does a price promotion. To which action are you more likely to react? To advertising or to the price promotion?	12%	88%
If you react to an action by a competing brand, with which marketing-mix instrument are you more likely to react?	20%	80%
Suppose you notice that a competing brand unexpectedly does a price promotion. In which situations are you more likely to react by doing a price promotion as well?		
If the competing brand:		
— is a private label	6%	
— is a national brand	94%	
— has a small market share	6%	
— has a large market share	94%	
Suppose you notice that a competing brand unexpectedly increases advertising expenditure. In which situations are you more likely to react by increasing advertising expenditure as well?		
If the competing brand:		
— is a private label	8%	
— is a national brand	92%	
— has a small market share	17%	
— has a large market share	83%	

tion. Across the four scenarios (attack with price promotion/advertising and possible reaction with price promotion/advertising), on average only 21% of the managers will react. Moreover, competitive reactions with price promotion are more common (34% averaged over price promotion and advertising attacks) than competitive reactions with advertising (8%). Finally, price-promotion reactions to price-promotion attacks are the most common of all. Thirty-six percent of the managers indicate they would react with a price promotion if attacked by a price promotion, versus 15% across the other three scenarios. These results are further validated by two other questions: 88% of the managers indicate they were more likely to react to a price-promotion attack than to an advertising attack, while 80% indicate they are most likely to react with price promotions when a competing brand made a competitive move. These results are consistent with our theorizing and econometric results.

Consistent with our expectations, the vast majority of managers (94%) indicate they are more likely to react when the price-promotion attack is made by a national brand compared to an attack by a private label. Our econometric results were in the expected direction, although not significant ($p > 0.10$). Future research could investigate the reason for this discrepancy. While we could not estimate econometrically the role of private labels in advertising attacks (since that information is not collected by the BBC advertising agency), most managers (93%) indicate they are more likely to react when the advertising attack is made by a national brand, which is consistent with our expectation. Finally, 94% of the managers indicate that they are more likely to react aggressively to a price-promotion attack with their own price promotion when the competing brand has a large market share, while 83% indicate they are more likely to do so with advertising in case of an advertising attack by a large brand. This is consistent with the findings reported in Table 6. In sum, the management survey provides an external validation of our econometrically derived results.

6. Is the Competitive Reaction Justified?

Notwithstanding the important differences in reaction patterns across brand and category characteristics analyzed above, one should not lose sight of our finding that the predominant competitive reaction is passive. This raises the fundamental question of whether this is good housekeeping behavior or a missed opportunity? What are the consequences for sales of the finding that managers predominantly opt not to retaliate? The answer to these questions is determined by two considerations: (i) Was it necessary to react because of the harmful *cross-sales* effect of the attack and (ii) would the reaction have been effective, i.e., is there a positive *own-sales* effect of advertising or promotion for the defending brand? Similarly, once an aggressive reaction is observed, the question becomes whether this was an effective retaliation or whether it resulted in "spoiled arms" (Leeflang and Wittink 1996). Finally, we examine whether there is some justification for instances where accommodating behavior is observed. We study these questions empirically for simple-reaction behavior only, since multiple reactions rarely occur in the first place (Table 5).

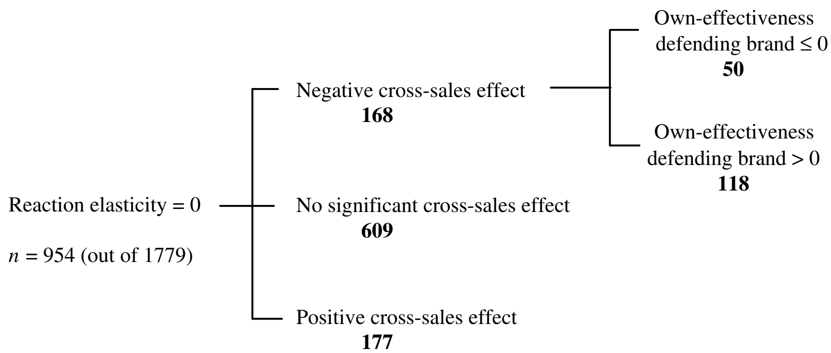
6.1. Implications of Not Reacting

Figure 2 combines the absence of competitive response with ultimate sales consequences for the defending brand, as derived from the impulse-response functions in the overall VARX model. The first conclusion is that *absence of reaction corresponds primarily to absence of harmful cross-sales effects.* For example, of the 954 brands that do not react (on average) to price-promotion attacks, 609, or 64%, experience no significant effect of the attack on their sales. Furthermore, an additional 177 brands, or 19%, feel a positive cross-sales impact. Therefore, for 82% of these passive brands, the decision not to react is *managerially sound* in the sense that sales protection was not needed. Moreover, for the 168 remaining brands where the attack has a negative cross-sales effect, retaliation would have been ineffective (nonpositive own-sales effect) in another 50 instances. Taking all these scenarios together, only 118 out of 954 passive brands experience a missed opportunity in that they could have defended their position, but chose not to.

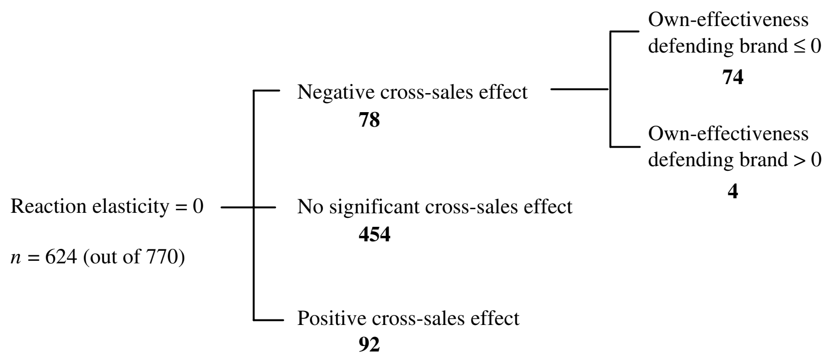
Are there long-run consequences of these missed opportunities? Using a similar reasoning, we find that in only 15 instances (less than 2%), a persistent, harmful cross-sales effect was found. Moreover, in only four instances does the defending brands' own promotional effectiveness put them in a position that would have allowed them to reduce or even nullify this long-run harm (see Ailawadi et al. 2001 for a similar conclusion).

The results of passive behavior in advertising are even more striking. Advertising attacks do not elicit any competitive reaction, on average, for 81% of the brands, i.e., 624 out of 770. Only 13% of these 624 passive brands (78 cases) experience a loss of sales. Furthermore, in those 78 cases, effective advertising retaliation would have been possible in only four instances. We therefore conclude that the decision not to react to advertising attacks is managerially sound in virtually all cases. In terms of long-run consequences, none of the missed opportunities resulted in permanent damage.

Figure 2 (a) Implications of *Not* Reacting to a Promotion Attack (Short-Run)*.



(b) Implications of *Not* Reacting to an Advertising Attack (Short-Run)*



* Given no reaction, ultimate attack impact on defender sales follows directly.

6.2. Implications of Retaliatory Behavior

While no reaction is the dominant competitive response mode, we should also address the consequences when managers opt to retaliate (positive reaction elasticity), which happens for 31% of brands under promotional attack and 15% of brands under advertising attack. Figure 3 shows a breakdown of cross-sales effects that occur in these 546 promotion and 115 advertising cases. We conclude, first, that effective retaliation (i.e., a positive own-sales effect) in promotion is much more prevalent (63%, i.e., 343/546) than in advertising (24%, or 28/115). Hence, for simple advertising reactions, retaliation often results in "spoiled arms." Second, when effective retaliation does occur, its magnitude is typically sufficient to at least neutralize the potentially harmful effects of the attack, i.e., the net resulting cross-sales effect is nonnegative. Effective but insufficient retaliation occurs in only 28 out of 343 promotion cases (8%) and only 1 out of 28 advertising cases (4%).

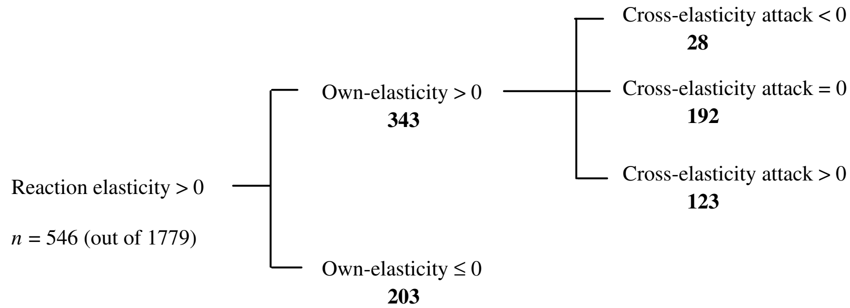
6.3. Implications of Accommodating Behavior

In a minority of cases (16% of promotion attacks and 4% of advertising attacks), the observed reaction was accommodation, i.e., a reduction in marketing support following a competitive attack. The potential optimality of accommodating behavior following a competitive entry was discussed in Hauser and Shugan (1983). In our setting, accommodating behavior is clearly justified when the defender's own marketing instrument has no positive sales impact.

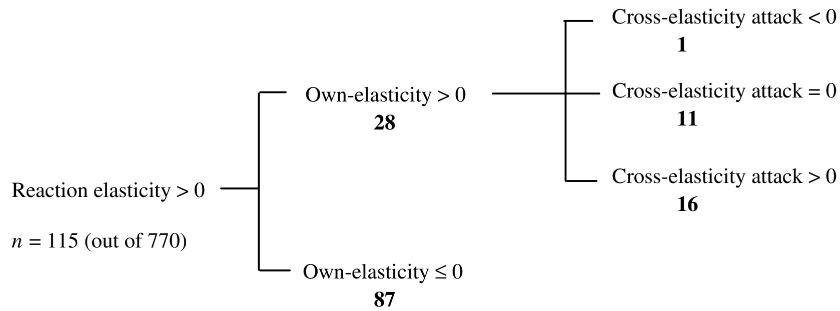
In 176 out of 279 accommodating instances (63%), the company opts to reduce its promotional support even though the own-elasticity is positive. In spite of this decision, no negative cross-sales effect is experienced in a majority (113) of instances, indicating that the brand is benefiting from the market expansion power of the competitive promotion. Still, its reduced use of an effective instrument reflects a lost sales opportunity. Similarly, the sales loss in the remaining 63 instances is due in part (if not entirely) to the reduced use of an effective defensive instrument. While this decision is not optimal from a sales-maximization point of view, one should keep in mind that accommodating behavior entails marketing cost savings, i.e., higher margins because of the reduced promotional support, that may render the decision justified from a profit-maximization perspective.

In 103 out of the 279 accommodating cases (37%), the promotional instrument had no positive impact, giving an economic rationale to the manager's accommodating behavior irrespective of the performance criterion (sales or profit) used. Interestingly, this percentage increased to 68% (21 instances out of 31) in

Figure 3 (a) Implications of Retaliatory Behavior Towards a Promotion Attack (Short-Run)*.



(b) Implications of Retaliatory Behavior Towards an Advertising Attack (Short-Run)*



*Given retaliation, reaction effectiveness affects ultimate attack impact on defender sales.

the case of accommodating behavior in advertising spending.

6.4. Do Short-Run Reactions Imply Myopic Behavior?

Finally, we comment on the apparent short-run nature of competitive reaction. Short-run reaction does not necessarily imply myopic behavior. In the case of advertising, negative long-run cross-sales effects are virtually nonexistent (less than 1% of cases); therefore, no long-run competitive reaction (i.e., permanent adjustments in spending) is needed. In the case of price promotion, negative long-run cross-sales effects are also rare (1% of cases), but when they do occur, they are often associated with significant short-run effects (the correlation is 0.42). Furthermore, when a significant long-run promotion effect occurs, it is almost always preceded by a significant short-run effect of the same direction (88% of harmful cases and 72% of beneficial cases, with no direction reversals). Even though many of these effects die out, making competitive retaliation discretionary from a long-run perspective, some managers (e.g., 5% in case of simple-promotional reactions; see Table 5A) on average may still "prefer to be safe than sorry" and interpret the *observed* short-term harm as a *signal* of potential long-term threat. This behavior is consistent with the observation of Keil et al. (2001, p. 68) that: "Brand managers face severe consequences if they do not react when in retrospect they should have (i.e., in case of a sustained decline in share). On the other hand, there is little consequence for reactions that would have been unnecessary."

7. Discussion

7.1. Conclusions

This paper has investigated competitive-reaction behavior in advertising and promotion for a large sample of frequently purchased product categories. We structure our main conclusions around three questions: How do brands react to a competitive attack, when are competitive reactions more aggressive, and is their competitive reaction justified?

How Do Brands React to a Competitive Attack? Overall, the most common form of competitive reaction is passive (i.e., no reaction). When reactions do occur, they are more often in response to price promotions than to advertising. Retaliation with price promotion to price-promotion attacks is more prevalent than any other action-reaction combination. Same-instrument reactions are generally retaliatory, while different-instrument reactions can be either retaliatory or accommodating. All forms of competitive reaction are largely restricted to short-run changes in brands' marketing patterns, without causing permanent changes in spending behavior.

When Are Competitive Reactions More Aggressive? This study also provides insights into another fundamental question in brand competition: Why do some actions fail to elicit retaliation from competitors, while others provoke an aggressive response? We find that, in general, simple reactions with price promotion and/or advertising are stronger when the attacker is more powerful, when the relative power structure in the dyad favors the defender, when the category is less concentrated, and when the interpurchase time is higher. In addition, price-promotion reactivity is stronger in categories that are higher on impulse buying, while advertising reactivity is lower in growing categories, for storable products, and in categories with lower advertising intensity. These empirical regularities were consistent with our prior literature-based expectations. They provide a first indication that there is a certain amount of rationality in managers' retaliation behavior.

Is Their Competitive Reaction Justified? Overall, from a sales-maximization point of view, most of the observed brands are justified in their decision not to react (88% of promotion cases and virtually all advertising instances). When accommodating behavior was observed, it was justified for 37% of promotion cases and 68% of advertising cases. Of those brands that opt to retaliate, 37% promote ineffectively and a dominant 76% advertise ineffectively. Furthermore, analyses not reported in the paper show that across all cases and situations, 45% respond with a promotion to a promotion attack even when they are not affected. These findings differ sharply from Chen's (1996) influential inference in the management literature. Chen states that "the ultimate effectiveness of an action depends largely on the defenders' response." We find no support for this claim, at least not at the most basic level of competition, viz., advertising and promotion rivalry between company brands. Indeed, in a majority of cases there is no competitive response at all, and when there is response, it is often with an instrument that has no significant own-sales effect. Combining the different scenarios, we can state that the net outcome of the majority of promotion and advertising attacks is *not* influenced by the defender's reaction. Put differently, the ultimate competitive impact of most advertising and promotion attacks is due primarily to the nature of consumer response, not to the vigilance of competitors.

7.2. Limitations and Future Research

Our study has various limitations that offer avenues for future research. Our observed lack of reaction could be due to various reasons, including (i) the action was either not noticed or not perceived as a threat (Chen 1996), (ii) lack of resources (Gatignon and Reibstein 1997), (iii) inability to react because of rigid, predetermined promotional calendars (cf. Leeflang and Wittink 2001), (iv) lack of cooperation on the part of the retailers to implement the desired changes (Steenkamp and Dekimpe 1997), (v) collusive behavior (Lipczynski and Wilson 2001),[14] or (vi) inherent difficulties in measuring competitive reactions on the basis of weekly data when competitive promotions/advertising changes are mixed-equilibrium strategies (Ailawadi et al. 2005, Rao et al. 1995). In our managerial survey, a majority of the respondents indicated that they could react (provided they had noticed the attack and wanted to react) within the eight weeks of our VARX model. Still, in a few instances (<10%), respondents indicated an inability to react within that time span. More research is needed on the underlying causes of an observed absence of reaction, for which other than econometric/time-series approaches may be called for. The behavioral work of Montgomery et al. (2005) may be especially useful in this respect.

We focus on the top three brands in each category. A more complete picture of the size and duration of the cross-sales effects, and the extent of price and advertising reactivity, would be obtained by also considering smaller brands. In doing so, we would likely obtain more variability in both the dependent and independent variables of the second-stage model, increasing the power of our analyses, which might, in turn, result in more significant effects, also for the multiple reactions. Further, we aggregated our scanner data across stores. When working with arithmetically averaged data, models estimated in log-log form may be sensitive to an aggregation bias when there is heterogeneity in marketing activities across stores (Christen et al. 1997). However, in their VARX-based study on the primary demand effects of price promotions, Nijs et al. (2001, pp. 15–16) concluded, after extensive validation exercises, that "the possible bias attributable to arithmetic averaging of the variables in the log-log model is minimal." Aside from this aggregation across stores, we also aggregated across SKUs. More research is needed to assess the sensitivity of our findings to this form of aggregation.

We conducted our study on the short- and long-run dynamics of competitive actions and reactions in the time domain, which is the dominant paradigm in the marketing literature (see, e.g., Dekimpe and Hanssens 2000). Alternatively, one could work in the frequency (or spectral) domain (see e.g., Bronnenberg et al. 2004). Bronnenberg et al. (2004) report different competitive interaction patterns at different frequencies (corresponding to different planning horizons). It

[14] We contacted the Dutch antitrust authorities on this issue. A recent study on the power division in the Dutch retail market, conducted by the Dutch Federal Trade Commission, found no evidence of widespread illegal collusive activities (G. ten Broeke, personal communication, April 2003). Still, we cannot rule out their occasional occurrence.

would be interesting to assess the convergent validity of our short- and long-run implications with the insights their approach would provide at, respectively, the high and low frequencies of the spectrum.

Our findings are based on data from The Netherlands. We established that The Netherlands closely resembles major European countries on key marketing statistics, while also being similar to the United States on a number of statistics and on price-promotion effectiveness. Nevertheless, future research could assess the generalizability of our findings to other countries.

Market power is a higher-order construct, reflected in such dimensions as feature and display support, distribution coverage, amount and quality of shelf space, etc. We used market share as proxy for market power (Gatignon et al. 1990), and there is indeed evidence of its validity as an indicator of these dimensions (e.g., Balasubramanian and Kumar 1990, Reibstein and Farris 1995). However, future research might estimate the moderating effects of specific dimensions of market power. One interesting candidate is the brand characteristic "percentage of price discounts supported by feature and display." We did not have information on this variable in the present dataset. Next, we had no information on private-label advertising. Even if these data were available, it is not easy to assign advertising effort to the private label in specific categories. Since the same private label may be more successful and credible in some categories than in others (Steenkamp and Dekimpe 1997), corporate advertising for the private label of the retailer may not be equally effective in each category. More research is needed to investigate the effectiveness of corporate private-label advertising in shaping private-label perceptions in specific categories. Moreover, in our work, we focused on competitive reactions based on changes in *aggregated* advertising *expenditures*. Future research could investigate advertising reactions at the media level as well as examine competitor reactions in terms of changes in message content.

We found no effects of our moderators on long-term competitive-reaction effects. This may be due to the small amount of variation in these long-term effects, but it can also be due to the fact that—with few exceptions (category growth, market concentration)—our moderators may primarily generate short-term effects. Future research could examine other moderators that might have long-term effects. Possible candidates are the stage in the product life cycle of the category (cf. Bronnenberg et al. 2000), the "brand capital" (Thomas 1995), and the competitive reputation (Kreps and Wilson 1982) of the attacking and defending brand, firm or industry excess capacity, and exit barriers (Heil and Helsen 2001).

In our paper, we considered marketing attacks carried out with price promotions or advertising. Companies can also attack with other marketing instruments, such as launching a new product (e.g., Shankar 1999). Future research could expand our work by examining competitive reactions to new-product introductions and examining interrelations with advertising and price-promotion reactions.

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References

Aaker, David A., George S. Day. 1986. The perils of high-growth markets. *Strategic Management J.* **7**(5) 409–421.

Ailawadi, Kusum L., Praveen K. Kopalle, Scott A. Neslin. 2005. Predicting competitive response to a major policy change: Combining game-theoretic and empirical analyses. *Marketing Sci.* **24**(1) 12–24.

Ailawadi, Kusum L., Donald R. Lehmann, Scott A. Neslin. 2001. Market response to a major policy change in the marketing mix: Learning from Procter and Gamble's value pricing strategy. *J. Marketing* **65**(January) 44–61.

Assael, Henry. 1998. *Consumer Behavior and Marketing Action*, 6th ed. SouthWestern College Publishing, Cincinnati, OH.

Bacharach, Samuel B., Edward J. Lawler. 1981. *Bargaining: Power, Tactics, and Outcomes.* Jossey-Bass, San Francisco, CA.

Balasubramanian, Siva K., V. Kumar. 1990. Analyzing variation in advertising and promotional expenditures: Key correlates in consumer, industrial and service market. *J. Marketing* **54**(April) 57–68.

Bell, David R., Jeongwen Chiang, V. Padmanabhan. 1999. The decomposition of promotional response: An empirical generalization. *Marketing Sci.* **18**(4) 504–526.

Blattberg, Robert C., Scott A. Neslin. 1990. *Sales Promotion, Concepts, Methods and Strategies.* Prentice Hall, Englewood Cliffs, NJ.

Bolton, Ruth N. 1989. The relationship between market characteristics and promotional price elasticities. *Marketing Sci.* **8**(2) 153–169.

Boulding, William, Eunkyu Lee, Richard Staelin. 1994. Mastering the mix: Do advertising, promotion, and sales force activities lead to differentiation? *J. Marketing Res.* **31**(2) 159–172.

Brodie, Roderick J., André Bonfrer, Justine Cutler. 1996. Do managers overreact to each others' promotional activity? Further empirical evidence. *Internat. J. Res. Marketing* **13**(4) 379–387.

Bronnenberg, Bart J., Vijay Mahajan, Wilfried R. Vanhonacker. 2000. The emergence of market structure in new repeat-purchase categories: The interplay of market share and retailer distribution. *J. Marketing Res.* **37**(February) 16–31.

Bronnenberg, Bart J., Carl Mela, William Boulding. 2005. The periodicity of competitor pricing. Submitted, *J. Marketing Res.*

Cabral, Luis M. B. 2000. *Introduction to Industrial Organization.* MIT Press, Cambridge, MA.

Carpenter, Gregory C., Lee G. Cooper, Dominique M. Hanssens, David F. Midgley. 1988. Modeling asymmetric competition. *Marketing Sci.* **7**(4) 393–412.

Chen, Ming-Jer. 1996. Competitor analysis and interfirm rivalry: Toward a theoretical integration. *Acad. Management Rev.* **21**(1) 100–134.

Chen, Ming-Jer, Ian C. MacMillan. 1992. Nonresponse and delayed response to competitive moves: The roles of competitor dependence and action irreversibility. *Acad. Management J.* **35**(3) 539–570.

Chen, Ming-Jer, Danny Miller. 1994. Competitive attack, retaliation and performance: An expectancy-valence framework. *Strategic Management J.* **15**(2) 85–102.

Chen, Ming-Jer, Ken G. Smith, Curtis M. Grimm. 1992. Action characteristics as predictors of competitive response. *Management Sci.* **38**(March) 439–455.

Christen, Markus, Sachin Gupta, John C. Porter, Richard Staelin, Dick R. Wittink. 1997. Using market-level data to understand promotion effects in a nonlinear model. *J. Marketing Res.* **34**(3) 322–334.

Cook, Karen S., Richard M. Emerson. 1978. Power, equity and commitment in exchange networks. *Amer. Sociological Rev.* **43** 721–739.

Corstjens, Judith, Marcel Corstjens. 1995. *Store Wars, The Battle for Mindspace and Shelfspace.* John Wiley and Sons, Chichester, U.K.

Dekimpe, Marnik G., Dominique M. Hanssens. 1999. Sustained spending and persistent response: A new look at long-term marketing profitability. *J. Marketing Res.* **36**(November) 397–412.

Dekimpe, Marnik G., Dominique M. Hanssens. 2000. Time series models in marketing: Past, present and future. *Internat. J. Res. Marketing* **17**(2–3) 183–193.

Deutsch, Moton. 1969. Socially relevant science: Reflections on some studies of interpersonal conflict. *Amer. Psychologist* **24** 1076–1092.

Dillon, William R., Thomas J. Madd, Neil H. Firtle. 1994. *Marketing Research in a Marketing Environment*, 3rd ed. Burr Ridge, Irwin, IL.

Dutton, Jane E., Susan E. Jackson. 1987. Categorizing strategic issues: Links to organizational action. *Acad. Management Rev.* **12**(1) 76–90.

Enders, Walter. 1995. *Applied Econometric Time Series.* John Wiley, New York.

Evans, Lewis, Graeme Wells. 1983. An alternative approach to simulating VAR models. *Econom. Lett.* **12**(1) 23–29.

Foekens, Eijte W., Peter S. H. Leeflang, Dick R. Wittink. 1999. Varying-parameter models to accommodate dynamic promotion effects. *J. Econometrics* **89**(1/2) 249–268.

Franses, Philip H. 1998. *Time Series Models for Business and Economic Forecasting.* Cambridge University Press, Cambridge, U.K.

Gatignon, Hubert, David J. Reibstein. 1997. Creative strategies for responding to competitive actions. George S. Day, David J. Reibstein, eds. *Wharton on Dynamic Competitive Strategy.* Wiley, New York, 237–255.

Gatignon, Hubert, Barton Weitz, Pradeep Bansal. 1990. Brand introduction strategies and competitive environments. *J. Marketing Res.* **27**(November) 390–401.

Hanssens, Dominique M., Leonard J. Parsons, Randall L. Schultz. 2001. *Market Response Models*, 2nd ed. Kluwer Academic Publishers, Boston, MA.

Hauser, John R., Steven M. Shugan. 1983. Defensive marketing strategies. *Marketing Sci.* **3**(Fall) 327–351.

Heil, Oliver P., Kristiaan Helsen. 2001. Toward an understanding of price wars: Their nature and how they erupt. *Internat. J. Res. Marketing* **18**(1–2) 83–98.

Kahn, Barbara E., Leigh McAlister. 1997. *Grocery Revolution.* Addison-Wesley, Reading, MA.

Keil, Sev K., David J. Reibstein, Dick R. Wittink. 2001. The impact of business objectives and the time horizon of performance evaluation on pricing behavior. *Internat. J. Res. Marketing* **18**(1–2) 67–81.

Kreps, David M., Robert Wilson. 1982. Reputation and imperfect information. *J. Econom. Theory* **27** 253–279.

Kumar, Nirmalya, Lisa K. Scheer, Jan-Benedict E. M. Steenkamp. 1998. Interdependence, punitive capability, and the reciprocation of punitive actions in channel relationships. *J. Marketing Res.* **35**(May) 225–235.

Leeflang, Peter S. H., Dick R. Wittink. 1992. Diagnosing competitive reactions using (aggregated) scanner data. *Internat. J. Res. Marketing* **9**(1) 39–57.

Leeflang, Peter S. H., Dick R. Wittink. 1996. Competitive reaction versus consumer response: Do managers overreact? *Internat. J. Res. Marketing* **13**(2) 103–119.

Leeflang, Peter S. H., Dick R. Wittink. 2001. Explaining competitive reaction effects. *Internat. J. Res. Marketing* **18**(1–2) 119–137.

Leeflang, Peter S. H., Dick R. Wittink, Michel Wedel, Philippe A. Naert. 2000. *Building Models for Marketing Decisions.* Kluwer Academic Publishers, Boston, MA.

Lipczynski, John, John Wilson. 2001. *Industrial Organization: An Analysis of Competitive Markets.* Pearson, Reading, MA.

Lodish, Leonard, Magid Abraham, Stuart Kalmenson, Jeanne Livelsberger, Beth Lubetkin, Bruce Richardson, May Ellen Stevens. 1995. How T.V. advertising works: A meta-analysis of 389 real world split cable T.V. advertising experiments. *J. Marketing Res.* **32**(May) 125–139.

Molm, Linda D. 1990. Structure, action, and outcomes: The dynamics of power in social exchange. *Amer. Sociological Rev.* **55**(3) 427–447.

Montgomery, David B., Marian Chapman Moore, Joel E. Urbany. 2005. Reasoning about competitive reactions: Evidence from executives. *Marketing Sci.* **24**(1) 138–149.

Narasimhan, Chakravarthi, Scott A. Neslin, Subrata K. Sen. 1996. Promotional elasticities and category characteristics. *J. Marketing* **60**(2) 17–30.

Neslin, Scott A. 2002. *Sales Promotion.* Marketing Science Institute, Cambridge, MA.

Nijs, Vincent, Marnik G. Dekimpe, Jan-Benedict E. M. Steenkamp, Dominique M. Hanssens. 2001. The category demand effects of price promotions. *Marketing Sci.* **21**(1) 1–22.

Pauwels, Koen, Dominique M. Hanssens, S. Siddarth. 2002. The long-term effects of price promotions on category incidence, brand choice and purchase quantity. *J. Marketing Res.* **39**(November) 421–439.

Pesaran, M. Hashem, Yongcheol Shin. 1998. Generalized impulse response analysis in linear multivariate models. *Econom. Lett.* **58**(1) 17–29.

Putsis, William P., Ravi Dhar. 1998. The many faces of competition. *Marketing Lett.* **9**(3) 269–284.

Ramaswamy, Venkatram, Hubert Gatignon, David J. Reibstein. 1994. Competitive marketing behavior in industrial markets. *J. Marketing* **58**(April) 45–55.

Rao, Ram C., Ramesh V. Arjunji, B. P. S. Murthi. 1995. Game theory and empirical generalizations concerning competitive promotions. *Marketing Sci.* **14**(3) G89–G100.

Reibstein, David J., Paul W. Farris. 1995. Market share and distribution: A generalization, a speculation, and some implications. *Marketing Sci.* **14**(3) G190–G202.

Robinson, William T. 1988. Marketing mix reactions to entry. *Marketing Sci.* **7**(4) 368–385.

Saunders, John, Philip Stern, Robin Wensley, Ros Forrester. 2000. In search of the lemmus lemmus: An investigation into convergent competition. *British J. Management* **11** S81–S95.

Shankar, Venkatesh. 1999. New product introduction and incumbent response strategies: Their interrelationship and the role of multimarket contact. *J. Marketing Res.* **36**(August) 327–344.

Srinivasan, Shuba, Koen Pauwels, Dominique M. Hanssens, Marnik G. Dekimpe. 2002. Do promotions benefit manufacturers, retailers, or both? *Management Sci.* **50**(5) 617–629

Steenkamp, Jan-Benedict E. M., Marnik G. Dekimpe. 1997. The increasing power of store brands: Building loyalty and market share. *Long Range Planning* **30**(6) 917–930.

Steenkamp, Jan-Benedict E. M., Katrijn Gielens. 2003. Consumer and market drivers of the trial rate of new consumer products. *J. Consumer Res.* **30**(December) 368–384.

Thomas, Louis A. 1995. Brand capital and incumbent firms' positions in evolving markets. *Rev. Econom. Statist.* **77**(August) 522–534.

van Heerde, Harald J., Peter S. H. Leeflang, Dick R. Wittink. 2001. Semiparametric analysis to estimate the deal effect curve. *J. Marketing Res.* **38**(May) 197–215.

van Heerde, Harald J., Peter S. H. Leeflang, Dick R. Wittink. 2004. Decomposing the sales promotion bump with store data. *Marketing Sci.* **23**(3) 317–334.

Zaltman, Gerald, Christine Moorman. 1989. The management and use of advertising research. *J. Advertising Res.* **28**(January) 11–18.