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MAARTEN J. GIJSENBERG*

Going beyond traditional seasonality, this research introduces the concept of the intrayear category demand cycle. This phenomenon reflects demand cycles most consumer packaged goods categories experience throughout the year, with periods of higher demand following periods of lower demand. The author argues that acknowledging the existence of these cycles and understanding their impact on both advertising and pricing effectiveness and practice is critical for marketers. Specifically, the author demonstrates how both advertising and price elasticities and observed advertising and prices evolve along these cycles for a unique set of 252 brands—ranging from high-advertising, high-priced “premium mass” brands to low-advertising, low-priced “value niche” brands—in 61 consumer packaged goods categories. Overall, both advertising effectiveness and observed advertising are found to be stronger at demand peaks. Surprisingly, consumer reactions to price decreases are weaker at demand peaks, whereas reactions to price increases remain unchanged. However, effectiveness evolutions and observed action patterns along these intrayear cycles are both markedly diverse across the different types of brands.

Keywords: advertising, price, intrayear cyclical, marketing-mix effectiveness, time series

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Riding the Waves: Revealing the Impact of Intrayear Category Demand Cycles on Advertising and Pricing Effectiveness

Demand for most consumer packaged goods (CPGs) fluctuates strongly over time. Category demand not only exhibits considerable week-to-week fluctuations but is also, to varying degrees, characterized by underlying intrayear cycles, that is, periods with higher demand following periods of lower

demand (e.g., Chevalier, Kashyap, and Rossi 2003) within the scope of one year. Such demand cycles, in turn, have a profound impact on brands. Not only do they determine the upper limits of brands' potential sales, they may also have a large influence on the sales outcomes of advertising and pricing actions, as well as on the actions themselves. However, surprisingly little research has addressed the impact of intrayear category demand cycles on advertising and pricing effectiveness and actions.

This research aims at uncovering and analyzing CPG demand fluctuation patterns within a year at both the category and brand levels. I answer repeated calls for increased marketing accountability (e.g., Verhoef and Leeflang 2009) by revealing the impact of such intrayear category demand cycles on advertising and pricing effectiveness. Because brands' advertising and prices could reinforce or attenuate the impact of category demand cycles on individual brands' sales, I also investigate how sensitive observed intrayear advertising and pricing cycles are

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to these intrayear category demand cycles. In this research, I more specifically address the following main research questions:

- What is the impact of intrayear cycles in category demand on brands' advertising and pricing effectiveness in terms of elasticities of sales?
- To what extent are (1) effectiveness (in terms of elasticities of sales) and (2) the impact of intrayear cycles in category demand on effectiveness (in terms of elasticities of sales) different for price increases relative to price decreases?
- To what extent do intrayear cycles in observed brand advertising and pricing follow intrayear cycles in category demand?
- To what extent are findings different for different types of brands?

Answers to these questions emerge from a large-scale analysis of the observed advertising and prices and the associated sales outcomes of 252 brands from 61 CPG categories in the United Kingdom over a period of four years (2002–2005). These brands range from high-advertising, high-priced “premium mass” brands to low-advertising, low-priced “value niche” brands. Because sales effects of advertising or price changes need not be limited to the week in which such changes take place, I do not focus on immediate sales effects. Instead, I investigate the long-term effectiveness of advertising and pricing by analyzing the long-term advertising and price elasticities of sales. I define these long-term elasticities as the cumulative percentage sales impact over the first 13 weeks (one quarter) for a 1% change in advertising or price (see, e.g., Villanueva, Yoo, and Hanssens 2008). This approach thus accounts for both the immediate and possibly delayed sales effects of advertising and price changes.

In this study, I focus on intrayear cyclical rather than typical seasonality because intrayear cyclical is a more flexible concept that overcomes the rigidities of seasonality. First, instead of imposing cycles exogenously, it starts from the actual data and lets them determine intrayear cycles. Second, instead of imposing a similar periodicity and shape to all cycles, intrayear cyclical allows cycles to take different periodicities and shapes for different categories and brands, and for sales, advertising, and pricing. Finally, these characteristics of the cycles do not need to be constant over the years but are allowed to change. Altogether, these features mean that individual brand cycles need not be perfectly aligned and may even cancel out at the category level. The flexibility of the core concept thus distinguishes this investigation from previous work that examines the impact of specific periods throughout the year (recurring events or holidays, months, or seasons) on, for example, marketing effectiveness and actions, thereby imposing a similar periodicity and shape—more or less constant over the years—on the cycles of all brands and categories (see, e.g., Chevalier, Kashyap, and Rossi 2003; MacDonald 2000; Nevo and Hatzitaskos 2006; Rotemberg and Saloner 1986).

INTRAYEAR CYCLES IN CATEGORY DEMAND

Category demand is not stable over time, even in mature markets without trends. Demand shows week-to-week fluctuations but also underlying intrayear cycles. Furthermore, the extent to which intrayear cycles can affect category demand can differ markedly, depending on the product itself. As an example, relatively stable demand patterns can be expected for product categories like washing machine products or razor blades, whereas strong cycles occur in the demand for categories like sun preparations or stout beer, with the strongest demand peaks concentrated in summer and winter, respectively. Figure 1 shows examples of such moderate and

strong intrayear cyclical behavior. Panel A shows strong week-to-week fluctuations in the demand for razor blades but a rather flat and stable line for the cyclical series. In contrast, Panel B shows smaller week-to-week fluctuations in the demand for stout beer relative to the strong evolution in the cyclical series.

While the observed patterns could be shaped by both supply-side and demand-side factors, the role of supply-side factors is likely limited in such CPG categories. First, these categories do not face season-induced production peaks as does, for example, fresh produce. Second, in these categories, seasonal stock clearances are not typical as they are, for example, in the fashion industry. Finally, consumers may react to temporary special offers by brands (e.g., Nijs et al. 2001), but such offers mostly last only one or two weeks—a time frame too short to profoundly affect the intrayear demand cycle. The observed intrayear cyclical variability in category demand is, consequently, rather driven by demand-side factors, and more, in particular, by the variability in consumers' need to purchase. While consumers need certain products on a relatively constant basis throughout the year, they need others more/less in certain periods of the year, or only during particular (recurring) events. The focus of this study is not on demand peaks related to the latter type of predictable seasonal events but on the intrayear demand cycles that must be inferred from the actual data. Alcoholic beverages, for example, display increased demand toward the end of the year. However, categories like rum and lager beer also show higher demand in sunnier and/or warmer periods of the year, whereas categories like whiskey and stout beer are preferred more in darker and/or colder periods of the year, somewhat resembling categories like tea and sweet biscuits. While sun preparations are much needed on sunny summer days, they are also required for outdoor activities like skiing on cold winter days. Observed demand patterns are thus shaped by circumstances that are likely to recur year after year but of which the timing, duration, and strength—as well as the demand impact of these three aspects—cannot be predicted exactly.

The fact that it is mainly consumers' needs that drive intrayear cyclical variability in category demand also distinguishes that variability from irregularity in consumers' behavior and advertising and pricing effectiveness at the business-cycle level (e.g., Deleersnyder et al. 2004; Frankenberger and Graham 2003; Gordon, Goldfarb, and Li 2013; Lamey et al. 2007, 2012; Steenkamp and Fang 2011; Van Heerde et al. 2013). Whereas intrayear cycles last for maximum 1 year, business cycles last for 1.5–8 years. Although consumers' needs may evolve within a single year, patterns are likely to stay more stable over the years. Consumers' ability to purchase, on the other hand, will change over the course of the business cycle, as budgets may come under pressure during economic downturns. In addition, during downturns, consumers may be less willing to purchase since they become more risk-averse and have different motivational orientations (Millet, Lamey, and Van den Bergh 2012). As a consequence, category demand cycles at the business-cycle level will mostly be influenced by consumers' ability to purchase. Category demand cycles at the intrayear-cycle level, on the other hand, are mainly influenced by consumers' need to purchase.¹

¹While this situation is prevalent in established economies—the setting of this study—migrant agrarian and emerging economies, for example, may face stronger intrayear fluctuations in consumers' purchase abilities. The generalizability of findings of this study may consequently be limited to CPG markets in established economies.

Figure 1
CATEGORY DEMAND EVOLUTION FOR A LOW AND A HIGH INTRAYEAR CYCLICAL CATEGORY

Notes: The unfiltered series are plotted against the primary axis and the intrayear cycles against the secondary axis.

While the recent stream of research on business cycles has provided an impressive body of knowledge on this phenomenon, remarkably little is known about the impact of the shorter intrayear demand cycles. Brands adjust their annual marketing budgets in reaction to lower-frequency multiple-year business cycles. Advertising and promotional agendas, in contrast, are usually set on a quarterly or yearly basis (e.g., Mantrala 2002). However, past studies have often regarded higher-frequency intrayear category demand cycles and their impact on brands' sales as a nuisance in the analysis of brands' marketing mix and hence advertising and pricing effectiveness. Possible effects found on brands' sales or market shares have been limited to seasonality effects and controlled for by the inclusion of monthly/four-weekly/quarterly dummies (e.g., Nijs, Srinivasan, and Pauwels 2007; Srinivasan et al. 2004; Steenkamp et al. 2005), holiday dummies (e.g., Guyt and Gijbrecchts 2014; Nijs, Srinivasan, and Pauwels 2007; Pauwels and Weiss 2008), or deterministic cycles (e.g., Fok, Franses, and Paap 2007), among others. Researchers have merely discarded the information contained by intrayear category demand cycles.

RESEARCH FRAMEWORK

This study traces the impact of intrayear cyclicity in category demand on (1) the long-term effectiveness of own-brand

advertising and pricing with regard to brand sales, and (2) intrayear cycles in brands' observed advertising and pricing. It thereby distinguishes between sales effects of price increases and price decreases. Finally, it examines to what extent findings are different for different types of brands. Figure 2 shows a schematic representation of the research framework of this study.²

Intrayear Advertising and Pricing Effectiveness Evolutions

Advertising effectiveness in terms of elasticities of sales could be higher at peak demand as consumers more actively search for products that best suit their needs (e.g., Haviv 2013). Increased attention to advertising and a stronger motivation to process it ultimately translates into higher purchase probabilities (e.g., Keller 1993; Morris et al. 2002; Petty and Cacioppo 1986; Rucker, Petty, and Priester 2007). In addition, the larger total market during peak demand enhances the potential to attract additional sales with a similar advertising investment. Conversely, greater competitive clutter in advertising

²While this study builds on previous literature to find guidance on what to expect, indications are often opposing. However, the intent of this study is to provide first empirical insights into this issue. Testing one theoretical explanation versus another is beyond its scope.

Figure 2
RESEARCH FRAMEWORK

reduces advertising effectiveness owing to interference effects (Burke and Srull 1988; Danaher, Bonfrer, and Dhar 2008). The ultimate outcome of these opposing processes is not clear a priori.

Several studies have found stronger price sensitivity at demand peaks and around seasonal events (e.g., Haviv 2013; Nevo and Hatzitaskos 2006), although some categories have shown weaker price sensitivity (Chevalier, Kashyap, and Rossi 2003). Overall, however, price sensitivity is expected to increase during periods of peak demand.

Intra-year Cycles in Observed Advertising and Pricing

Previous research has reported increased advertising for certain categories that show higher demand around recurring major sports events (Gijzenberg 2014) and stronger retailer (feature) advertising during peak demand (Chevalier, Kashyap, and Rossi 2003). Advertising pull, in turn, can be used to increase channel push (Farris and Reibstein 1984; Olver and Farris 1989), which is especially attractive in high-demand periods. Categories in which a major part of annual sales is gained in a short period of time also show stronger competitive behavior (e.g., Villas-Boas 1993), which prompts brands to concentrate their advertising in these periods (e.g., Metwally 1978).

For certain product categories, prices are lower during demand peaks related to specific events (e.g., Guler, Misra, and Vilcassim 2014; MacDonald 2000; Rotemberg and Saloner 1986). Manufacturers could deviate from colluding behavior (Rotemberg and Saloner 1986), while retailers, in turn, could apply loss-leader strategies (Chevalier, Kashyap, and Rossi 2003) as they try to maximize category profits (e.g., Sudhir 2001). The observed prices then depend on the relative

bargaining power of manufacturers and retailers (e.g., Ailawadi and Harlam 2009; Nijs, Srinivasan, and Pauwels 2007; Pauwels 2007). Whether the observed patterns are generalizable across brands and categories is consequently not clear a priori.

Asymmetries in Reactions to Price Changes

Following Kahneman and Tversky (1979), researchers have argued that price increases (losses) should have a stronger effect on sales than price decreases (gains). However, evidence is mixed and mostly opposes this argument. Whereas some researchers find support for the price increase effect (Kalyanaram and Winer 1995), other investigators show that consumers react more strongly to price decreases in the short run (e.g., Greenleaf 1995; Krishnamurthi, Mazumdar, and Raj; 1992; Pauwels, Srinivasan, and Franses 2007), with similar results for long-term effects (Yoo and Pauwels 2011). On the basis of these findings, I expect stronger reactions to price reductions.

This asymmetry in reactions to price changes is expected to be amplified during periods of peak demand. In such periods, consumers are more actively looking for the best deal (Haviv 2013), which bolsters the memorization of exact prices (Mazumdar and Monroe 1990). Reactions to price reductions/increases should then become stronger as consumers gain a better understanding of the profits/losses. Because price reductions form the more salient of the two types of price change, they are likely to exhibit a greater effect from this increased attention to prices.

A Typology of Brands

Overall evolutions could mask differential evolutions for different types of brands. I therefore also analyze evolutions for separate types of brands that differ in their positioning,

marketing mix, and relation to the consumer. In line with earlier work (Van Heerde et al. 2013), this study categorizes brands along two managerially relevant dimensions: their advertising intensity and their price level. A median split per category yields four types of brands: (1) high-advertising, high-priced brands, termed “premium mass brands,” (2) low-advertising, high-priced brands, termed “premium niche brands,” (3) high-advertising, low-priced brands, termed “value mass brands,” and (4) low-advertising, low-priced brands, termed “value niche brands.” Within each category, brands can be categorized as “low” on these dimensions if their value is below the median value and “high” otherwise. Table 1 summarizes the positions of these brands and the expected advertising and pricing effectiveness evolutions, as well as advertising and pricing action patterns.

METHODOLOGY

To provide answers to the questions raised earlier, the study proceeds in the following way. First, I determine the intrayear cyclical components of category demand and of individual brands’ advertising, price, and sales. Second, I investigate the extent to which the intrayear cyclical components in category demand affects brands’ advertising and pricing effectiveness. I thereby take into account potential differential effects for price increases relative to decreases. Third, I judge the extent to which the individual brands’ intrayear cyclical components move together with the category demand intrayear cyclical component. Finally, I combine insights from individual brands into overall and brand-type insights.

Extracting Intrayear Cyclical Components and Judging Intrayear Cyclical Volatility

I first capture the intrayear cyclical component in the different series. I do so by applying spectral tools similar to those used in prior research (e.g., Deleersnyder et al. 2004, 2009; Lamey et al. 2007, 2012; Van Heerde et al. 2013) to let the data define the intrayear cycles. More specifically, I follow Van Heerde et al. (2013) and use the Christiano–Fitzgerald (2003) (CF) random-walk filter.³

I apply the CF filter to the log-transformed category volume sales series, brand advertising series, brand price series, and brand volume sales series. All series consist of weekly observations. In the filtering procedure, I allow for intrayear cycles ranging between 13 weeks (one quarter) and 52 weeks (four quarters, or one year). This range allows the capture of any intrayear cycles at periodicities that are most relevant to managers in their within-year advertising and pricing decisions (e.g., Mantrala 2002). These periodicities are also most important with regard to price variation (Bronnenberg, Mela, and Boulding 2006). This approach removes from the series any lower-frequency evolutions, like business cycles that typically range from 6 to 32 quarters (e.g., Christiano and Fitzgerald 2003), as well as high-frequency weekly deviations due to brands’ tactical actions (e.g., Bronnenberg, Mela, and Boulding 2006). Log-transforming the series before the filtering results in cyclical components (multiplied by 100) that represent the percentage deviation from the series’ underlying

evolution (Stock and Watson 1999, p. 29). The extent of the cyclical volatility in the different series is judged by the standard deviation of the intrayear cyclical components. The log transformation of the series before filtering assures comparability (Deleersnyder et al. 2004).⁴

This approach differs from other research related to intrayear variation in demand (e.g., Chevalier, Kashyap, and Rossi 2003; Keller, Deleersnyder, and Gedenk 2013; MacDonald 2000) in that it both investigates multiple categories and does not prespecify peak periods or events or impose intrayear cycles. Instead, the individual category and brand series determine the cycles. This approach is more flexible and general than traditional seasonality because it allows for a full accounting for the heterogeneity (1) in the strength and duration of the cycles for the same category or brand, (2) among categories and brands, and (3) between advertising and price planning horizons. Therefore, findings are not determined by the idiosyncrasies of one product category or by any specific choice of peak periods or events.

Judging the Advertising and Pricing Effectiveness Evolution

Basic model specification. I start from a VARX model at the brand level, which relates the current values of each variable to the past values of that variable and the past values of the other variables. I include as endogenous variables brand sales, brand advertising, brand price, total competitor advertising, average competitor price, and the category demand intrayear seasonal component. I also add the interactions of brand advertising and brand price with the category demand intrayear cyclical component and with each other as endogenous variables, and I include a deterministic time trend.⁵ Because the sales, advertising, and price series are expressed in natural logarithms and because the intrayear cyclical component of category demand represents percentage changes, parameter estimates represent elasticities.

A key next step is determining whether the time series are stationary or show a unit root (e.g., Dekimpe and Hanssens 1995). The CF filtering ensures the stationarity of the category demand intrayear cyclical components. Stationarity of the other endogenous variables was assessed by analyzing these (log-transformed) series using Phillips and Perron’s (1988) test with an intercept and trend as exogenous variables. In all but 34 (2.70%) of the 252×5 individual series, the unit-root null hypothesis was rejected at the 5% level. This result of 34 nonstationary series was mainly driven by the average competitor price series in a small number of categories. This led to 28 of these series at the brand level for which the unit-root hypothesis could not be rejected. Because tests based on individual series lack power compared with panel-based unit-root tests, the stationarity analysis was repeated using Levin, Lin, and Chu’s (2002) test and Im, Pesaran, and Shin’s (2003) panel unit-root test. Both tests reject the null hypothesis of a unit root for all five series at the 5% level, showing that the data are (trend) stationary. Because all series are stationary, equations are specified in levels. To facilitate interpretability of

⁴More information on the cyclical filtering can be found in Web Appendix A.

³Although similar to other band-pass filters such as the Baxter–King filter, the CF filter shows a clear benefit over these filters in that it does not lose observations at the beginning and the end of the series. It thus uses all available information.

⁵Inclusion of the interaction effects allows me to judge the extent to which advertising and pricing effectiveness depend on the cyclical component, as well as possible synergy effects between advertising and price. In line with, for example, Aghion, Howitt, and Mayer-Foulkes (2005); Cleeren, Van Heerde, and Dekimpe (2013); and Van Heerde et al. (2013), I treat any interactions with endogenous variables as endogenous.

Table 1
TYPOLOGY OF BRANDS

A: Premium Brands		
	Premium Mass	Premium Niche
Overall position	Typical A-brands; high brand equity, price premiums	Less known; loyal fan base, price premiums
Advertising and Pricing Effectiveness Evolution		
Advertising	More visible, less affected by clutter	Less visible, more affected by clutter
Price	Cater to less price-sensitive segments; salience of price increases less at peak demand	Cater to less price-sensitive segments; salience of price increases less at peak demand
Observed Advertising and Price		
Advertising	Massive advertising at peaks, maintenance advertising in troughs; strong procyclical	Concentrate limited advertising at peaks; procyclical
Price	Stronger margins; enable lower prices at peaks, but still higher than value brands	Stronger margins; enable lower prices at peaks, but still higher prices than value brands
B: Value Brands		
	Value Mass	Value Niche
Overall position	Cheaper popular alternatives to A-brands	Economy option; core features, limited or no additional value
Advertising and Pricing Effectiveness Evolution		
Advertising	More visible, less affected by clutter	Less visible, more affected by clutter
Price	Cater to price-sensitive segments; salience of price increases more at peak demand	Cater to price-sensitive segments; salience of price increases more at peak demand
Observed Advertising and Price		
Advertising	Massive advertising at peaks, maintenance advertising at troughs; strong procyclical	Concentrate limited advertising at peaks; procyclical
Price	Smaller margins; equal or increased prices at peaks to increase profits	Smaller margins; equal or increased prices at peaks to increase profits

the outcomes, all variables are mean-centered before estimation. The resulting basic model is specified as follows:

$$\begin{aligned}
 (1) \quad & \begin{bmatrix} \ln \text{Sales}_{bc,t} \\ \text{Demand}_{c,t}^{\text{cyc}} \\ \ln \text{Adv}_{bc,t} \\ \ln \text{Adv}_{bc,t} \times \text{Demand}_{c,t}^{\text{cyc}} \\ \ln \text{Price}_{bc,t} \\ \ln \text{Price}_{bc,t} \times \text{Demand}_{c,t}^{\text{cyc}} \\ \ln \text{Adv}_{bc,t} \times \ln \text{Price}_{bc,t} \\ \ln \text{CompAdv}_{bc,t} \\ \ln \text{CompPrice}_{bc,t} \end{bmatrix} = \Lambda_{bc} \\
 & + \sum_{i=1}^I \Psi_{bc,i} \begin{bmatrix} \ln \text{Sales}_{bc,t-i} \\ \text{Demand}_{c,t-i}^{\text{cyc}} \\ \ln \text{Adv}_{bc,t-i} \\ \ln \text{Adv}_{bc,t-i} \times \text{Demand}_{c,t-i}^{\text{cyc}} \\ \ln \text{Price}_{bc,t-i} \\ \ln \text{Price}_{bc,t-i} \times \text{Demand}_{c,t-i}^{\text{cyc}} \\ \ln \text{Adv}_{bc,t-i} \times \ln \text{Price}_{bc,t-i} \\ \ln \text{CompAdv}_{bc,t-i} \\ \ln \text{CompPrice}_{bc,t-i} \end{bmatrix} \\
 & + \xi_{bc} \text{Trend}_t + \Upsilon_{bc,t},
 \end{aligned}$$

where

$\ln \text{Sales}_{bc,t}$ = sales of brand b in category c at time t ,
 $\text{Demand}_{c,t}^{\text{cyc}}$ = cyclical component of category demand in category c at time t ,

$\ln \text{Adv}_{bc,t}$ = advertising of brand b in category c at time t ,

$\ln \text{Price}_{bc,t}$ = price of brand b in category c at time t ,
 $\ln \text{CompAdv}_{bc,t}$ = total advertising by competitors of brand b in category c at time t ,

$\ln \text{CompPrice}_{bc,t}$ = average price of competitors of brand b in category c at time t ,

Λ_{bc} = vector of intercepts of brand b in category c ,
 $\Psi_{bc,i}$ = matrix of coefficients at lag i for brand b in category c ,

ξ_{bc} = coefficient of the exogenous trend variable for brand b in category c , and

$\Upsilon_{bc,t}$ = vector of errors at time t for brand b in category c , $\sim N(0, \Omega_{bc})$.

Allowing for asymmetric pricing effects. Previous research has indicated that consumers show asymmetric reactions to price increases versus price decreases (e.g., Kahneman and Tversky 1979; Yoo and Pauwels 2011). However, integration of asymmetric effects in VARX models is not common. Gijsenberg, Van Heerde, and Verhoef (2015) allow for asymmetries in their double-asymmetric structural VAR model, depending on the state at the specific lag. However, the present setting does not allow for a predefined causal ordering of the variables as exists in a structural VAR model. An alternative approach uses a threshold VAR model with sales and price as endogenous variables and allows effects of price on sales to depend on the specific state at time t (Yoo and Pauwels 2011). A simple extension of this approach to the present setting would be undesirable, as the effects of *all* variables become conditional on the brand's price evolution,

and the effects of the included lags become conditional on the *current* state of the price evolution.

To accommodate asymmetric reactions to price increases and decreases, I borrow from both studies and introduce two indicator functions for the price evolution from $t - 1$ to t : $\mathbf{I}(\Delta\text{Price}_{bc,t} > 0)$ for a price increase, equaling 1 when the price increases from $t - 1$ to t and 0 otherwise, and $\mathbf{I}(\Delta\text{Price}_{bc,t} \leq 0)$ for a price decrease, equaling 1 when the price decreases or stays the same from $t - 1$ to t and 0 otherwise. At each lag, I multiply the price variable and its interactions with both indicator functions. I thus allow for asymmetric reactions to price increases and decreases, and take into account that different evolutions from the past can have different effects on the current sales. The resulting asymmetric model specification is

$$(2) \quad \begin{bmatrix} \ln\text{Sales}_{bc,t} \\ \text{Demand}_{c,t}^{\text{cyc}} \\ \ln\text{Adv}_{bc,t} \\ \ln\text{Adv}_{bc,t} \times \text{Demand}_{c,t}^{\text{cyc}} \\ \ln\text{Price}_{bc,t} \\ \ln\text{Price}_{bc,t} \times \text{Demand}_{c,t}^{\text{cyc}} \\ \ln\text{Adv}_{bc,t} \times \ln\text{Price}_{bc,t} \\ \ln\text{CompAdv}_{bc,t} \\ \ln\text{CompPrice}_{bc,t} \end{bmatrix} = \Lambda_{bc} + \sum_{i=1}^I \Psi_{bc,i} \begin{bmatrix} \ln\text{Sales}_{bc,t-i} \\ \text{Demand}_{c,t-i}^{\text{cyc}} \\ \ln\text{Adv}_{bc,t-i} \\ \ln\text{Adv}_{bc,t-i} \times \text{Demand}_{c,t-i}^{\text{cyc}} \\ \mathbf{I}(\Delta\text{Price}_{bc,t-i} > 0) \times \ln\text{Price}_{bc,t-i} \\ \mathbf{I}(\Delta\text{Price}_{bc,t-i} > 0) \times \ln\text{Price}_{bc,t-i} \times \text{Demand}_{c,t-i}^{\text{cyc}} \\ \mathbf{I}(\Delta\text{Price}_{bc,t-i} > 0) \times \ln\text{Adv}_{bc,t-i} \times \ln\text{Price}_{bc,t-i} \\ \mathbf{I}(\Delta\text{Price}_{bc,t-i} \leq 0) \times \ln\text{Price}_{bc,t-i} \\ \mathbf{I}(\Delta\text{Price}_{bc,t-i} \leq 0) \times \ln\text{Price}_{bc,t-i} \times \text{Demand}_{c,t-i}^{\text{cyc}} \\ \mathbf{I}(\Delta\text{Price}_{bc,t-i} \leq 0) \times \ln\text{Adv}_{bc,t-i} \times \ln\text{Price}_{bc,t-i} \\ \ln\text{CompAdv}_{bc,t-i} \\ \ln\text{CompPrice}_{bc,t-i} \end{bmatrix} + \xi_{bc} \text{Trend}_t + \Upsilon_{bc,t}.$$

In the final model, I allowed for up to four lags in the equation, according to the Bayesian information criterion (BIC). Overall, a model with one lag appeared to be the most appropriate.

Immediate and long-term effects. The residual variance-covariance matrix of the nine equations yields insights on the immediate effects of advertising and price on brands' sales. I thereby build on the multivariate normality of the residual vector. In line with prior research (e.g., Dekimpe and Hanssens 1999; Nijs et al. 2001), immediate effects are defined as the result of a one-unit shock to the residuals of these equations. In this method, I follow the generalized, simultaneous shock approach (Evans and Wells 1983), which does not impose a temporal (causal) ordering between the different endogenous variables but allows for immediate effects. For the effect of advertising on brands' sales, I rely on the variance-covariance matrix Ω_{bc} based on the

full residual matrix. For the effect of price increases and price decreases, I follow the approach of Yoo and Pauwels (2011). I thus create two additional variance-covariance matrices Ω_{bc}^+ and Ω_{bc}^- by splitting the residual matrix into two matrices, corresponding respectively to whether a price increase or a price decrease occurred.⁶ Immediate effects of price increases can then be derived from the Ω_{bc}^+ matrix and immediate effects of price decreases from the Ω_{bc}^- matrix. Web Appendix B provides details.

Because I am more interested in the effect of the advertising and pricing decisions over time, I derive impulse response functions (IRFs) according to the parameters obtained. More specifically, I apply similar shocks as for the immediate effects and track the cumulative incremental sales impact of these shocks over a 13-week (one-quarter) period. I apply such shocks at the three weeks of each category demand intrayear cycle that have the highest and lowest demands, thus obtaining insights on the difference in effect at periods of high and low demand.⁷ Given the asymmetric nature of the model, traditional IRF methods, which make abstraction of the history preceding a shock, are unsuitable (e.g., Gijzenberg, Van Heerde, and Verhoef 2015; Kilian and Vigfusson 2011). A detailed description of the applied IRF methodology, taking into account the asymmetries and their consequences, appears in the Appendix.

Determining the Advertising and Pricing Comovements

Next, I quantify the extent to which the individual brand intrayear cyclical components derived in the first step move together with (or against) the overall intrayear cyclical category demand evolution. I therefore regress brands' advertising and price intrayear cyclical components on the intrayear category demand cycle. I account for possible feedback and competitive effects by including brands' intrayear sales cycles and competitor advertising and pricing cycles. I embed the analyses in a second VAR model, thus also accounting for possible endogeneity of the included variables (e.g., Mela, Gupta, and Lehmann 1997; Nijs et al. 2001; Van Heerde, Leeflang, and Wittink 2004; Van Heerde et al. 2013). The preliminary insights section presents more insights on the (limited) extent of the endogeneity of the cyclical component of category demand. This approach results in the following model specification:

$$(3) \quad \begin{bmatrix} \text{Demand}_{c,t}^{\text{cyc}} \\ \text{Sales}_{bc,t}^{\text{cyc}} \\ \text{Adv}_{bc,t}^{\text{cyc}} \\ \text{Price}_{bc,t}^{\text{cyc}} \\ \text{CompAdv}_{bc,t}^{\text{cyc}} \\ \text{CompPrice}_{bc,t}^{\text{cyc}} \end{bmatrix} = B_{bc} + \sum_{i=1}^I \Gamma_{bc,i} \begin{bmatrix} \text{Demand}_{c,t-i}^{\text{cyc}} \\ \text{Sales}_{bc,t-i}^{\text{cyc}} \\ \text{Adv}_{bc,t-i}^{\text{cyc}} \\ \text{Price}_{bc,t-i}^{\text{cyc}} \\ \text{CompAdv}_{bc,t-i}^{\text{cyc}} \\ \text{CompPrice}_{bc,t-i}^{\text{cyc}} \end{bmatrix} + E_{bc,t},$$

⁶Immediate effects of advertising and pricing are derived while keeping price and advertising, respectively, at their average levels. One thus can make abstraction of the interaction effect because variables are mean-centered.

⁷An alternative specification based on only the highest and lowest week of each cycle provided similar results.

Table 2
OVERVIEW OF INCLUDED PRODUCT CATEGORIES

Product Class	Number of Categories	Example Categories	Example Brands
Beverages	18	Lager, mineral water, soft drinks	Heineken, Evian, Coca-Cola
Food	17	Breakfast cereal, savory snacks, yogurt	Kellogg's, Pringles, Danone
Household care	9	Household cleaners, dishwashing liquid, laundry detergent	Flash, Fairy, Ariel
Personal care	17	Cleansers, toothpaste, shampoo	Oil of Olay, Colgate, L'Oréal
Total number	61		252

where

Demand_{c,t}^{cyc} = cyclical component of category demand in category *c* at time *t*,

Sales_{bc,t}^{cyc} = cyclical component of sales for brand *b* in category *c* at time *t*,

Adv_{bc,t}^{cyc} = cyclical component of advertising for brand *b* in category *c* at time *t*,

Price_{bc,t}^{cyc} = cyclical component of price for brand *b* in category *c* at time *t*,

CompAdv_{bc,t}^{cyc} = cyclical component of total competitor advertising for brand *b* in category *c* at time *t*,

CompPrice_{bc,t}^{cyc} = cyclical component of average competitor price for brand *b* in category *c* at time *t*,

B_{bc} = vector of intercepts for brand *b* in category *c*,

Γ_{bc,i} = matrix of coefficients at lag *i* for brand *b* in category *c*, and

E_{bc,t} = vector of errors at time *t* for brand *b* in category *c*, ~N(0, Σ_{bc}).

Because the intrayear cyclical components of all series represent percentage changes, the parameter estimates represent elasticities. For each brand, the equation allows for up to four lags, according to the BIC.⁸ For all brands, four lags appeared optimal. Because the CF filtering procedure ensures the stationarity of the filtered seasonal components, equations are specified in levels.

Insights on the extent to which the individual brand cyclical components follow the category demand intrayear cyclical components are obtained by judging the so-called comovement elasticities, the immediate effects of changes in the latter on the former (Deleersnyder et al. 2004). I derive these immediate effects from the residual variance–covariance matrix Σ of the six equations. I thereby follow the same generalized simultaneous shock approach as when deriving the immediate advertising and pricing effects. Web Appendix C provides a more detailed description.

Providing Insights Across Brands

I combine individual-brand effect sizes and significance levels both across all brands and across specific subsets of brands, and I evaluate them by means of the added Z method (Rosenthal 1991).⁹ Reported effect sizes represent the weighted

mean parameters across brands. The applied weights are the inverse of the standard error of the estimate, normalized to 1. I apply this procedure twice: once to provide overall insights for all brands together, and once to provide insights for the four different types of brands discussed in the introduction.

DATA AND PRELIMINARY INSIGHTS

Data

Insights provided in this article are based on weekly data from 2002 through 2005 for 61 CPG categories in the United Kingdom. Included brands were not required to meet a certain size threshold but had to advertise at least 20% of the time. In total, the sample comprises 252 brands, showing an average market share of 8.77% (SD = 10.04). These brands and categories provide a good representation of a typical supermarket assortment, covering a wide range of beverage, food, household care, and personal care products. Table 2 presents an overview of the number of categories and brands included in these wider product classes, as well as some illustrative examples of categories and brands.

Brand volume sales and price information were obtained from Kantar Worldpanel UK. Data from this panel have been used in prior research (e.g., Gijsenberg 2014; Van Heerde et al. 2013). Members of the panel are provided with a scanning device that they subsequently use to scan, on a daily basis, all the fast-moving consumer goods purchases they take home. The data cover purchases across all types of retailers, ranging from mom-and-pop stores and drugstores to large supermarket chains like Asda, Sainsbury's, and Tesco. Participants made purchases both offline and online, with the latter accounting for less than 5% of purchase volume at that time. Price data are the prices paid by the customer, including any discounts. Thus, the data are the observed outcome of the interplay between manufacturers and retailers, who each pursue their own objectives. However, no specific information on discounts (such as depth) is available in the data. This information is subsequently aggregated over the 17,000 British households in this consumer panel.¹⁰ To ensure a correct representation of the full population, weighting is applied along the following dimensions: region, social grade, household size, housewife age, and family makeup. Advertising data, in turn, come from NielsenMedia and are aggregated across television, radio, print, direct mail, outdoor, and cinema advertising. These data comprise advertising expenditures by brands themselves and do not extend to feature advertising by retailers. Advertising and price series are inflation-adjusted using the U.K. Consumer Price Index. All brands were available in the market for the full four years. In addition, all of these brands are national brands, as private labels typically follow different marketing strategies (Lamey et al. 2012).

⁸To account for possible forward-looking behavior by brands in their advertising and price decisions, I also allowed for a symmetric number of leads and lags. According to the average BIC across brands, the model with 4 lags and 0 leads (BIC = −14.900) was preferred: it outperformed all symmetric models (BIC 1–4 leads and lags: −3.801, −7.471, −10.762, and −13.759, respectively) and models with fewer lags and 0 leads (BIC 1–3 lags: −3.662, −7.158, and −10.085, respectively).

⁹A detailed description of the procedure can be found in Web Appendix D. For recent applications of this method in marketing, see, for example, Gijsenberg (2014), Lamey et al. (2012), and Van Heerde et al. (2013).

¹⁰I thank AiMark for providing the data.

Table 3
EXPLANATORY POWER OF CATEGORY DEMAND DRIVERS

	Weekly Category Demand Models		Intrayear Cyclical Category Demand Models	
	R^2 Contribution	Percentage of Incremental R^2 Beyond Own Past	R^2 Contribution	Percentage of Incremental R^2 Beyond Own Past
Own past	35.98%		91.96%	
Seasonal effects	12.75%	60.05%	4.70%	90.86%
Holidays	5.33%	25.13%	.12%	2.23%
Weather influence	1.29%	6.07%	.09%	1.77%
Advertising and price	1.86%	8.74%	.27%	5.14%
Total	57.20%	100.00%	97.14%	100.00%

Category volume sales (category demand) refers to total volume sales by *all* brands in the category, regardless of whether they met the advertising activity threshold. Competitor advertising and price, in turn, are defined as the total advertising by all other brands in the same category (e.g., breakfast cereals, soft drinks) and the (unweighted) average price across these brands, respectively. Here as well, to account for the full competitive environment, information relating to *all* other brands active in the category was included.

Preliminary Insights

Drivers of category demand intrayear cycles. As prior studies have argued, category demand could be driven by brands' advertising and pricing actions (e.g., Mela, Gupta, and Lehmann 1997; Nijs et al. 2001; Van Heerde, Leeflang, and Wittink 2004; Van Heerde et al. 2013). I judge this effect by relating the total category demand to the total category advertising and average price across all brands in the category. To obtain a correct assessment of the advertising and pricing effects, I follow previous work and first include the traditional controls for carryover effects, seasonality (four-week dummies), holidays, and weather (temperature and rainfall). I thereby judge the incremental explanatory information of the different sets of variables. I apply this method twice: once to the unfiltered sales, advertising, and price series, and once to their intrayear cyclical components. The results are presented in Table 3 and are based on the median values across brands.

In both of these applications, the own past of the category demand shows the strongest explanatory power (35.98% and 91.96%, respectively).¹¹ Seasonal dummies, holidays, and weather variables account for 60.05% (90.86%), 25.13% (2.23%), and 6.07% (1.77%) of the additional explanatory power beyond the own past of the category demand series for the unfiltered (cycle) series. The advertising and price series together account for 8.74% (5.14%) of this additional explanatory power, explaining 1.86% (.27%) of the total variance for the unfiltered (cycle) series.¹² These results confirm that weekly changes in advertising and price affect weekly spikes

in category sales more than advertising and price cycles affect category demand cycles. Endogeneity of the category demand intrayear cyclical component series is thus limited.

Extent of intrayear cyclical volatility. Table 4 reports descriptives on the extent of intrayear cyclical volatility of the category demand series and of the individual brand advertising and price series. Reported numbers represent the median values of the standard deviations of the CF-filtered cyclical components of the series, with higher values indicating stronger volatility.

Although the overall volatility of category demand equals .083, individual categories show strong variability around this value. As could be expected, household care and personal care categories like washing machine products (.041), razor blades (.048), and cleansers (.049) are much more stable in their sales patterns than, for example, sun preparations (.611), selflines (.314), and spirit-based drinks (.296).¹³ Prices are relatively stable over time with a median value of .049. Advertising, however, is extremely volatile, with clear periods of high and low spending, showing a median value of 1.067. These findings are in line with observed inertia in price setting (Nijs, Srinivasan, and Pauwels 2007) and the practice of concentrating advertising in pulses instead of spreading it evenly (e.g., Doganoglu and Klapper 2006; Dubé, Hitsch, and Manchanda 2005). Table 4 also indicates a clear distinction between premium niche brands and value mass brands, both in their advertising (.813 and 1.221 vs. 1.067 overall) and in their price behavior (.071 and .040 vs. .049 overall). The low-advertising, high-price premium niche brands combine stable advertising with actively offering price reductions, whereas the high-advertising, low-price value mass brands have less margin to offer such reductions and rely more on advertising.

Figure 3 shows the evolutions for a premium niche brand (Panel A) and a value mass brand (Panel B). The solid gray line represents the category demand cycle (high volatility in Panel A, medium in Panel B), the dotted black line the brand price cycle, and the dashed gray line the brand advertising cycle (values at the right-hand axis). This figure provides a good

¹¹The large difference between the two values is a consequence of the filtering procedure, which eliminates short-term weekly spikes from the series.

¹²Reversing the order by including the advertising and price variables first before the seasonal, holiday, and weather controls increases the former's part of the overall R^2 of the unfiltered and filtered category demand series to 3.47% and 1.05%, respectively. However, this reverse order may be less appropriate because it would first provide biased estimates of the advertising and pricing effects due to not controlling for all kinds of other phenomena that affect the sales outcome.

¹³Individual brands' sales show stronger intrayear cyclical volatility (.196) than category demand. This result indicates that individual brands' intrayear sales cycles are not perfectly aligned. If all individual brands' cycles were perfectly aligned, all brands in a category would show peaks and troughs at the same time, thus inflating the volatility at the category level beyond that at the brand level. Correlation between the individual brands' sales cycles and the category demand cycle should then equal 1, whereas the median correlation is now limited to .570. This finding is also in line with the finding that the cyclical volatility in overall category demand is driven by brands' advertising and pricing actions and resulting sales to only a minor extent.

Table 4
MEDIAN STANDARD DEVIATIONS OF THE CF-FILTERED CYCLICAL COMPONENT SERIES

	Overall	Premium Mass	Premium Niche	Value Mass	Value Niche
<i>Category Level</i>					
Sales	.083				
<i>Brand Level</i>					
Advertising	1.067	1.173	.813	1.222	.985
Price	.049	.041	.071	.040	.052

example of the relatively stronger (weaker) volatility in brand price and weaker (stronger) volatility in brand advertising for the premium niche (value mass) brands.

RESULTS

Advertising and Pricing Effectiveness

Advertising. Table 5 shows the advertising and price (increase/decrease) elasticity estimates for intrayear cyclical peaks and the differences with troughs in category demand. Overall, advertising elasticities are stronger at peaks (.028) than in troughs (difference: .004, $p < .01$). While premium mass brands show the strongest advertising effects overall (.041 at peaks, .036 in troughs), premium niche brands show the strongest relative change (.019 vs. .014, a 25% drop in effectiveness). Value niche brands, in contrast, are most stable in their advertising effectiveness, with no significant change from peaks to troughs. The distribution of the differences between peak and trough elasticities, shown in Table 6, indicates that about 60% of all brands experience stronger effects at peaks than in troughs. This picture is rather stable across brand types, except for value niche brands, for which about the same proportions of brands experience stronger effects (50.9%) and weaker effects (49.1%). This, in turn, explains the overall nonsignificant difference between advertising effectiveness at peaks versus troughs for those brands.

Pricing. Confirming the work by Kahneman and Tversky (1979), reactions to price increases are stronger than those to price decreases (−.991 vs. .789). While no significant overall differences emerge for price increases in peaks versus troughs, price decreases in general show stronger effects at troughs (peak vs. trough: −.020, $p < .01$). Price sensitivity is smallest for the high-priced premium mass and premium niche brands (price increases vs. decreases: −.808 vs. .381 for premium mass brands; −.764 vs. .741 for premium niche brands). Counter to expectations, for both types of brands, reactions to both price increases and decreases are weaker at demand peaks (peak vs. trough: for increases, .101 for premium mass brands and .091 for premium niche brands, both with $p < .05$; for decreases, −.082 for premium mass brands and −.064 for premium niche brands, both with $p < .01$). During periods of peak demand, consumers will thus be less responsive to price changes for these brands than during periods of low demand. Value mass and value niche brands cater to the more price-sensitive segments in the market and, as expected, show considerably stronger price sensitivities (price increases vs. decreases: −1.487 vs. 1.052 for value mass brands; −.907 vs. 1.008 for value niche brands). In line with expectations, value mass brands show stronger price sensitivity at peak demand for both increases and decreases (peak vs. trough: −.217 for increases and .135 for decreases, both with $p < .01$). Interestingly,

value niche brands strongly resemble premium brands as they show weaker reactions to both price increases and decreases at peak demand (peak vs. trough: .194 for increases and −.077 for decreases, both with $p < .01$). The distribution of the differences between effects at peaks versus troughs confirms these deviating evolutions for value mass and value niche brands. More brands show stronger reactions to price increases and decreases at peaks for value mass brands (66.1% for increases and 59.7% for decreases) and weaker reactions to increases and decreases at peaks for value niche brands (56.4% for increases and 56.4% for decreases). The distribution also shows the strong tendency for premium mass brands to be less sensitive to price decreases at peaks (56.2% of brands show this tendency, vs. 52.0% overall).

Observed Advertising and Pricing

Advertising. Table 5 also shows the advertising and pricing comovement elasticity estimates. Overall, advertising is procyclical (higher at peaks) and elastic (1.421, $p < .01$). Advertising thus follows the intrayear category demand cycles, but this evolution is more extreme. High-advertising value mass brands show the strongest comovement (2.337, $p < .01$), whereas low-advertising premium niche brands show inelastic but still procyclical behavior (.295, $p < .01$). The distribution over the individual brands in Table 7 shows that advertising comovements are mainly elastic (absolute values larger than 1) and that most brands show a strong elastic procyclical (54.4%) comovement. These distributions also confirm the different tendencies for value mass brands (59.7% of elastic procyclical comovements) and premium niche brands (48.4% of elastic procyclical comovements).

Pricing. Overall, category demand cycles do not seem to influence prices ($p > .10$). However, this global view masks different evolutions at the brand-type level. Whereas high-priced premium brands tend to lower prices at peak demand (premium mass: −.038, $p > .10$; premium niche: −.130, $p < .01$), low-priced value brands increase them (value mass: .014, $p < .10$; value niche: .003, $p < .01$). Premium niche brands' higher baseline prices allow them to lower prices more during peak demand. Value brands, in contrast, may try to benefit from the higher demand to increase their margins. The distribution over the individual brands confirms the inelastic nature of the pricing comovements as well as the relatively even spread of procyclical (49.2% with higher prices at peak demand) and countercyclical (50.8% with lower prices at peak demand) comovements. These distributions also confirm the tendency toward lower prices at peak demand for the premium niche brands (61.3%; 11.3% even elastic) and toward higher prices for the value mass (53.2%) and especially value niche (61.9%) brands.

Figure 3
CYCLICAL EVOLUTIONS FOR A PREMIUM NICHE AND A VALUE MASS BRAND

DISCUSSION

Summary of Findings

Although numerous studies have examined advertising and pricing effectiveness and decisions, this study is the first to systematically investigate how intrayear category demand cycles may influence both advertising and pricing effectiveness and observed advertising and prices. Insights emerge from an analysis of weekly advertising, price, and sales data

of 252 brands from 61 CPG categories in the United Kingdom over a period of four years.

In general, long-term advertising effects are stronger in periods of peak demand. While premium mass brands show the strongest overall advertising effects, premium niche brands show the strongest change in their advertising effects. Value niche brands, in turn, are most stable in their advertising effectiveness, showing overall no significant difference between periods of peak demand versus low demand. Confirming prior

Table 5
ACROSS-BRAND ADVERTISING AND PRICING EFFECTIVENESS AND COMOVEMENT ESTIMATES

	Overall	Premium Mass	Premium Niche	Value Mass	Value Niche
<i>Advertising and Pricing Effectiveness</i>					
Advertising					
Peak	.028***	.041***	.019***	.032***	.017***
Peak – Trough	.004***	.005***	.005***	.005***	.001
Price Increase					
Peak	-.991***	-.808***	-.764***	-1.487***	-.907***
Peak – Trough	.035	.101**	.091**	-.217***	.194***
Price Decrease					
Peak	.789***	.381***	.741***	1.052***	1.008***
Peak – Trough	-.020***	-.082***	-.064***	.135***	-.077***
<i>Advertising and Pricing Cyclical Comovement</i>					
Advertising	1.421***	1.906***	.295***	2.337***	1.748***
Price	-.034	-.038	-.130***	.014*	.003***

* $p < .10$.

** $p < .05$.

*** $p < .01$.

work (e.g., Kahneman and Tversky 1979), study results show that long-term price-increase elasticities are stronger than price-decrease elasticities. In general, although reactions to price increases will not differ significantly at demand peaks versus troughs, reactions to decreases will be weaker at demand peaks. This finding opposes previous findings on price sensitivity around seasonal events (Keller, Deleersnyder, and Gedenk 2013). Price sensitivity is weakest for premium brands and will be even weaker at demand peaks for both price increases and decreases. For value mass brands, price sensitivity overall will be stronger at peak demand for both price increases and decreases. For value niche brands, price sensitivity will be weaker for both increases and decreases at peak demand.

In line with expectations, observed advertising cycles in general follow the demand cycles, showing more advertising at peak demand, and in an elastic way. This finding extends prior findings on retailer advertising (Chevalier, Kashyap, and Rossi 2003) to brand-initiated advertising. Value mass brands show overall the most elastic behavior, while premium niche brands show overall much more inelastic behavior. In general, prices do not differ significantly between demand peaks and troughs. However, for the different brand types, high-priced premium brands tend to show lower prices at peak demand, while low-priced value brands seemingly try to benefit from the increased demand by raising their prices. This mixed picture is in line

with earlier findings on heterogeneity in price evolutions (e.g., Chevalier, Kashyap, and Rossi 2003).

Managerial Implications

Firms are under constant and ever-increasing pressure to both prove and improve the effectiveness of their marketing investments in general and, more specifically, of their advertising and pricing actions. The findings of this study should alert managers to the fact that this effectiveness is not constant throughout the year. While in general consumers will react more strongly to advertising during demand peaks, they will be less influenced by price decreases. Buying the right brand may become more important when consumers are already convinced they need to buy the product category. Thus, brand-focused strategies that communicate the distinct features and advantages of the focal product over competitors' products will be most effective during demand peaks. Conversely, when the need for the product is relatively low, consumers may not care much about buying the right brand, as they already care less about the product as such. They may be more inclined to buy any brand that does the trick, as long as it does not cost too much. Price then becomes a more salient factor, increasing the importance of charging the right price.

This general view, however, is not without some caveats. First, types of brands differ considerably in their effectiveness

Table 6
DISTRIBUTION OF BRAND ADVERTISING AND PRICING EFFECTIVENESS DIFFERENCES BETWEEN PEAKS AND TROUGHS

	Overall	Premium Mass	Premium Niche	Value Mass	Value Niche
<i>Advertising Elasticity Difference</i>					
$\Delta > 0$	59.5% (59.5%)	63.0% (63.0%)	61.3% (61.3%)	61.3% (61.3%)	50.9% (50.9%)
$\Delta < 0$	40.5% (40.5%)	37.0% (37.0%)	38.7% (38.7%)	38.7% (38.7%)	49.1% (49.1%)
<i>Price Increase Elasticity Difference</i>					
$\Delta > 0$	49.2% (49.2%)	53.4% (53.4%)	53.2% (53.2%)	33.9% (33.9%)	56.4% (56.4%)
$\Delta < 0$	50.8% (50.4%)	46.6% (46.6%)	46.8% (46.8%)	66.1% (66.1%)	43.6% (41.8%)
<i>Price Decrease Elasticity Difference</i>					
$\Delta > 0$	48.0% (47.6%)	43.8% (42.5%)	45.2% (45.2%)	59.7% (59.7%)	43.6% (43.6%)
$\Delta < 0$	52.0% (51.2%)	56.2% (54.8%)	54.8% (53.2%)	40.3% (40.3%)	56.4% (56.4%)

Notes: Numbers in parentheses indicate the percentage of significant differences ($p < .05$).

Table 7
DISTRIBUTION OF BRAND ADVERTISING AND PRICING CYCLICAL COMOVEMENT ELASTICITIES

	Overall	Premium Mass	Premium Niche	Value Mass	Value Niche
<i>Advertising Comovement</i>					
[., -1]	32.5% (28.2%)	35.6% (26.0%)	33.9% (30.6%)	30.6% (29.0%)	29.1% (27.3%)
[-1, 0]	6.0% (2.0%)	4.1% (.0%)	8.1% (4.8%)	4.8% (.0%)	7.3% (3.6%)
[0, 1]	7.1% (2.8%)	9.6% (5.5%)	9.7% (3.2%)	4.8% (1.6%)	3.6% (.0%)
[1, .]	54.4% (50.4%)	50.7% (46.6%)	48.4% (46.8%)	59.7% (54.8%)	60.0% (54.5%)
<i>Pricing Comovement</i>					
[., -1]	6.0% (6.0%)	5.5% (5.5%)	11.3% (11.3%)	3.2% (3.2%)	3.6% (3.6%)
[-1, 0]	44.8% (36.1%)	49.3% (34.2%)	50.0% (43.5%)	43.5% (37.1%)	34.5% (29.1%)
[0, 1]	45.6% (36.1%)	42.5% (34.2%)	33.9% (25.8%)	51.6% (43.5%)	56.4% (41.8%)
[1, .]	3.6% (3.6%)	2.7% (2.7%)	4.8% (4.8%)	1.6% (1.6%)	5.5% (5.5%)

Notes: Deviations from 100% of totals within each type are due to rounding. Numbers in parentheses indicate the percentage of significant comovements ($p < .05$).

evolutions. While advertising elasticities overall are rather stable for value niche brands, they are sharply reduced for premium niche brands in demand troughs. While price sensitivity is much lower for high-priced premium mass and premium niche brands at demand peaks, it is much stronger for low-priced value mass brands. Because price has become a much more salient factor for value mass brands, it should be included in their brand communication as well. Second, even within these types of brands, considerable heterogeneity still exists. The overall view thus may differ from the evolution for individual brands.

Furthermore, in negotiating with retailers, brands should also use insights on the impact of intrayear cycles on their advertising and pricing effectiveness. While brands still largely determine advertising agendas themselves, price promotion agendas—and thus observed prices in the market—are usually the result of negotiations with retailers, who have different objectives and therefore follow different strategies (e.g., Ailawadi and Harlam 2009; Guyt and Gijsbrechts 2014; Nijs, Srinivasan, and Pauwels 2007; Pancras, Gauri, and Talukdar 2013). Showing retailers the evolutions in reactions to the brands' price increases and decreases could strengthen manufacturers' negotiation positions and might result in improved promotional agendas, thus creating win-win situations for manufacturers and retailers.

The stronger (negative) reactions to price increases require some additional attention. The reported long-term cumulative elasticities are the result of a dynamic process through the system of endogenous variables that affect each other. This process reflects the observed decision patterns of the brands over time. Through this process, price increases trigger increases in advertising (cumulative elasticity of advertising to a one-unit price increase of .723 at peaks and .838 in troughs). The negative impact of a price increase on brands' sales is thus already partly mitigated by increased advertising expenditures. Managers should consequently be aware that raising prices without additional investments in advertising will likely lower sales even more. In addition, the question arises of whether the price increase will be enough to cover the reduced sales volume and the additional advertising expenditures—that is, whether the price increase will be profitable. The ultimate outcomes and choices for individual brands will depend on the brand-specific price-increase elasticities, amount of advertising, adjustment speed of brand demand and prices, cost structures, and chosen focal performance measure—sales volume/market share, revenues, or profits, among others.

Limitations and Future Research Directions

While this study provides a broad overview of brands' advertising and pricing effectiveness and observed actions along intrayear cyclical demand fluctuations, it also has some limitations that offer interesting paths for future research. First, this study focuses on branded products. With the continuing growth of the private-label share and the introduction of multitier private labels (economy, standard, premium; see, e.g., Geyskens, Gielens, and Gijsbrechts 2010), extending the analyses to these different types of private labels would complete the picture of the market.

Second, our analyses are limited to consumer packaged goods. However, durables can be highly cyclical in their sales evolution with regard to the overall state of the economy (Deleersnyder et al. 2004). These categories are also often characterized by intrayear peaks in promotional actions. Future work could therefore investigate whether the findings from the current study also hold in a durables setting.

Third, data were not available on the relative role of the retailer in setting advertising and promotional agendas, or on the pass-through of promotional actions (e.g., Ailawadi and Harlam 2009; Guyt and Gijsbrechts 2014; Nijs, Srinivasan, and Pauwels 2007; Pancras, Gauri, and Talukdar 2013). Insights come from the observed outcomes in the market, without knowledge on the drivers of the observed decisions. Information on the manufacturer–retailer relationship would foster a better understanding of the observed decisions and the extent to which these originate with the manufacturer or the retailer.

Finally, data on the marketing mix were limited to brands' advertising and pricing. Information on the full marketing mix, including, for example, use of display and feature advertising, would allow for a more complete analysis, extending to possible synergy effects in an integrated marketing program (e.g., Naik and Raman 2003). This examination could provide insights into the soundness of brands' budget allocation decisions with regard to the effectiveness evolutions of the different instruments.

APPENDIX: DERIVATION OF THE LONG-TERM EFFECTS

To derive the long-term effects of brands' advertising and pricing from the VARX estimates, I use impulse response functions (IRFs). However, in the case of asymmetric effects of certain variables (as exist with the lagged price variables in

combination with the indicator functions), the history of these variables preceding the shock will matter. As a consequence, one cannot use traditional impulse response methods, which make abstraction of the history preceding the shock. Instead, I integrate the Monte Carlo approach as proposed by Dekimpe and Hanssens (1999) and applied by, for example, Nijs et al. (2001) and Steenkamp et al. (2005) for the derivation of IRFs into the asymmetric IRF approach as proposed by Gijzenberg, Van Heerde, and Verhoef (2015). To derive IRFs that take these asymmetries into account, I adopt a seven-step approach. The idea is to calculate the IRFs for shocks that are applied at different moments in time. For a given starting moment (time = t), the history prior to t will affect the response to a shock.

For each brand, I take the following steps:

1. I first determine two sets of histories. The first set $\mathbf{I}^{\text{hi}} = (\mathbf{I}_1^{\text{hi}}, \dots, \mathbf{I}_{T_{\text{hi}}}^{\text{hi}})$ contains the histories of the variables in the model prior to the T_{hi} peak periods in the category demand intrayear cycles. The second set $\mathbf{I}^{\text{lo}} = (\mathbf{I}_1^{\text{lo}}, \dots, \mathbf{I}_{T_{\text{lo}}}^{\text{lo}})$ contains the histories prior to the T_{lo} trough periods in the category demand intrayear cycles. A peak or trough period is defined as the three-week period whose middle week is the highest or lowest point of the intrayear cycle. For each of the weeks, I determine the history prior to that week. Each history consists of as many lags of the included variables as included in the model for that specific brand, according to the best BIC for that brand.
2. For a specific history $\mathbf{I}_t$, I follow Dekimpe and Hanssens (1999) in taking the initial start-up values of the different variable series as given and sampling from the multivariate normal distribution $N(0, \hat{\Omega}_{\text{bc}})$, where $\hat{\Omega}_{\text{bc}}$ represents the estimated variance-covariance matrix of the VARX model. I subsequently combine these sampled residuals with the estimated equations and create new “artificial” variable series. I then re-estimate the model according to these new series and obtain new parameter estimates. I determine the new full variance-covariance matrix $\hat{\Omega}_{\text{bc}}^{\text{IRF}}$ on the basis of the full residual matrix. I also determine the two additional variance-covariance matrices $\hat{\Omega}_{\text{bc}}^{\text{IRF}+}$ and $\hat{\Omega}_{\text{bc}}^{\text{IRF}-}$ by splitting the residual matrix into two matrices, depending on whether there was a price increase ($\hat{\Omega}_{\text{bc}}^{\text{IRF}+}$) or a price decrease ($\hat{\Omega}_{\text{bc}}^{\text{IRF}-}$).
3. Impulse response functions track the incremental impact of a shock in one of the series on the other series. As such, I want to judge the incremental impact of a shock to the brand’s advertising or price on its sales. I thus simulate for each instrument two time paths for the endogenous variables, each with a length of 13 weeks (one quarter). The first time path $\Psi^{t,1}$ constitutes the benchmark time path in which no shock occurs. The second time path $\Psi^{t,2}$ is the shock time path. For both time paths, I start from the history $\mathbf{I}_t$ at hand and construct the subsequent values using the parameter estimates obtained in Step 2. I thereby follow the generalized, simultaneous-shocking approach introduced by Evans and Wells (1983) and apply unit shocks to the log-transformed advertising and price variables. Immediate effects of an advertising shock are obtained through the full variance-covariance matrix $\hat{\Omega}_{\text{bc}}^{\text{IRF}}$ obtained in Step 2. Immediate effects of upward and downward price shocks are obtained through the variance-covariance matrices $\hat{\Omega}_{\text{bc}}^{\text{IRF}+}$ and $\hat{\Omega}_{\text{bc}}^{\text{IRF}-}$, respectively.
4. As I now know the sales evolution in a situation without and with a shock, I subsequently calculate the difference between the two time paths of the sales series: $\Delta^t = (\ln \text{Sales}_{t+0}^2 - \ln \text{Sales}_{t+0}^1, \dots, \ln \text{Sales}_{t+12}^2 - \ln \text{Sales}_{t+12}^1)$.
5. I repeat Steps 2–4 5,000 times and average the difference across these iterations: $\bar{\Delta}^t = (\ln \text{Sales}_{t+0}^2 - \ln \text{Sales}_{t+0}^1, \dots, \ln \text{Sales}_{t+12}^2 - \ln \text{Sales}_{t+12}^1)$. This provides me with the effect of

an advertising or upward/downward price shock at time t on the brand’s sales, conditional upon the specific history $\mathbf{I}_t$ preceding the shock.

6. I repeat Steps 2–5 for each of the histories $\mathbf{I}^{\text{hi}} = (\mathbf{I}_1^{\text{hi}}, \dots, \mathbf{I}_{T_{\text{hi}}}^{\text{hi}})$ and $\mathbf{I}^{\text{lo}} = (\mathbf{I}_1^{\text{lo}}, \dots, \mathbf{I}_{T_{\text{lo}}}^{\text{lo}})$ specified in Step 1.
7. After having determined the incremental effects of an advertising or up/downward price shock for all histories, I can then determine the average effect for the set of peak histories $\mathbf{I}^{\text{hi}}$, as well as the difference in effect between the two sets of histories $\mathbf{I}^{\text{hi}}$ (peak) and $\mathbf{I}^{\text{lo}}$ (trough). I therefore first determine the average effect across the histories for peaks,

$$\bar{\Delta}^{\text{hi}} = \left(\frac{\ln \text{Sales}_{t+0}^{\text{hi},2} - \ln \text{Sales}_{t+0}^{\text{hi},1}}{n}, \dots, \frac{\ln \text{Sales}_{t+12}^{\text{hi},2} - \ln \text{Sales}_{t+12}^{\text{hi},1}}{n} \right),$$

and its standard deviation. Subsequently, I combine the two sets of histories and calculate the difference in effect for each peak week history with each trough week history and determine the average difference,

$$\bar{\Delta}^{\text{hi-lo}} = \left(\frac{\left(\frac{\ln \text{Sales}_{t+0}^{\text{hi},2} - \ln \text{Sales}_{t+0}^{\text{hi},1}}{n} \right) - \left(\frac{\ln \text{Sales}_{t+0}^{\text{lo},2} - \ln \text{Sales}_{t+0}^{\text{lo},1}}{n} \right)}{2}, \dots, \frac{\left(\frac{\ln \text{Sales}_{t+12}^{\text{hi},2} - \ln \text{Sales}_{t+12}^{\text{hi},1}}{n} \right) - \left(\frac{\ln \text{Sales}_{t+12}^{\text{lo},2} - \ln \text{Sales}_{t+12}^{\text{lo},1}}{n} \right)}{2} \right),$$

and its standard deviation.

For each of the 252 brands in the sample, I apply this seven-step approach three times. The first sequence covers the effect of a positive advertising shock (given symmetric advertising effects), the second sequence covers the effect of a positive price shock, and the third sequence investigates the effect of a negative price shock. I subsequently combine the insights of individual brands to provide overall and brand-type-specific insights.

REFERENCES

- Aghion, Philippe, Peter Howitt, and David Mayer-Foulkes (2005), “The Effect of Financial Development on Convergence: Theory and Evidence,” *Quarterly Journal of Economics*, 120 (1), 173–222.
- Ailawadi, Kusum L., and Bari A. Harlam (2009), “Findings: Retailer Promotion Pass-Through: A Measure, Its Magnitude, and Its Determinants,” *Marketing Science*, 28 (4), 782–91.
- Bronnenberg, Bart J., Carl F. Mela, and William Boulding (2006), “The Periodicity of Pricing,” *Journal of Marketing Research*, 43 (August), 477–93.
- Burke, Raymond R., and Thomas K. Srull (1988), “Competitive Interference and Consumer Memory for Advertising,” *Journal of Consumer Research*, 15 (1), 55–68.
- Chevalier, Judith A., Anil K. Kashyap, and Peter E. Rossi (2003), “Why Don’t Prices Rise During Periods of Peak Demand? Evidence from Scanner Data,” *American Economic Review*, 93 (1), 15–37.
- Christiano, Lawrence J., and Terry J. Fitzgerald (2003), “The Band Pass Filter,” *International Economic Review*, 44 (2), 435–65.
- Cleeren, Kathleen, Harald J. van Heerde, and Marnik G. Dekimpe (2013), “Rising from the Ashes: How Brands and Categories Can Overcome Product-Harm Crises,” *Journal of Marketing*, 77 (March), 58–77.
- Danaher, Peter J., André Bonfrer, and Sanjay Dhar (2008), “The Effect of Competitive Advertising Interference on Sales for Packaged Goods,” *Journal of Marketing Research*, 45 (April), 211–25.

- Dekimpe, Marnik G., and Dominique M. Hanssens (1995), "Empirical Generalizations About Market Evolution and Stationarity," *Marketing Science*, 14 (3), G109–21.
- Dekimpe, Marnik G., and Dominique M. Hanssens (1999), "Sustained Spending and Persistent Response: A New Look at Long-Term Marketing Profitability," *Journal of Marketing Research*, 36 (November), 397–412.
- Deleersnyder, Barbara, Marnik G. Dekimpe, Miklos Sarvary, and Philip M. Parker (2004), "Weathering Tight Economic Times: The Sales Evolution of Consumer Durables over the Business Cycle," *Quantitative Marketing and Economics*, 2 (4), 347–83.
- Deleersnyder, Barbara, Marnik G. Dekimpe, Jan-Benedict E.M. Steenkamp, and Peter S.H. Leeflang (2009), "The Role of National Culture in Advertising's Sensitivity to Business Cycles: An Investigation Across Categories," *Journal of Marketing Research*, 46 (October), 623–36.
- Doganoglu, Toker, and Daniel Klapper (2006), "Goodwill and Dynamic Advertising Strategies," *Quantitative Marketing and Economics*, 4 (1), 5–29.
- Dubé, Jean-Paul, Günther J. Hitsch, and Puneet Manchanda (2005), "An Empirical Model of Advertising Dynamics," *Quantitative Marketing and Economics*, 3 (2), 107–44.
- Evans, Lewis, and Graeme Wells (1983), "An Alternative Approach to Simulating VAR Models," *Economics Letters*, 12 (1), 23–29.
- Farris, Paul W., and David J. Reibstein (1984), "Over Control in Advertising Experiments," *Journal of Advertising*, 24 (3), 37–44.
- Fok, Dennis, Philip Hans Franses, and Richard Paap (2007), "Seasonality and Non-Linear Price Effects in Scanner-Data-Based Market-Response Models," *Journal of Econometrics*, 138 (1), 231–51.
- Frankenberger, Kristina D., and Roger G. Graham (2003), "Should Firms Increase Advertising Expenditures During Recessions?" MSI Working Paper 03-115, Marketing Science Institute.
- Geyskens, Inge, Katrijn Gielens, and Els Gijsbrechts (2010), "Proliferating Private-Label Portfolios: How Introducing Economy and Premium Private Labels Influences Brand Choice," *Journal of Marketing Research*, 47 (October), 791–807.
- Gijsenberg, Maarten J. (2014), "Going for Gold. Investigating the (Non)Sense of Increased Advertising Around Major Sports Events," *International Journal of Research in Marketing*, 33 (1), 2–15.
- Gijsenberg, Maarten J., Harald J. van Heerde, and Peter C. Verhoef (2015), "Losses Loom Longer than Gains: Modeling the Impact of Service Crises on Perceived Service Quality over Time," *Journal of Marketing Research*, 52 (October), 642–56.
- Gordon, Brett R., Avi Goldfarb, and Yang Li (2013), "Does Price Elasticity Vary with Economic Growth? A Cross-Category Analysis," *Journal of Marketing Research*, 50 (January), 4–23.
- Greenleaf, Eric A. (1995), "The Impact of Reference Price Effects on the Profitability of Price Promotions," *Marketing Science*, 14 (1), 82–104.
- Guler, Ali Umut, Kanishka Misra, and Naufel Vilcassim (2014), "Countercyclical Pricing: A Consumer Heterogeneity Explanation," *Economics Letters*, 122 (2), 343–47.
- Guyt, Jonne E., and Els Gijsbrechts (2014), "Take Turns or March in Sync? The Impact of the National Brand Promotion Calendar on Manufacturer and Retailer Performance," *Journal of Marketing Research*, 51 (December), 753–72.
- Haviv, Avery (2013), "Does Purchase Without Search Explain Counter-Cyclic Pricing?" working paper, Rotman School of Management, University of Toronto.
- Im, Kyung So, M. Hashem Pesaran, and Yoncheol Shin (2003), "Testing for Unit Roots in Heterogeneous Panels," *Journal of Econometrics*, 115 (1), 53–74.
- Kahneman, Daniel, and Amos Tversky (1979), "Prospect Theory: An Analysis of Decision Under Risk," *Econometrica*, 47 (2), 263–91.
- Kalyanaram, Gurumurthy, and Russell S. Winer (1995), "Empirical Generalizations from Reference Price Research," *Marketing Science*, 14 (3), G161–69.
- Keller, Kevin L. (1993), "Conceptualizing, Measuring, and Managing Customer-Based Brand Equity," *Journal of Marketing*, 57 (January), 1–22.
- Keller, Wiebke, Barbara Deleersnyder, and Karen Gedenk (2013), "Promotions and Popular Seasonal Events," working paper, Tilburg University.
- Kilian, Lutz, and Robert J. Vigfusson (2011), "Are the Responses of the U.S. Economy Asymmetric in Energy Price Increases and Decreases?" *Quantitative Economics*, 2 (3), 419–53.
- Krishnamurthi, Lakshman, Tridib Mazumdar, and S.P. Raj (1992), "Asymmetric Response to Price in Consumer Brand Choice and Purchase Quantity Decisions," *Journal of Consumer Research*, 19 (3), 387–400.
- Lamey, Lien, Barbara Deleersnyder, Marnik G. Dekimpe, and Jan-Benedict E.M. Steenkamp (2007), "How Business Cycles Contribute to Private-Label Success: Evidence from the United States and Europe," *Journal of Marketing*, 71 (January), 1–15.
- Lamey, Lien, Barbara Deleersnyder, Jan-Benedict E.M. Steenkamp, and Marnik G. Dekimpe (2012), "The Effect of Business Cycle Fluctuations on Private-Label Share: What Has Marketing Conduct Got to Do with It?" *Journal of Marketing*, 76 (January), 1–19.
- Levin, Andrew, Chien-Fu Lin, and Chia-Shang J. Chu (2002), "Unit Root Tests in Panel Data: Asymptotic and Finite-Sample Properties," *Journal of Econometrics*, 108 (1), 1–24.
- MacDonald, James M. (2000), "Demand, Information, and Competition: Why Do Food Prices Fall at Seasonal Demand Peaks?" *Journal of Industrial Economics*, 48 (1), 27–45.
- Mantrala, Murali K. (2002), "Allocating Marketing Resources," in *The Handbook of Marketing*, B. Weitz and R. Wensley, eds. Thousand Oaks, CA: Sage Publications.
- Mazumdar, Tridib, and Kent B. Monroe (1990), "The Effects of Buyers' Intentions to Learn Price Information," *Journal of Retailing*, 66 (1), 15–32.
- Mela, Carl F., Sunil Gupta, and Donald R. Lehmann (1997), "The Long-Term Impact of Promotions and Advertising on Consumer Brand Choice," *Journal of Marketing Research*, 34 (May), 248–61.
- Metwally, Mokhtar M. (1978), "Escalation Tendencies of Advertising," *Oxford Bulletin of Economics and Statistics*, 40 (2), 153–64.
- Millet, Kobe, Lien Lamey, and Bram Van den Bergh (2012), "Avoiding Negative vs. Achieving Positive Outcomes in Hard and Prosperous Economic Times," *Organizational Behavior and Human Decision Processes*, 117 (2), 275–84.
- Morris, Jon D., Chongmoo Woo, James A. Geason, and Jooyoung Kim (2002), "The Power of Affect: Predicting Intention," *Journal of Advertising Research*, 42 (3), 7–18.
- Naik, Prasad A., and Kalyan Raman (2003), "Understanding the Impact of Synergy in Multimedia Communications," *Journal of Marketing Research*, 40 (November), 375–88.
- Nevo, Aviv, and Konstantinos Hatzitaskos (2006), "Why Does the Average Price Paid Fall During High Demand Periods?" Working Paper No. 0086, Centre for Study of Insurance Operations.
- Nijs, Vincent, Marnik G. Dekimpe, Jan-Benedict E.M. Steenkamp, and Dominique M. Hanssens (2001), "The Category Demand Effects of Price Promotions," *Marketing Science*, 20 (1), 1–22.
- Nijs, Vincent, Shuba Srinivasan, and Koen Pauwels (2007), "Retail Price Drivers and Retailer Profits," *Marketing Science*, 26 (4), 473–85.
- Olver, James M., and Paul W. Farris (1989), "Push and Pull: A One-Two Punch for Packaged Products," *MIT Sloan Management Review*, 31 (1), 53–61.
- Pancras, Joseph, Dinesh K. Gauri, and Debabrata Talukdar (2013), "Loss Leaders and Cross-Category Retailer Pass-Through: A Bayesian Multilevel Analysis," *Journal of Retailing*, 89 (2), 140–57.

- Pauwels, Koen (2007), "How Retailer and Competitor Decisions Drive the Long-Term Effectiveness of Manufacturer Promotions for Fast Moving Consumer Goods," *Journal of Retailing*, 83 (3), 297–308.
- Pauwels, Koen, and Allen Weiss (2008), "Moving from Free to Fee: How Online Firms Market to Change Their Business Model Successfully," *Journal of Marketing*, 72 (May), 14–31.
- Pauwels, Koen, Shuba Srinivasan, and Philip Hans Franses (2007), "When Do Price Thresholds Matter in Retail Categories?" *Marketing Science*, 26 (1), 83–100.
- Petty, Richard E., and John T. Cacioppo (1986), *The Elaboration Likelihood Model of Persuasion*. New York: Springer.
- Phillips, Peter C.B., and Pierre Perron (1988), "Testing for a Unit Root in Time Series Regression," *Biometrika*, 75 (2), 335–46.
- Rosenthal, Robert (1991), *Meta-Analytic Procedures for Social Research*. Newbury Park, CA: Sage Publications.
- Rotemberg, Julio, and Garth Saloner (1986), "A Supergame-Theoretic Model of Price Wars During Booms," *American Economic Review*, 76 (3), 390–407.
- Rucker, Derek D., Richard E. Petty, and Joseph R. Priester (2007), *Understanding Advertising Effectiveness from a Psychological Perspective: The Importance of Attitudes and Attitude Strength*. Newbury Park, CA: Sage Publications.
- Srinivasan, Shuba, Koen Pauwels, Dominique M. Hanssens, and Marnik G. Dekimpe (2004), "Do Promotions Benefit Manufacturers, Retailers, or Both?" *Management Science*, 50 (5), 617–29.
- Steenkamp, Jan-Benedict E.M., and Eric Fang (2011), "The Impact of Economic Contractions on the Effectiveness of R&D and Advertising: Evidence from U.S. Companies Spanning Three Decades," *Marketing Science*, 30 (4), 628–45.
- Steenkamp, Jan-Benedict E.M., Vincent R. Nijs, Dominique M. Hanssens, and Marnik G. Dekimpe (2005), "Competitive Reactions to Advertising and Promotion Attacks," *Marketing Science*, 24 (1), 35–54.
- Stock, James H., and Mark W. Watson (1999), "Business Cycle Fluctuations in U.S. Macroeconomic Time Series," in *The Handbook of Macroeconomics*, John B. Taylor and Michael Woodford, eds. Amsterdam: Elsevier Science, 3–64.
- Sudhir, K. (2001), "Structural Analysis of Manufacturer Pricing in the Presence of a Strategic Retailer," *Marketing Science*, 20 (3), 244–64.
- Van Heerde, Harald J., Maarten J. Gijzenberg, Marnik G. Dekimpe, and Jan-Benedict E.M. Steenkamp (2013), "Price and Advertising Effectiveness over the Business Cycle," *Journal of Marketing Research*, 50 (April), 177–93.
- Van Heerde, Harald J., Peter S.H. Leeftang, and Dick R. Wittink (2004), "Decomposing the Sales Promotion Bump with Store Data," *Marketing Science*, 23 (3), 317–34.
- Verhoef, Peter C., and Peter S.H. Leeftang (2009), "Understanding the Marketing Department's Influence within the Firm," *Journal of Marketing*, 73 (March), 14–37.
- Villanueva, Julian, Shijin Yoo, and Dominique M. Hanssens (2008), "The Impact of Marketing-Induced Versus Word-of-Mouth Customer Acquisition on Customer Equity Growth," *Journal of Marketing Research*, 45 (February), 48–59.
- Villas-Boas, Miguel J. (1993), "Predicting Advertising Pulsing Policies in an Oligopoly: A Model and Empirical Test," *Marketing Science*, 12 (1), 88–102.
- Yoo, Shijin, and Koen Pauwels (2011), "Should Firms Raise Prices Based on Price Discount Elasticities? Asymmetry and Thresholds in Long-Term Price Effects," working paper.