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Firms are under increasing pressure to justify their marketing expenditures. This evolution toward greater accountability is reinforced in harsh economic times when marketing budgets are among the first to be reconsidered. To make such decisions, managers must know whether, and to what extent, marketing's effectiveness varies with the economic tide; however, surprisingly little research addresses this issue. Therefore, the authors conduct a systematic investigation of the business cycle's impact on the effectiveness of two important marketing instruments: price and advertising. To do so, they estimate time-varying short- and long-term advertising and price elasticities for 150 brands across 36 consumer packaged goods categories, using 18 years of monthly U.K. data from 1993 to 2010. The long-term price sensitivity tends to decrease during economic expansions, whereas long-term advertising elasticities increase. During contractions, the long-term own and cross price elasticities increase. Moreover, throughout the observation period, the short-term price elasticity became significantly stronger. Finally, patterns differ across categories and brands, which presents opportunities for firms that know how to ride the economic tide.

Keywords: marketing-mix effectiveness, market-response models, recession, business cycle.

Price and Advertising Effectiveness over the Business Cycle

During economic downturns, managers feel the urge to make changes to their marketing mix. Indeed, in a survey of 1400 managers, 96% indicated that they had made changes in the wake of the global financial crisis (McKinsey & Company 2009). One of the most common actions was the reduction of marketing support for the firm's brands (Deleersnyder et al. 2009; Srinivasan, Rangaswamy, and Lilien 2005). According to MagnaGlobal Interpublic, in 2009, worldwide advertising expenditures dropped 10.8% (in the United States, –15.8%) (*Advertising Age* 2011). In their 2003 article, Marn, Roegner, and Zawada discuss how many managers increase their prices during a contraction to offset the revenue losses caused by reduced sales volumes. Yet, recent academic studies have shown that these responses to the business cycle may be counterproductive (Deleersnyder et al. 2009; Lamey et al. 2012; Steenkamp and Fang 2011). This leaves brand managers struggling with questions whether, in what direction, and how much economic conditions influence the effectiveness of key marketing instruments such as advertising and price. This is an unfortunate state of affairs, because knowledge of marketing's impact is crucial to make informed decisions (Hanssens 2009).

The purpose of this study is to provide brand managers with these insights. More specifically, we investigate whether and how short- and long-term advertising and price

elasticities change over the business cycle. We conduct a large-scale empirical study spanning 18 years (1993–2010) of monthly data—including the effects of the global financial crisis—for 150 brands in the United Kingdom, across 36 consumer packaged goods (CPG) categories. The single-source data enable us to use a consistent measurement and modeling scheme across all brands, which eliminates the confounding factors identified by earlier meta-analyses on price and advertising (Bijmolt, Van Heerde, and Pieters 2005; Sethuraman, Tellis, and Briesch 2011).

PREVIOUS RESEARCH ON BUSINESS CYCLES

In recent years, marketing researchers have paid increasing attention to the link between marketing phenomena and macroeconomic fluctuations. Deleersnyder et al. (2004) study the evolution in consumer durables sales during expansions and contractions, whereas Lamey et al. (2007) document the effect of the business cycle on the evolution of private-label share in several Western countries. Deleersnyder et al. (2009) consider cross-national variation in the cyclical fluctuations in aggregate (country-level) advertising spending, and Millet, Lamey, and Van den Bergh (2012) show that consumers' motivational orientations differ across economic expansion and contraction periods. These studies document that over-time variation in the level of the focal variable is strongly related to the business cycle.

A few studies have begun to investigate the implications of pro- versus countercyclical marketing spending. Frankenberger and Graham (2003) find that advertising expenditures during economic downturns offer more financial benefits (e.g., operating income, shareholder value) than advertising expenditures in expansions. Deleersnyder et al. (2009) report that companies whose advertising expenditures behave procyclically show poorer stock-price performance than companies that set their advertising investments independent of business cycles. Srinivasan, Rangaswamy, and Lilien (2005) document that firms that rate high on the latent construct of "proactive marketing response in a recession" report higher business performance. Finally, Steenkamp and Fang (2011) find that an increase in share of voice has a stronger impact on profit and market share than increasing advertising share in expansions.

Collectively, these studies suggest that the effectiveness of marketing-mix instruments differs between expansion and contraction periods. However, the researchers conducted all studies at the firm level. While insights derived from firm-level analyses are undoubtedly important for the boardroom, they do not necessarily help individual brand or category managers with decision making. Especially for firms that are "a house of brands," as most CPG companies are (Kapferer 2008), aggregate firm-level results may be less relevant because the competitive battle is fought at the individual brand level. The results might even be misleading, due to aggregation bias (Christen et al. 1997). Relatedly, previous studies often focused on aggregate accounting/ financial metrics (stock-price reaction, firm profit). Although Steenkamp and Fang (2011) also consider firm market share, this measure is an aggregate across the different industries (Standard Industrial Classification codes) in which the company is active.

Moreover, the aforementioned studies focus on advertising. Although advertising is undoubtedly one of the most important marketing weapons, existing empirical generalizations indicate that price elasticities are typically 10–20 times larger than advertising elasticities (Bijmolt, Van Heerde, and Pieters 2005; Sethuraman, Tellis, and Briesch 2011). This supports the argument that pricing decisions are even more important for brand performance than advertising decisions.

Gordon, Goldfarb, and Li (2013) analyze how price elasticities vary with the state of the economy using six years of Information Resources Inc. panel data, finding that price sensitivity rises when the economy weakens. Their price elasticity measures the current-period (short-term) effect but does not address what happens to long-term price elasticity. In addition, this study does not examine how short- and long-term advertising elasticity changes with the business cycle, nor does it allow for differential effects of expansions versus contractions. Moreover, their data period (2001–2006) is relatively short in terms of both the number of ups and downs in the economy and the magnitude of these changes. Finally, they do not study differences between brands.

Our study is designed to address these limitations in previous research. We are the first to document how brand-level elasticities in both price and advertising evolve over the business cycle in the short run as well as the long run. To do so, we employ a data set that is unprecedented in its composition in that we estimate, using monthly data, elasticities for 150 brands over a period of 18 years, covering multiple expansion and contraction periods.

RESEARCH FRAMEWORK

Our study focuses on the effect of the business cycle on the short- and long-term effectiveness of own brand advertising and price on brand sales. Previous research has established that performance metrics such as category sales (Deleersnyder et al. 2004) and private-label share (Lamey et al. 2007, 2012) as well as marketing-support variables (Deleersnyder et al. 2009) react differently (i.e., asymmetrically) to economic expansions and contractions. This also applies to consumers' motivational orientations (Millet, Lamey, and Van den Bergh 2012). Given these findings, we do not impose symmetry in effectiveness either and allow for different response parameters along both phases of the business cycle.

Although this article's primary focus is the moderating effect of the business cycle on a brand's own price and advertising effectiveness, we also consider three additional managerially important issues. First, we investigate whether the effectiveness of advertising or price systematically declines or increases with the passage of time. Second, we examine whether advertising systematically moderates a brand's price elasticity. Third, we examine whether the effect of competitor advertising and price varies across the business cycle. Figure 1 provides a schematic overview of the major aspects of our study.

Own Price Effectiveness over the Business Cycle

Own price elasticity. In a large-scale meta-analysis, Tellis (1988) covers 367 elasticities related to 220 different brands or markets, showing a grand mean of –1.76. More recently, from a meta-analysis of 1851 elasticities, Bijmolt, Van Heerde, and Pieters (2005) report an average price elasticity

Figure 1
RESEARCH FRAMEWORK
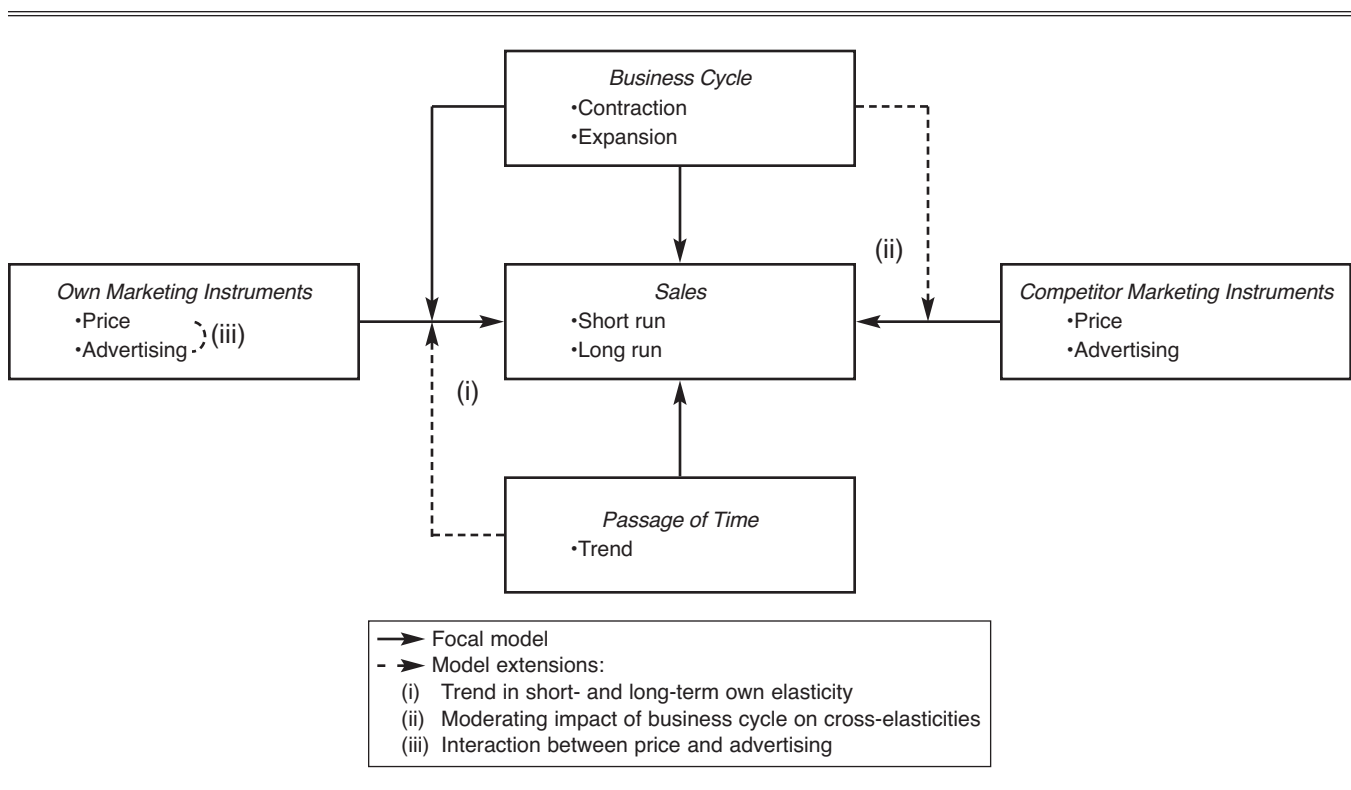
of −2.62 (SD = 2.21). The latter authors have also shown that over time, consumers have become increasingly price sensitive. This is consistent with Mela, Jedidi, and Bowman (1998), who find that households develop price expectations on the basis of their previous exposure to promotions over a long period of time. They report that offering frequent price promotions (as has become increasingly common in the grocery industry) leads to (1) a reduced likelihood of purchase incidence on a given shopping trip but (2) an increase in the quantity bought when households do decide to buy, typically with a promotional offer. In line with these findings, we expect that the magnitude of price elasticity increases over time (i.e., becomes more negative).

Role of the business cycle. We predict that during economic downturns, price elasticity becomes stronger (i.e., more negative). Consumers' disposable income is lower in such periods, creating a higher level of price awareness and fostering a search for lower prices (Estelami, Lehmann, and Holden 2001). Consumers are looking more often for price deals (Quelch 2008) and switch more frequently to lower-priced private-label offerings (Lamey et al. 2007). We therefore expect an increase in the magnitude of both short- and long-term price elasticity (i.e., more negative value) during economic downturns and a decrease in magnitude (i.e., less negative value) during economic expansions.

Own Advertising Effectiveness over the Business Cycle

Own advertising elasticity. Allenby and Hanssens (2004) review advertising-response research from the last 25 years and find that short-term advertising elasticities for established products are very small (approximately .01). In a

recent meta-analysis, Sethuraman, Tellis, and Briesch (2011) find a mean long-term elasticity of .24 across 402 observations, with 40% of these elasticities between 0 and .1. Srinivasan, Vanhuele, and Pauwels (2010) report an average long-term advertising elasticity of .036 across 74 brands in four CPG categories. Sethuraman, Tellis, and Briesch (2011) also find that advertising elasticity is lower in more recent studies, which suggests that advertising elasticity declines over time. This is "because of increased competition, ad clutter, the advent of the Internet as an alternate information source, and the consumer's ability to opt out of television commercials through devices such as TiVo" (Sethuraman, Tellis, and Briesch 2011, p. 460).

Role of the business cycle. Whereas price elasticities are expected to become stronger during economic downturns, there are opposing predictions for advertising elasticities. On the one hand, advertising elasticities may increase during a contraction. Decreasing advertising budgets (Deleersnyder et al. 2009) will result in less competitive clutter (Danaher, Bonfrer, and Dhar 2008), which may make it easier for customers to notice individual firms. In addition, media rates are lower during contractions (Parekh 2009), meaning that the same advertising dollar buys more advertising coverage. Both factors contribute to an increased effectiveness of firms' advertising dollars during a contraction.

On the other hand, Sethuraman, Tellis, and Briesch (2011, p. 46) argue that during contractions, consumers become more price conscious and generally tend to ignore image-based advertising. Moreover, in contractions, brands relying heavily on advertising may be perceived as being less sympathetic to the consumer's tight economic situation

(Ang, Leong, and Kotler 2000). This suggests that advertising elasticity is lower during bad times than during good times.

The net effect of these processes on advertising's short- and long-term sales elasticity is not clear a priori. It is possible that they cancel each other out. This may explain why Sethuraman, Tellis, and Briesch (2011) find no evidence that advertising elasticity is lower in recessions. In contrast, working with firm-level data, and in relative terms (i.e., the impact of share of voice on market share), Steenkamp and Fang (2011) find higher effectiveness during economic downturns. However, from a financial accountability point of view, managers must also consider the sales impact of their absolute spending levels. In so doing, not only does the *share* of the market captured by their brand matter but also the *size* of that market, which may shrink or expand considerably due to changes in the economic climate.

Interaction Between Own Advertising and Own Price

In addition to the direct effects of advertising on brand sales, it is possible that advertising affects sales through its effect on price sensitivity (e.g., Ataman, Van Heerde, and Mela 2010). There are two predictions regarding this issue. Information theory posits that advertising informs consumers about the available alternatives, making price elasticities more negative. In contrast, power theory argues that advertising may increase product differentiation, thus making price elasticity less negative (Mitra and Lynch 1995).

Our data are national-brand advertising, which typically consists of brand-differentiating messages that emphasize nonprice motivations to buy a brand (Mela, Gupta, and Jedidi 1998; Nijs et al. 2001). Such information should lead to increased product differentiation and reduced price (promotion) sensitivity (Boulding, Lee, and Staelin 1994; Kaul and Wittink 1995; Mela, Jedidi, and Bowman 1998). Thus, we expect a positive interaction: more advertising should decrease the magnitude of the price elasticity (i.e., make it less negative).

Cross Brand Effects of Advertising and Price

In line with the main thrust of this article, the discussion thus far has focused on own effects—in other words, a brand's own price and advertising elasticities. However, to estimate own effects accurately, it is paramount to take competitive activity into account as well. Moreover, cross price and advertising elasticities are of interest in their own right. What is the effect of the business cycle on cross price and cross advertising effects? It stands to reason that the general increase in price sensitivity in contractions increases not only own price sensitivity but also the sensitivity of the focal brand sales to its competitor's prices (Estelami, Lehmann, and Holden 2001). As for the cross advertising effect, a contraction may lead to either more cross brand stealing (less clutter, so advertising becomes more noticeable) or less stealing (consumers rely less on brand image and advertising and more on value for money; Steenkamp and Fang 2011).

DATA

We use monthly volume sales from Kantar Worldpanel for 36 mature CPG categories in the United Kingdom over an 18-year period (1993–2010). In each CPG category, we select up to five leading national brands. Another requirement is that a brand needs to advertise sufficiently often: at least twice during a contraction and at least twice during an expansion. In total, we included 150 national brands.[1] To illustrate the range of products available in our data set, we have grouped them into broader product classes—food, beverages, household care, and personal care. Table 1 shows the number of categories in these product classes and some illustrative examples for several sample categories. The table highlights that our data cover many well-known household names.

We obtained price information on the 150 brands from Kantar Worldpanel UK and acquired information about their monthly advertising expenditure from Nielsen Media (United Kingdom). All marketing-mix series are inflation-adjusted using the U.K. Consumer Price Index, which we obtained from the Organisation for Economic Co-operation and Development.

We use data on real gross domestic product (GDP) as a proxy for general economic activity. Stock and Watson (1999) have shown the cyclical component of the GDP series to be a good indicator of overall economic cycle. We obtained GDP data, expressed in constant prices, from the Organisation for Economic Co-operation and Development. The time span considered covers various economic conditions ranging from periods of relative stability to periods of economic decline (including the recent global financial crisis) and periods with considerable growth.

METHODOLOGY

Given our research objectives, our modeling approach needs to address several issues. First, our model should provide short- and long-term advertising and price elasticities. Second, it should allow for interactions between these elasticities and the state of the economy. Third, because consumers may react differently to economic contractions and expansions, it should allow for asymmetric effects. Fourth, because it is unlikely that expansions and contractions affect all brands in the same way, the response parameters should be able to vary across brands. Fifth, we need to allow for possible error correlations between brands from the same

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[1]The maximum number of brands to be considered is $36 \times 5 = 180$. However, in some categories (e.g., artificial sweeteners, frozen fish, razor blades), there were fewer than five brands, which reduced the number of brands to 163. Furthermore, of these brands, 13 did not meet the minimum advertising frequency, which leaves us with 150 brands.

Table 1
DATA COVERAGE

Product Class	Number of Categories	Example Categories	Example Brands
Food	14	Breakfast cereals	Kellogg's
		Canned fruits	Del Monte
		Yogurt	Danone
Beverages	7	Fruit juices and drinks	Ocean Spray
		Mineral water	Evian
		Soft drinks	Coca-Cola
Household care	7	Household cleaners	Mr. Muscle
		Machine wash products	Ariel
		Liquid detergents	Fairy
Personal care	8	Bath additives	Palmolive
		Toothpaste	Crest
		Shampoo	Head & Shoulders
Total number	36		150

product category. Sixth, we need to account for possible endogeneity of price and advertising decisions. Subsequently, we formulate an error correction model that addresses these six challenges.[2] First, however, we present the derivation of the business cycle.

Assessing the State of the Business Cycle

To assess the impact of business cycles on marketing-mix effectiveness, we must first capture the business cycle itself. To do so, we adopt the Christiano–Fitzgerald (CF) random-walk filter (Christiano and Fitzgerald 2003). The CF filter is a band-pass filter built on the same principles as the Baxter and King filter used in Deleersnyder et al. (2004). However, unlike the Baxter and King filter, which loses several observations at the end of the series, the CF filter is designed to use the entire time series (and thus also uses information from the most recent economic crisis).[3] We refer to Christiano and Fitzgerald (2003) and Nilsson and Gyomai (2011) for a detailed discussion on the relative merits of the CF filter.

We apply the CF filter to log-transformed quarterly GDP data and transform the resulting series to a monthly sequence (the temporal aggregation level of our sales and marketing-support series) through linear interpolation (for similar practices, see Pauwels et al. 2004 and Srinivasan et

al. 2009).[4] The black line in Figure 2 shows the CF-filtered cyclical component ("Gross Domestic Product Cyclical"; $gdpc_t^c$). This is the cyclical deviation from the long-term trend in the log-transformed GDP series. The up- and down-swing at the end of the data period reflects the strong performance of the U.K. economy in 2006 and 2007, followed by the global financial crisis that hit the United Kingdom in 2008.[5] We categorize periods with an increase in the cyclical component as expansions and periods with a decrease as contractions (Lamey et al. 2007, 2012; Steenkamp and Fang 2011; see also Kontolemis 1997). In Figure 2, white zones represent expansions and gray zones represent contractions.[6]

Following Lamey et al. (2007) and Steenkamp and Fang (2011), we define the magnitude of the expansion at any point in time ($Expansion_t$) as the difference between the actual level of the cyclical component at time t and the prior trough. The prior trough is the most recent point in the cyclical component in which the month-on-month growth turned from negative to positive. Similarly, the extent of the contraction ($Contraction_t$) is the difference between current level and the prior peak (i.e., the most recent point in the cyclical component in which the month-on-month growth turned from positive to negative). The peaks and troughs also determine the transition points between the gray and white bars in Figure 2. Formally, we define the terms with the following equation:

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[2]There are also other approaches to accommodate time-varying parameters, such as dynamic linear models (e.g., Ataman et al. 2010). However, estimating these models for our setting with its numerous brands, categories, and time periods would be prohibitive in terms of the amount of computer time it would take.

[3]Given that we work with quarterly data, a band-pass filter is more appropriate than the Hodrick–Prescott filter (which is a high-pass filter) used in other marketing applications (e.g., Deleersnyder et al. 2009). Business-cycle fluctuations happen with a periodicity between 1.5 and 8 years (Christiano and Fitzgerald 2003). Researchers can design band-pass filters to pass through all components of the time series with a periodicity between 6 and 32 quarters. The Hodrick–Prescott filter, in contrast, suppresses only the low-frequency fluctuations, implying that what is passed through consists of both the cyclical fluctuations (of main interest) and higher-frequency noise. Although this does not make a difference when working with annual data (as in Deleersnyder et al. 2009), it does have an impact when working with more disaggregate (e.g., quarterly) data (for a more in-depth discussion, see Deleersnyder et al. 2004, p. 357).

[4]Because the series is log-transformed before filtering, the resulting cyclical component (multiplied by 100) represents the percentage deviation from the economy's underlying growth path (for a detailed discussion, see Lamey et al. 2012; Stock and Watson 1999).

[5]For a correct assessment of the last peak/trough preceding the 1993–2010 analysis period, we applied the CF filter to a data series that included several years before the analysis period.

[6]An alternative approach to identify contraction periods would be to use the recession periods, defined as at least two successive quarters of negative growth, as declared by such governmental agencies as the National Bureau of Economic Research Business Cycle Dating Committee (in the United States). However, researchers have criticized the committee's judgment-based procedure for a lack of statistical foundation and for its rigid focus on absolute declines (as opposed to growth slowdowns) in output and other measures (Stock and Watson 1999). For these reasons, business-cycle filters have become the norm to study cyclical phenomena in contemporary business-cycle research.

Figure 2

CYCLICAL DEVIATIONS FROM THE LONG-TERM TREND IN THE LOG-TRANSFORMED GDP SERIES FOR THE U.K. ECONOMY
(1993–2010)
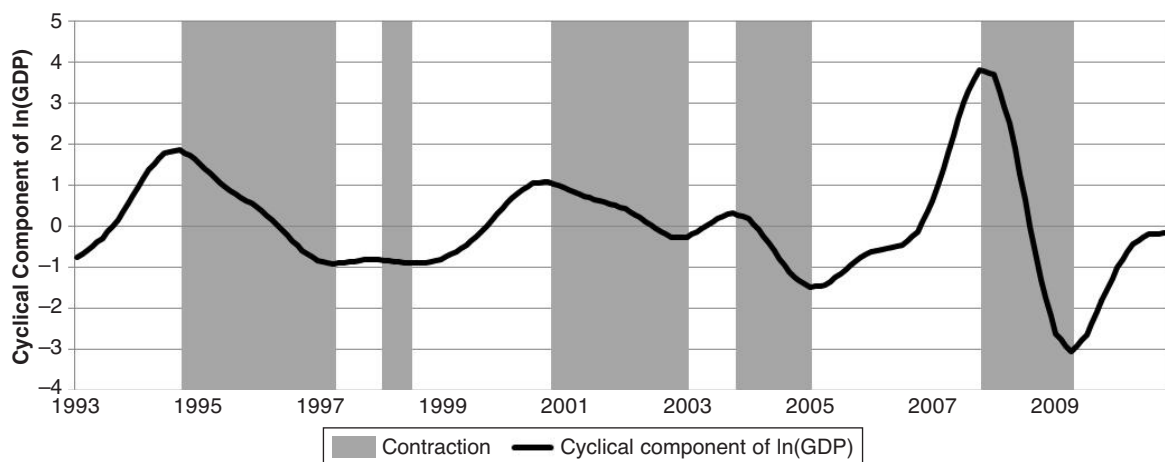
$$(1)\ \text{Expansion}_t \begin{cases} = \text{gdpc}_t^c - \left(\text{prior trough in gdpc}^c\right) & \text{if } \Delta\text{gdpc}_t^c > 0 \\ = 0 & \text{if } \Delta\text{gdpc}_t^c \leq 0 \end{cases}$$

$$\text{Contraction}_t \begin{cases} = 0 & \text{if } \Delta\text{gdpc}_t^c > 0 \\ = (\text{prior peak in gdpc}^c) - \text{gdpc}_t^c & \text{if } \Delta\text{gdpc}_t^c \leq 0. \end{cases}$$

With this operationalization, Expansion_t takes positive values during economic upswings and 0 values during downturns, whereas Contraction_t takes positive values during downturns and 0 values during periods of growth. Stronger growth will result in higher values for Expansion_t, whereas a stronger decline will result in higher values for Contraction_t. By working with the continuous Expansion_t and Contraction_t variables, we not only account for the occurrence of the different business-cycle phases (as would be captured when working with dummy variables; see, e.g., Kontolemis 1997; Lamey et al. 2012) but also capture the intensity of the up- or downswing. Beaudry and Koop (1993) and Steenkamp and Fang (2011), among others, stress the importance of accounting for the current depth of the contraction/expansion. Many governmental agencies also define the depth of a recession relative to the previous trough (Siems 2012).

Model for Assessing Price and Advertising Effectiveness over the Business Cycle

Before specifying the model, we tested the (log-transformed) sales series for stationarity. Of the 150 individual sales series, the unit-root null hypothesis was rejected ($p < .10$) in all but 7 (4.6%) instances on the basis of the Phillips–Perron (1988) test, using an intercept and trend as exogenous variables. Recent literature has pointed out that panel-based unit-root tests have higher power than tests based on the individual series. Therefore, we also applied Levin, Lin, and Chu's (2002) test, allowing for both a fixed-effects correction and brand-specific trend, lag-lengths, and autoregressive parameters. Again, the unit-root null hypothesis was rejected ($p < .05$) in favor of the no-unit-root alternative hypothesis. Therefore, the combined evidence of these tests supports the (trend) stationarity of brand sales, in line with other studies in the CPG industry (Dekimpe and Hanssens 1995a).

To capture the short- and long-term effects of advertising and price on brand sales, we adopt the parsimonious error correction specification (for recent marketing applications, see Fok et al. 2006; Pauwels, Srinivasan, and Franses 2007; Van Heerde, Helsen, and Dekimpe 2007; Van Heerde, Srinivasan, and Dekimpe 2010). For exposition purposes, we begin with a model with main effects only and subsequently add interactions with the business cycle:

$$(2)\ \Delta\ln\text{Sales}_t^{cb} = \beta_0^{cb} + \beta_1^{cb}\Delta\ln\text{Price}_t^{cb} + \beta_2^{cb}\Delta\ln\text{Advertising}_t^{cb}$$
$$+ \beta_3^{cb}\Delta\ln\text{CompPrice}_t^{cb} + \beta_4^{cb}\Delta\ln\text{CompAdvertising}_t^{cb}$$
$$+ \varphi^{cb}\begin{bmatrix} \ln\text{Sales}_{t-1}^{cb} - \beta_5^{cb}\ln\text{Price}_{t-1}^{cb} \\ \\ - \beta_6^{cb}\ln\text{Advertising}_{t-1}^{cb} - \beta_7^{cb}\ln\text{CompPrice}_{t-1}^{cb} \\ \\ - \beta_8^{cb}\ln\text{CompAdvertising}_{t-1}^{cb} \\ \\ - \beta_9^{cb} \times \text{trend} \end{bmatrix}$$
$$+ \varepsilon_t^{cb},$$

where Δ is the first difference operator: $\Delta X_t = X_t - X_{t-1}$; Sales_t^{cb} is the volume sales of brand b (b = 1 … B_c) in category c (c = 1 … C) during month t (t = 1 … T), and ln indicates the natural logarithm. Price_t^{cb} is the deflated price of the brand at time t, whereas $\text{Advertising}_t^{cb}$ is the deflated advertising expenditures. We control for cross effects of competing brands' actions by including the market-share-weighted average competitor price CompPrice_t^{cb} and total competitor advertising $\text{CompAdvertising}_t^{cb}$.

In Model 2, β_1^{cb} is the short-term (same period) own price elasticity, β_2^{cb} is the short-term own advertising elasticity, β_3^{cb} is the short-term cross price elasticity, and β_4^{cb} is the short-term cross advertising elasticity; their long-term counterparts (same period + future periods) are β_5^{cb}, β_6^{cb}, β_7^{cb}, and β_8^{cb}, respectively. This long-term impact reflects the cumulative impact of a one-period shock to advertising or price, respectively. We refer to Fok et al. (2006) for an in-depth discussion of the error correction model. The term β_9^{cb} captures the long-term trend in brand sales as a proxy for other variables that gradually changed over the observed 18-year time span (Dekimpe and Hanssens 1995b; for a discussion of the role of this trend variable in error correction specifications, see Franses 2001). The trend variable runs from –1 in the first observation to +1 in the last. This enables us to interpret the main effect of the elasticity to hold for the middle observation (in which the trend variable = 0), and it makes the interactions and main effects of a similar magnitude. For the overall size and change in elasticity, it does not matter whether we define trend like this or, more traditionally, as running from 1 to T. For a discussion of the interpretational advantages of different coding schemes for trends, see Stoolmiller (1994). The parameter φ^{cb} reflects the speed of adjustment toward the underlying (long-term) equilibrium (Dekimpe and Hanssens 1999; Powers et al. 1991).

Equation 3 expands Equation 2 by adding the interactions between the own price and advertising variables and the Expansion and Contraction variables as well as the main effects of the latter variables:

$$(3)\ \Delta\ln\text{Sales}_t^{cb} = \beta_0^{cb} + \beta_1^{cb}\text{Expansion}_t + \beta_2^{cb}\text{Contraction}_t$$
$$+ \beta_3^{cb}\Delta\ln\text{Price}_t^{cb} + \beta_4^{cb}\Delta\ln\text{Price}_t^{cb} \times \text{Expansion}_t$$
$$+ \beta_5^{cb}\Delta\ln\text{Price}_t^{cb} \times \text{Contraction}_t + \beta_6^{cb}\Delta\ln\text{Advertising}_t^{cb}$$
$$+ \beta_7^{cb}\Delta\ln\text{Advertising}_t^{cb} \times \text{Expansion}_t$$
$$+ \beta_8^{cb}\Delta\ln\text{Advertising}_t^{cb} \times \text{Contraction}_t$$
$$+ \beta_9^{cb}\Delta\ln\text{CompPrice}_t^{cb} + \beta_{10}^{cb}\Delta\ln\text{CompAdvertising}_t^{cb}$$
$$+ \varphi^{cb}\begin{bmatrix} \ln\text{Sales}_{t-1}^{cb} - \beta_{11}^{cb}\ln\text{Price}_{t-1}^{cb} \\ \\ - \beta_{12}^{cb}\ln\text{Price}_{t-1}^{cb} \times \text{Expansion}_t \\ \\ - \beta_{13}^{cb}\ln\text{Price}_{t-1}^{cb} \times \text{Contraction}_t \\ \\ - \beta_{14}^{cb}\ln\text{Advertising}_{t-1}^{cb} \\ \\ - \beta_{15}^{cb}\ln\text{Advertising}_{t-1}^{cb} \times \text{Expansion}_t \\ \\ - \beta_{16}^{cb}\ln\text{Advertising}_{t-1}^{cb} \times \text{Contraction}_t \\ \\ - \beta_{17}^{cb}\ln\text{CompPrice}_{t-1}^{cb} \\ \\ - \beta_{18}^{cb}\ln\text{CompAdvertising}_{t-1}^{cb} - \beta_{19}^{cb} \times \text{trend} \end{bmatrix}$$
$$+ \varepsilon_t^{cb}.$$

Model 3 is the base model to test the evolution of price and advertising elasticities over the business cycle. It puts the

focus squarely on the moderating role of the business cycle on own price and own advertising elasticities.

Model Extensions

We also consider three extensions to the base model. First, we allow for the possibility that own price elasticities or own advertising elasticities have changed over time. We do this by adding the four interactions of the trend with short- and long-term own elasticities to the base model: $\Delta \ln Price_t^{cb} \times trend$, $\Delta \ln Advertising_t^{cb} \times trend$, $\ln Price_{t-1}^{cb} \times trend$, $\ln Advertising_{t-1}^{cb} \times trend$. Second, we investigate whether advertising moderates the effect of price by adding both the interaction between short-term own price and short-term own advertising ($\Delta \ln Price_t^{cb} \times \Delta \ln Advertising_t^{cb}$) and the interaction between long-term own price and long-term own advertising ($\ln Price_{t-1}^{cb} \times \ln Advertising_{t-1}^{cb}$) to Equation 3. Third, we consider whether the impact of short- and long-term effects of competitive advertising and competitive price varies across the business cycle, for a total of eight interaction terms. For example, to investigate the possible cyclical sensitivity of short-term cross price elasticities, we add $\Delta \ln CompPrice_t^{cb} \times Expansion_t$ and $\Delta \ln CompPrice_t^{cb} \times Contraction_t$. Adding all 14 interactions simultaneously to the base model leads to an overburdened model and unstable parameter estimates due to an excessive number of interaction terms (Cohen et al. 2003). Therefore, we examined each model extension separately by adding the terms to Equation 3 to evaluate their significance.

Endogeneity

Price and advertising decisions may depend on unobserved demand shocks. In addition, previous research has shown that not accounting for endogeneity may bias the elasticity estimates (Bijmolt, Van Heerde, and Pieters 2005; Sethuraman, Tellis, and Briesch 2011). We account for endogeneity by adopting a three-stage least squares approach (3SLS). The endogenous variables are $\Delta \ln Price_t^{cb}$ and $\Delta \ln Advertising_t^{cb}$ as well as any of the interactions of which they are a part. The lagged variables are predetermined.

As instrumental variables (IVs), we use lagged price and advertising variables from other product classes (not from the brand itself). We distinguish dairy food, nondairy food, beverages, household care, and personal care. So, for a beverage brand, we use as IVs average lagged log-price and average lagged log-advertising, separately for dairy food, nondairy food, household care, and personal care. We chose these IVs because the same underlying cost structures may determine price and advertising changes for other product classes. These cost structures are likely to be independent of the demand shocks observed for the focal product class. Lamey et al. (2012) and Ma et al. (2011), among others, recently adopted similar IVs in their studies. Because we also instrument for the interactions involving the first difference of price and advertising (e.g. $\Delta \ln Price_t^{cb} \times Expansion_t$), the IVs also include the interactions between the original IVs and Expansion and Contraction (Wooldridge 2002, pp. 121–22). Because we have more IVs than endogenous regressors, our model is overidentified.

We formally test for both the strength (using the Angrist–Pischke [Angrist and Pischke 2009] multivariate F statistic) and the validity (using the Sargan test) of our instruments. These tests confirmed that our instruments are indeed correlated with the endogenous variables of interest (*p*-value F-tests < .05) but uncorrelated with the error term in the demand of the focal brand ε_t^{cb} (*p*-value Sargan test > .10).

Model Estimation Procedure

We use 3SLS to estimate the models, which takes into account error correlations between brands within category. For the base model (Equation 3), we multiply the parameter φ^{cb} through with the term in the square brackets. Estimating the model, we initially obtain estimates for the different products of parameters (e.g., $-\varphi^{cb} \times \beta_{11}^{cb}$), from which we can derive the estimate for the parameter of interest (e.g., β_{11}^{cb}). We subsequently derive the associated standard error with the Delta method (Greene 2000, p. 330–31).

We thus obtain brand-specific 3SLS estimates for all model parameters in Equation 3. To summarize the effect sizes and significance across all brands, we use Rosenthal's method of added Zs (Rosenthal 1991).[7] The effect size of parameter β is the weighted mean response parameter across brands. The weight is the inverse of the estimate's standard error, normalized to one. Thus, we can interpret β as a reliability-weighted mean, where estimates with higher reliability (lower standard error) obtain a higher weight, similar in spirit to a hierarchical mean in a Bayesian model (e.g., Chib and Greenberg 1995).

We next add the interactions, one block at a time, and retain only the interactions that were significant at 10% across all brands, using the method of added Zs. Specifically, when we test the four interactions between trend and price and advertising (first difference and lag), the only term that is significant at 10% is $\Delta \ln Price_t^{cb} \times trend$. When we test the short-term and long-term interactions between price and advertising, only the long-term interaction is significant: $\ln Price_{t-1}^{cb} \times \ln Advertising_{t-1}^{cb}$. Finally, of the eight interactions between the various cross effects and the business cycle, only one is significant: $\ln CompPrice_{t-1}^{cb} \times Contraction_t$. To avoid overspecifying the model, we retain only these three significant interactions (for a similar approach, see Bijmolt, Van Heerde, and Pieters 2005; Steenkamp and De Jong 2010). We call this the "extended model."

RESULTS

Overall Descriptive Findings

Table 2 reports some descriptive statistics on the direction and extent to which the business cycle affects brand sales. This sets the stage for our main findings pertaining to the effect of the business cycle on our model parameters. Table 2 compares the average monthly sales during expansions (white areas in Figure 2) versus contractions (gray areas in Figure 2). Approximately the same number of CPG brands experienced a significant increase during a contraction as those that experienced a significant decrease. This may seem counterintuitive; however, it is consistent with Du and Kamakura's (2008) finding that as discretionary income decreases, expenditures for essential categories (e.g., food at home) increase relative to nonessential cate-

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[7]We refer to Web Appendix A (www.marketingpower.com/jmr_webappendix) for more details on this procedure and to Deleersnyder et al. (2002, 2009) or Lamey et al. (2007, 2012) for recent marketing applications.

Table 2

CYCLICAL SENSITIVITY OF BRAND SALES

Effect	Number of Brands	Typical Categories	Average Change
Increased sales during contractions ($p < .10$)	29	Conditioners Cooking sauces Pasta Stout beer	4% 2% 8% 6%
Decreased sales during contractions ($p < .10$)	29	Household cleaner Liquid detergents	–5% –2%
No significant effect	92	Shower products Cereal bars Instant coffee	–5% –.2% 1%
Total number	150		

gories (e.g., food outside the home). Gicheva, Hastings, and Villas-Boas (2008) also document such a positive substitution effect. These authors show that, following an increase in gasoline prices, consumers substitute away from food-away-from-home and toward groceries to partially offset their reduced discretionary income.

Table 2 is also consistent with several recent observations in the business press that during tough economic times, consumers tend to switch from out-of-home consumption (e.g., restaurant, hairdresser) to more in-home consumption (Cendrowski 2012; Helm 2009; *The Wall Street Journal Europe* 2009). This favors grocery sales in those categories in which such a trading-in strategy is feasible, such as cooking sauces, pasta, stout beer, and hair conditioners. Conversely, restored consumer confidence during economic expansions tends to revive out-of-home consumption, putting pressure on grocery sales (Drake 2009).

Main Effects of Price and Advertising

Table 3 reports the parameter estimates for both the base model (Equation 3) and the extended model. Our discussion focuses on the results of the extended model. For parameters in which theory offers unidirectional predictions, we use one-sided *p*-values. For all other parameters, we use two-sided *p*-values. Table 3 includes a column with expectations for all model parameters.

We find a significant short-term ($\beta = -1.4266$, $p < .01$) and long-term price elasticity ($\beta = -.8379$, $p < .01$), which are consistent with the meta-analysis of Bijmolt, Van Heerde, and Pieters (2005) for CPG brands. We also find a significant short-term ($\beta = .0021$, $p < .10$) and long-term advertising elasticity ($\beta = .0127$, $p < .01$), both of which are small, but this is not uncommon in CPG categories (Allenby and Hanssens 2004; Sethuraman, Tellis, and Briesch 2011; Srinivasan, Vanhuele, and Pauwels 2010).

Is there evidence that price or advertising effectiveness has systematically declined or increased over time? For this, we consider the interactions between short- and long-term price and advertising elasticities with the trend. We find no evidence that advertising effectiveness declines over time. Although the parameter of both interaction terms is negative, indicating a tendency of declining advertising effectiveness over time, neither effect is significant ($p > .10$). However, price sensitivity has increased significantly over

the past two decades. The relentless focus on price in the CPG industry has made consumers increasingly responsive to price reductions (Mela, Gupta, and Lehmann 1997; Mela, Jedidi, and Bowman 1998). The short-term price elasticity has become increasingly strong (i.e., more negative) over time, as implied by the significant interaction effect with the trend term ($\beta = -.5716$, $p < .01$). Because the trend variable runs from –1 to +1, this means that across the 18 years of data (1993–2010), the magnitude of the short-term price elasticity grew by 1.1432 percentage points. We find corroborating evidence by comparing our results with the meta-analysis of Bijmolt, Van Heerde, and Pieters (2005). We observe that the annual change rate in the short-term price elasticity equals $2 \times (-.5716/18) = -.0635$, which is close to the annual change rate of –.04 reported by Bijmolt, Van Heerde, and Pieters (2005, p. 146).

Interaction Between Own Advertising and Own Price Effectiveness

We also examine whether price and advertising interact. From the notion that brand advertising should lead to increased product differentiation and reduced price sensitivity, we expect a positive interaction: more advertising should decrease the magnitude of the price elasticity (i.e., make it less negative). When we add the two interactions terms (for short-term and long-term elasticities, respectively) to the base model, we find that both have the expected positive sign, and the term for the long-term interaction is significant at 10%. However, in the extended model, which includes other interaction terms, this interaction effect is no longer significant. Therefore, we do not find compelling evidence that advertising effectiveness reduces price sensitivity across all brands and product categories.

Main Effect of the Business Cycle on Brand Sales

A correct interpretation of the effect of the business cycle parameters requires knowledge of the values of the two economy variables. Expansion_t (Contraction_t) shows an average value of 1.39 (1.45), with a minimum of 0 for both and a maximum of 5.31 (6.87), respectively. By multiplying the corresponding parameters with these values, we obtain an estimate of the size of the effect of the economy on the respective parameters.

We find that an expansion has a significant, negative main effect on brand sales ($\beta = -.0103$, $p < .01$). This is consistent with the finding that during booms, the base sales of many CPG products will come under pressure because higher economic growth is associated with increased out-of-home consumption (Du and Kamakura 2008). To validate this finding, we calculated the correlation between the parameter estimate for the main effect of expansion on the intercept in the model (i.e., model-based evidence) and the percentage difference in average log sales between contractions and expansions (i.e., model-free evidence). The out-of-home argument suggests a negative correlation: the stronger the negative effect of expansion on the intercept, the larger (i.e., more positive) is the difference between average log sales in a contraction versus an expansion. In line with this argument, we find a correlation of –.25 ($p < .01$). The main effect of contractions is not significant, reflecting that the beneficial effects of contractions on some brands are balanced by the detrimental effects on other

Table 3
PARAMETER ESTIMATES

Variable	Interpretation	Expectation	Base Model			Extended Model		
			Weighted Mean β	Meta-Analytic Z	Meta-Analytic p	Weighted Mean β	Meta-Analytic Z	Meta-Analytic p
Intercept		≠ 0	.0747***	2.6715	.0076	.0835**	2.4704	.0135
$Expansion_t$	Main effect expansion on sales	≠ 0	−.0103****	−4.8699	.0000	−.0103***	−4.4726	.0000
$Contraction_t$	Main effect contraction on sales	≠ 0	.0004	.2346	.8146	−.0004	−.0677	.9460
$\Delta lnPrice_t^{cb}$	Short-term price elasticity	< 0	−1.4355****	−20.9974	.0000	−1.4266***	−18.4458	.0000
$\Delta lnPrice_t^{cb} \times Expansion_t$	Impact of expansion on short-term price elasticity	> 0	−.0284	−.7907	.7854	.0422	1.0014	.1583
$\Delta lnPrice_t^{cb} \times Contraction_t$	Impact of contraction on short-term price elasticity	< 0	−.0435**	−2.0143	.0220	.0169	.6012	.7262
$\Delta lnAdvertising_t^{cb}$	Short-term advertising elasticity	> 0	.0017*	1.4517	.0733	.0021*	1.6015	.0546
$\Delta lnAdvertising_t^{cb} \times Expansion_t$	Impact of expansion on short-term advertising elasticity	≠ 0	.0006	.8460	.3976	.0004	.5996	.5487
$\Delta lnAdvertising_t^{cb} \times Contraction_t$	Impact of contraction on short-term advertising elasticity	≠ 0	−.0003	−.7113	.4769	−.0004	−.8252	.4092
$\Delta lnCompAdvertising_t^{cb}$	Short-term cross advertising elasticity	> 0	.0011**	2.2799	.0226	.0012**	2.4836	.0130
$\Delta lnCompPrice_t^{cb}$	Short-term cross price elasticity	> 0	.5902****	20.2601	.0000	.4803****	14.9085	.0000
$lnPrice_{t-1}^{cb}$	Long-term price elasticity	< 0	−.8117****	−18.1477	.0000	−.8379****	−13.6927	.0000
$lnPrice_{t-1}^{cb} \times Expansion_t$	Impact of expansion on long-term price elasticity	> 0	.0072*	1.3204	.0934	.0097*	1.6338	.0512
$lnPrice_{t-1}^{cb} \times Contraction_t$	Impact of contraction on long-term price elasticity	< 0	−.0048	−.9751	.1647	−.0084*	−1.4800	.0694
$lnAdvertising_{t-1}^{cb}$	Long-term advertising elasticity	> 0	.0121***	6.8236	.0000	.0127****	2.4222	.0077
$lnAdvertising_{t-1}^{cb} \times Expansion_t$	Impact of expansion on long-term advertising elasticity	≠ 0	.0018***	2.1602	.0308	.0017*	1.9076	.0564
$lnAdvertising_{t-1}^{cb} \times Contraction_t$	Impact of contraction on long-term advertising elasticity	≠ 0	−.0003	−.4485	.6538	−.0006	−.6042	.5457
$lnCompAdvertising_{t-1}^{cb}$	Long-term cross advertising elasticity	≠ 0	.0085****	7.0154	.0000	.0086****	6.5488	.0000
$lnCompPrice_{t-1}^{cb}$	Long-term cross price elasticity	> 0	.4569****	9.5098	.0000	.4128****	7.8211	.0000
$lnSales_{t-1}^{cb}$	Speed of adjustment parameter	< 0	−.3905****	−72.1529	.0000	−.3880****	−66.1678	.0000
Trend	Main effect trend	≠ 0	.1195***	11.2935	.0000	.1137***	10.0474	.0000
$\Delta lnPrice_t^{cb} \times trend$	Impact of trend on short-term price elasticity	< 0				−.5716***	−4.5521	.0000
$lnPrice_{t-1}^{cb} \times lnAdvertising_{t-1}^{cb}$	Long-term interaction advertising and price	> 0				.0053	1.0897	.1380
$lnCompPrice_{t-1}^{cb} \times Contraction_t$	Impact of contraction on long-term cross price elasticity	> 0				.0360**	1.8148	.0348

*$p < .10$.
**$p < .05$.
***$p < .01$.

Notes: p-values are one-sided for directional hypotheses and two-sided otherwise. Weight for β is inverse of its standard error, normalized to 1.

brands. Correspondingly, the correlation between this main effect and the difference in average log-sales between contraction and expansion is an insignificant .027 (p = .743).

Moderating Role of the Business Cycle on Price and Advertising Elasticities

Although we find no evidence that the business cycle affects short-term elasticities, we find clear evidence that it affects the long-term impact of both price and advertising. It takes time for a firm to feel the full effects of economic ups and downs. Thus, myopic managers may well underestimate the full impact of economic contractions and expansions on the effectiveness of their marketing instruments. This is especially pertinent in economically difficult times, when managers are already under more stock market pressure to reach their (quarterly) targets (Deleersnyder et al. 2009; Steenkamp and Fang 2011) and when there is already less room for mistakes or suboptimal decisions.

More specifically, the interaction between long-term price elasticity and expansion is positive (β = .0097, p < .10). Conversely, long-term price elasticity becomes more negative during contractions (β = –.0084, p < .10). This implies that when the economy is doing well, consumers become less price sensitive, whereas price sensitivity increases in bad times (and more so the more severe the contraction).

Advertising elasticities increase significantly during expansions (β = .0017, p < .10), which means that demand becomes more responsive to advertising when the economy is in good shape. Our finding that the net impact of an expansion on advertising effectiveness is positive implies that in an expansion, the positive forces (e.g., consumers who are receptive to image advertising and more able to respond [Ang, Leong, and Kotler 2000; Sethuraman, Tellis, and Briesch 2011]) outweigh the negative forces (e.g., more clutter during expansions [Danaher, Bonfrer, and Dhar 2008]). Finally, advertising effectiveness is lower in bad economic times, though not significantly.

To get a sense of the magnitude of the cyclical swings in advertising and price elasticity, consider what is arguably the most important business cycle event in the post–World War II world, namely, the global financial crisis, which hit the United Kingdom in 2008 (see Figure 2). Figure 3 displays the long-term elasticities evaluated at the top of the peak in the economic cycle in November 2007 (indicated as "Expansion") versus at the bottom of the trough (May 2009) of the global financial crisis (indicated as "Contraction"). The differences are substantial. The average long-term price sensitivity increases by 14% (from –.7863 to –.8956), whereas the advertising effectiveness drops approximately 60% (from .0218 to .0088).

Cross Brand Effects

What about the sensitivity of own brand sales to competitive price and advertising activity? Although our model controls for competitive prices and advertising in deriving own brand elasticities, cross brand elasticities are of managerial interest in their own right. Own brand sales are higher if the prices of competing brands increase. We find this effect both for the short run (β = .4803, p < .01) and the long run (β = .4128, p < .01). Both estimates are close to the meta-analytic average cross price elasticity of .52 in Sethuraman,

Figure 3
THE EFFECT OF THE GLOBAL FINANCIAL CRISIS: LONG-TERM PRICE AND ADVERTISING ELASTICITIES AT THE PEAK OF THE ECONOMY AND AT ITS NADIR

A: Long-Term Price Elasticity

B: Long-Term Advertising Elasticity
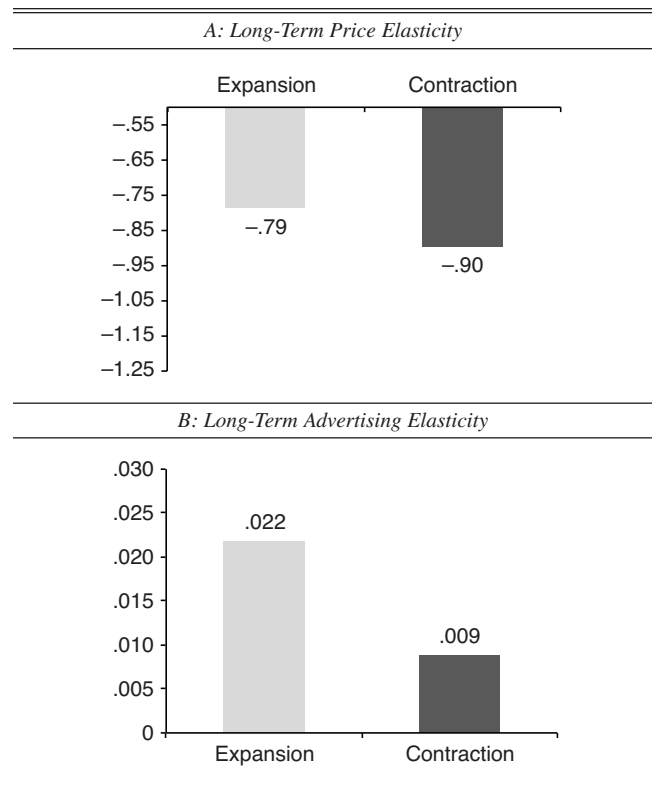
Srinivasan, and Kim (1999). When we compare the magnitude of own versus cross price elasticities for the short run (–1.4266 vs. .4803) and the long run (–.8379 vs. .4128), it is clear that competitive pricing has a substantial effect on own brand sales. This is what we may expect in mature markets.[8]

Both the short-term (β = .0012, p < .05) and the long-term (β = .0086, p < .01) cross brand advertising elasticities are positive and significant. Thus, competitive advertising has a positive effect on own brand sales. Schultz and Wittink (1976) distinguish three advertising effects: primary sales effect (in which a brand's advertising increases own sales without affecting competitive sales), primary demand effect (in which advertising increases own brand sales and those of its competitors), and competitive advertising (in which advertising increases own brand sales and decreases those of its competitors) (see also Hanssens, Parsons, and Schultz 2001, pp. 322–25). They use these effects to analytically derive six "cases of advertising effect" (Schultz and

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[8]In contrast, Steenkamp et al. (2005) documented relatively *few* significant cross brand effects. However, our analysis differs from their study on several dimensions, such as (1) the time span covered (4 years vs. 18 years), (2) the temporal aggregation level (weekly vs. monthly), (3) model specification (impulse-response functions derived from a vector autoregression model vs. specific parameters in an error correction specification), and (4) level of entity aggregation (cross effects from individual brands vs. the cross effect of the combined (share-weighted) competition). Each of these factors can contribute to an observed difference in the obtained cross effects. An in-depth investigation of the relative contribution of each of these factors is beyond the scope of the current study.

Wittink, pp. 72–73). Given that we find that both own brand advertising and cross brand advertising increase sales and that own advertising elasticities are higher than cross elasticities, it appears that across all brands and categories, Schultz and Wittink's (1976) "Case IV" describes the CPG market (at least in the United Kingdom). Case IV occurs if brand advertising positively affects sales of all brands, but has a stronger effect on the own brand.

There is little evidence that the magnitude of the cross elasticities systematically varies across the business cycle, though we acknowledge that the large number (eight) of possible interaction effects may have affected model stability (Cohen et al. 2003). However, we do find a significant effect of contractions on the long-term competitive price elasticity ($\beta = .0360$, $p < .05$), implying that markets become more competitive when the going gets tough (Estelami, Lehmann, and Holden 2001).

Cyclical Sensitivity of Price and Advertising Effectiveness Across Four Types of Brands

Thus far, we have focused on findings aggregated across a large number of brands. These findings provide input for empirical generalizations, which are much valued by marketing academics (Hanssens 2009). However, brand managers (and some marketing academics) may be more interested in findings for specific types of brands. Our model allows for heterogeneity in cyclical sensitivity of price and advertising effectiveness across brands.

To provide insights into the differences between brands, we categorize brands along two managerially relevant

dimensions: their price level and their advertising support. From a median split, we obtain four types of brands: (1) high-advertising, high-price "premium mass brands" (e.g., Coca-Cola); (2) high-advertising, low-price "value mass brands" (e.g., Cif household cleaner); (3) low-advertising, high-price "premium niche brands" (e.g., Yorkshire Tea); and (4) low-advertising, low-price "value niche brands" (e.g., Bic razor blades). To avoid confounding brand and category characteristics, we carried out the median split within each category separately, with "low" < median value and "high" ≥ median value. We briefly discuss key differences between the four types of brands. Because the sample size in each cell is modest and differs between cells, we focus on relative magnitude of effects across the four types of brands rather than on significance levels. Web Appendix B (www.marketingpower.com/jmr_webappendix) reports detailed results, offering insights into which effects are significant and which are insignificant.

We focus on long-term effects to keep the discussion concise and because we have observed that the business cycle primarily affects long-term effectiveness of price and advertising. We again illustrate the effects of the business cycle using the global financial crisis. Figures 4 and 5 show the mean long-term price elasticity and mean long-term advertising elasticity, respectively, for each type of brand just before the crisis hit (labeled "Expansion") versus the trough of the business cycle ("Contraction").

On average, "premium mass brands" have comparatively high price elasticity and substantial advertising elasticity. However, the business cycle works out differently for these

Figure 4
THE EFFECT OF THE GLOBAL FINANCIAL CRISIS: LONG-TERM PRICE ELASTICITY FOR FOUR TYPES OF BRANDS
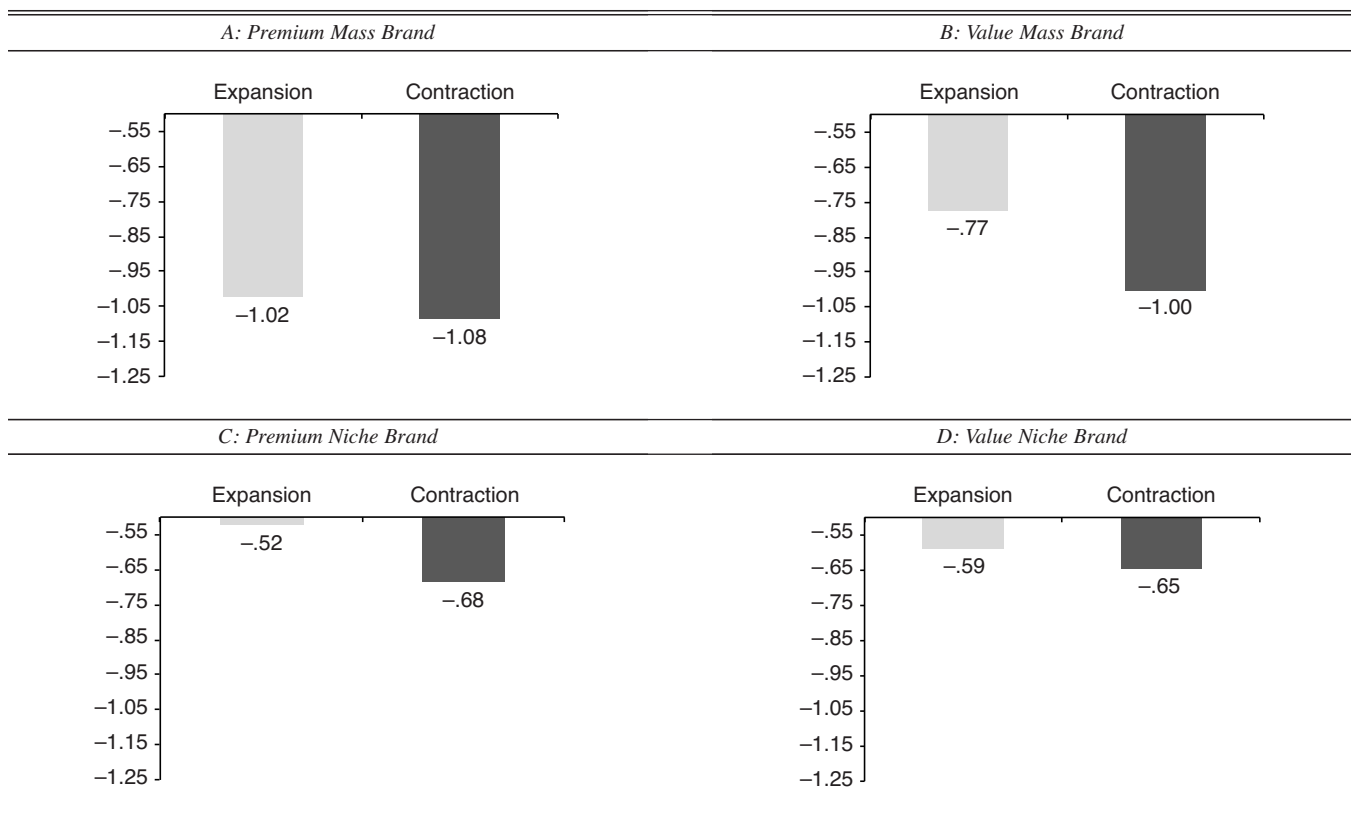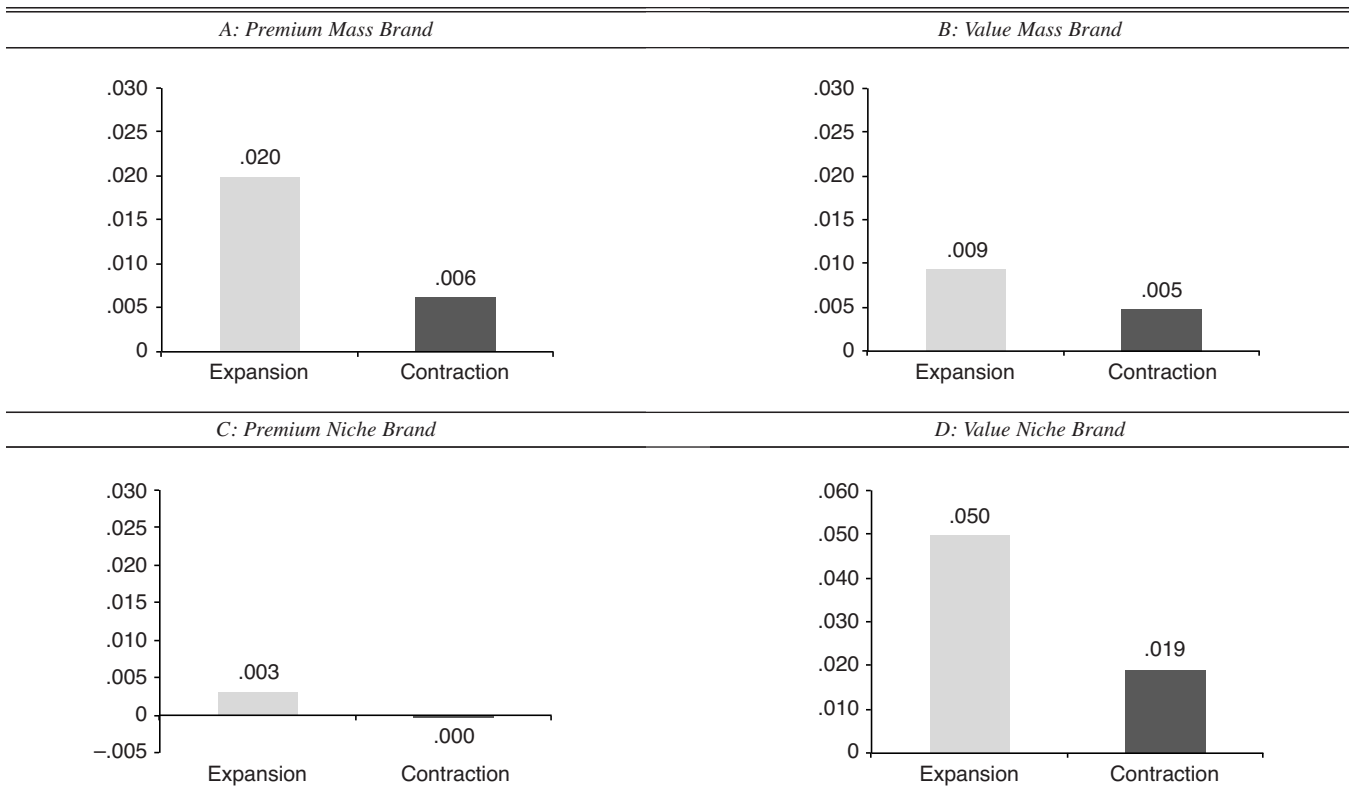
Figure 5
THE EFFECT OF THE GLOBAL FINANCIAL CRISIS: LONG-TERM ADVERTISING ELASTICITY FOR FOUR TYPES OF BRANDS

A: Premium Mass Brand

B: Value Mass Brand

C: Premium Niche Brand

D: Value Niche Brand

two instruments. The direct effect of advertising on sales drops by about two-thirds in a contraction, but notably, price sensitivity hardly increases. Furthermore, premium mass brands are the only class of brands for which advertising substantially reduces the long-term price sensitivity through brand differentiation (β = .0122). Thus, it appears that for this brand type, high advertising buffers the negative price effect that would otherwise hit these mass brands.

Like premium mass brands, "value mass brands" exhibit comparatively high price sensitivity, but unlike the former, advertising does not buffer price sensitivity in contractions. The interaction between price and advertising is negligible, and these brands exhibit the largest absolute increase in price sensitivity in contractions. Figure 4, Panel B, illustrates this: the long-term price elasticity goes from –.7735 at the peak of the expansion to –1.0035 at the bottom of the contraction. Advertising is not particularly effective, and its relative magnitude declines substantially in a contraction. Sales of value mass brands are also much more vulnerable to competitive pricing than premium mass brands (long-term cross price elasticity is .4610 and .2141, respectively). To maintain sales in a contraction, value mass brands will have little alternative but to resort to price competition. This will be a tough battle, because value brand prices are already low.

Niche brands exhibit lower price sensitivity than mass brands. Indeed, they have an advantage in that their downward potential is dampened because some consumers prefer their characteristics no matter what. On the downside, their upward potential is also limited because a lot of people sim-

ply are not interested in the brand proposition. But this is where the similarity between premium niche and value niche brands ends. "Premium niche brands" find it difficult to justify the price premium in an economic decline, with a large percentage increase in price elasticity during contractions (31%, albeit from a lower basis). Moreover, the cross price elasticity increases substantially in contractions (β = .1014). Managers cannot employ advertising to counter price pressure because it essentially has no effect on sales during contractions (see Figure 5, Panel C). However, these brands are still in a better position than value mass brands. Their price sensitivity is lower and their higher price gives them more room to reduce prices in tough times.

Finally, though "value niche brands" do not advertise often, it is rather effective when they do. Advertising effectiveness declines substantially in contractions, but it can still offer an antidote to the negative effects of increased price sensitivity. Regardless of the instrument used, however, additional stress will affect an already-strained bottom line, as either the margin is further reduced (in case of stronger price reduction) or a higher increase in fixed costs (in case of advertising hikes) is called for.

Cyclical Sensitivity of Price and Advertising Effectiveness Across Product Classes

Whereas the cyclical sensitivity of price and advertising effectiveness is important for brand managers, senior managers (typically [vice] presidents) who are responsible for entire business units may be especially interested in the cyclical sensitivity of broad product classes. In this section,

we provide results for four main types of CPG products: (1) food, (2) beverages, (3) household care, and (4) personal care. We again focus on the long-term elasticities. In Figures 6 and 7, we show how the effectiveness of advertising and price changes from the expansion days near the end of 2007 to the trough around mid-2009.

Beverages show the strongest overall impact of the business cycle. Their price sensitivity increases 27% (from –.9483 to –1.2096), and their advertising becomes largely ineffective (–76%, from .0251 to .0059). The decline in advertising effectiveness is not buffered by a moderating effect of advertising on price sensitivity, which is the smallest of all product classes (β = .0004). Furthermore, the long-term cross price elasticity (β = .6668) is higher than in any other product class. The message is clear: in steep contractions, beverage brands need to stay competitive on price. If the goal is to protect brand sales, the person responsible for the beverages division may consider shifting money from advertising to pricing.

The business cycle does not affect *food* brands nearly as much as is does beverage brands. Food brands become somewhat more price sensitive (increasing from –.8786 to –1.0101, a 14% change), but their advertising effectiveness is hardly affected. In this product class, it makes sense to remain price competitive during contractions (after all, the price elasticity is substantial) and to invest in advertising. In bad times, one witnesses a shift from out-of-home to in-home consumption. In the words of investment fund manager Jeff Auxier, "People will eat more meals at home....They do not eat dinner out, but they'll still buy Ben & Jerry's for dessert" (Cendrowski 2012, p. 76). Clearly, in such conditions, advertising helps to keep the brand top-of-mind and to communicate core values.

The business cycle has little effect on the price sensitivity of *household care* brands, but advertising effectiveness is nearly cut in half, although it remains relatively effective. Furthermore, the cross price elasticity is lowest of all product classes (β = .2299). In contractions, companies that are active in multiple product classes (e.g., Unilever, Procter & Gamble) may consider shifting marketing dollars from household care brands to brands in other product classes, particularly food brands, which have higher price and advertising elasticities in contractions, and possibly beverage brands, which need more price support in contractions.

Finally, the price sensitivity of *personal care* brands is relatively low, and the business cycle hardly affects it. In favorable times, the direct effect of advertising on sales is low (see Figure 7, Panel D), but personal care is the only product class in which there is an appreciable interaction between advertising and price (β = .0099). This indicates that by reducing pricing sensitivity, advertising has a secondary effect on sales. In contractions, advertising's direct effect becomes negative. As we discussed previously, Ang, Leong, and Kotler (2000) argue that in contractions, consumers focus less on brands' image aspects (which are relatively more important in personal care) and, moreover, that brands relying heavily on advertising may be viewed as being less sympathetic to the consumer's tight economic situation. This can explain why we find that for personal care brands, advertising can indeed be in danger of becoming counterproductive (note that it still exerts an indirect positive effect through price sensitivity). We further find that the

Figure 6
THE EFFECT OF THE GLOBAL FINANCIAL CRISIS: LONG-TERM PRICE ELASTICITY FOR FOUR PRODUCT CLASSES
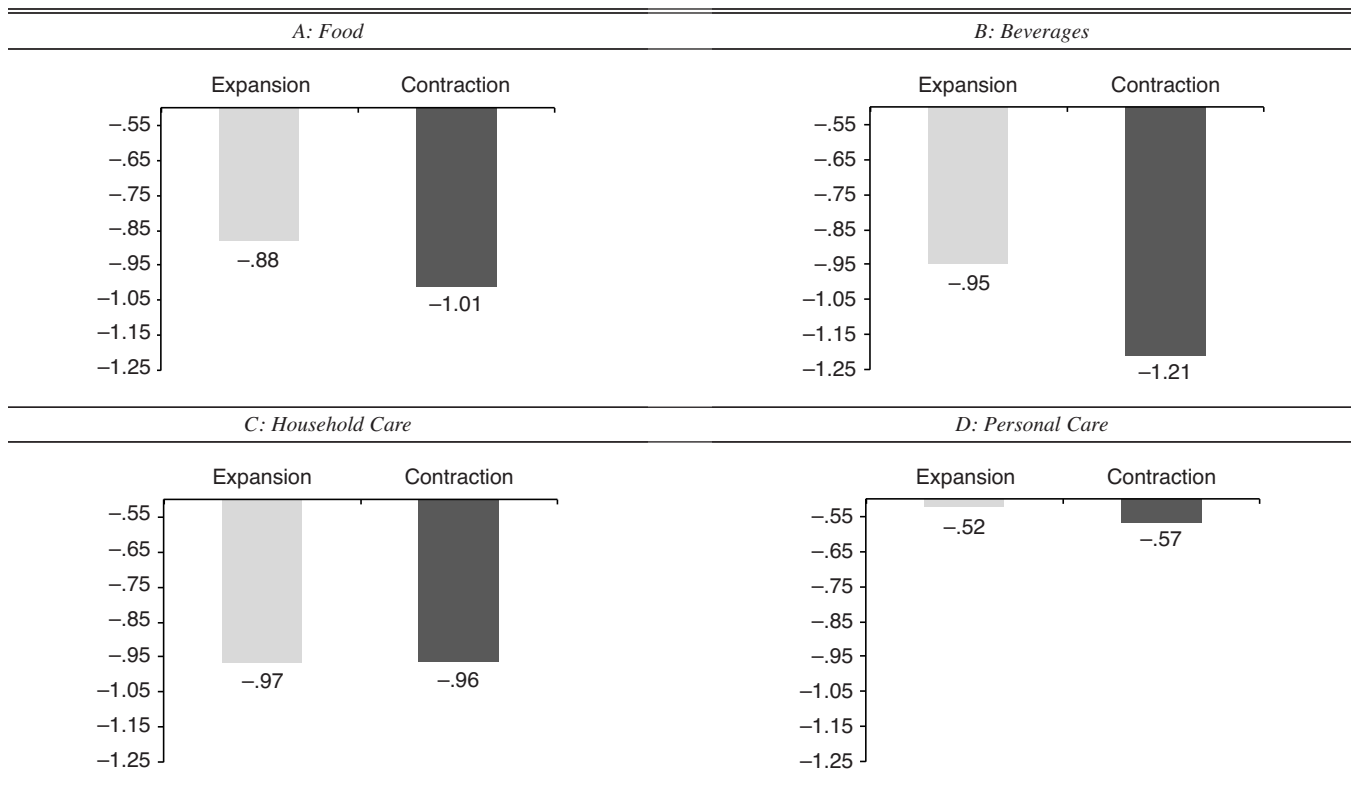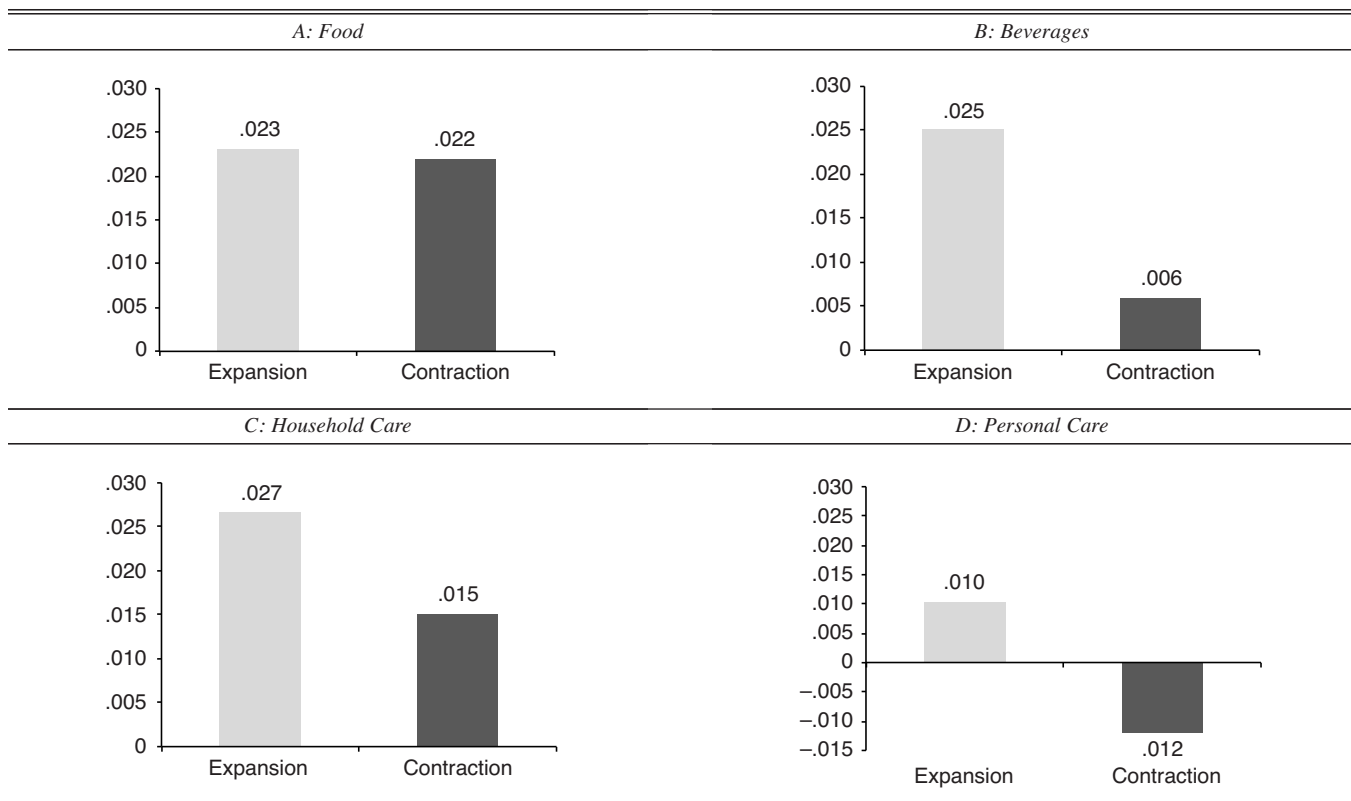
Figure 7
THE EFFECT OF THE GLOBAL FINANCIAL CRISIS: LONG-TERM ADVERTISING ELASTICITY FOR FOUR PRODUCT CLASSES

cross price elasticity strongly increases in economic downturns (.1379). Thus, in contractions, personal care brands might consider cutting back on advertising and reserve money to respond more vigorously to rival pricing moves.

DISCUSSION

Summary

Although marketing effectiveness has been the subject of a wide stream of research, to the best of our knowledge, this is the first study that investigates how general economic conditions may influence the effectiveness of both brand advertising and brand pricing, using a single-source dedicated data set for many brands over a long period of 18 years encompassing multiple expansions and contractions, including the global financial crisis. Our single-source data enable us to use a consistent measurement and modeling scheme across all brands, which eliminates the confounding factors identified by earlier meta-analyses on price and advertising, such as differences in measures, temporal intervals, aggregation, model specification, estimation method, endogeneity, and heterogeneity (Bijmolt, Van Heerde, and Pieters 2005; Sethuraman, Tellis, and Briesch 2011).

We estimate an error correction model that provides both short- and long-term price and advertising elasticities, accommodates potentially asymmetric effects of the business cycle on these elasticities, and allows for heterogeneity between brands. We account for the possible endogeneity of price and advertising decisions by using a 3SLS approach. We investigate the magnitude of short- and long-term price and advertising elasticities, their interaction and evolution

over time, and most pertinently, how price and advertising brand elasticities vary across the business cycle. Furthermore, we examine to what extent the cyclical sensitivity of advertising and price differs for four types of brands (premium mass brands, value mass brands, premium niche brands, and value niche brands) and four product classes (food, beverages, household care, and personal care).

Our findings show that although the short-term price and advertising elasticities do not change with the business cycle, the long-term elasticities do. The long-term price sensitivity decreases during expansions, whereas it increases during economic downturns. Contractions also make the long-term competitive price effects stronger. The long-term advertising elasticity, in turn, becomes stronger during economic expansions. Finally, patterns are not symmetric across contraction and expansion periods and differ systematically between premium mass brands, value mass brands, premium niche brands, and value niche brands as well as across major product classes. We also find that across the 18 years we observed, consumers' short-term price elasticity has gradually grown in magnitude, whereas advertising effectiveness has not declined appreciably.

Managerial Implications

Firms are under increasing pressure to improve both the accountability and the effectiveness of their marketing investments. Our findings can guide managers in choosing strategies when deciding marketing investments to build brand sales across the business cycle. During contractions, managers are under especially close scrutiny as to how they

allocate their budgets over price reductions (by lowering the margins) and advertising. This article offers answers to this quandary. Compared with expansions, during contractions, consumers are less responsive to advertising; at the same time, they react more strongly to price reductions. Application of the Dorfman–Steiner rule (Dorfman and Steiner 1954) leads us to recommend reallocation of budgets from advertising to price discounts in tough times.

However, this recommendation is not without several caveats. First, it is made in the context of maintaining brand sales. Firms can have other objectives, such as maintaining profits or securing shelf space. Second, there is considerable heterogeneity *across* product classes in the cyclical sensitivity of their long-term price and advertising elasticities. For example, advertising elasticity remains comparatively high in contractions for food brands, but not so for beverages. Third, there is also considerable heterogeneity depending on the brand's positioning *within* the category. Premium mass brands, such as Gillette, Kellogg's, or Coca-Cola, present an interesting case. Whereas advertising's direct effect on sales declines dramatically in contractions, advertising has an important indirect effect on sales by reducing price sensitivity. Therefore, in these cases there is less reason to follow a procyclical advertising strategy and lower prices during downturns than for other brands. As such, we identify another way through which advertising may enhance brand performance: it not only increases the willingness to pay (Steenkamp, Van Heerde, and Geyskens 2010) and lowers the price sensitivity (Ataman, Van Heerde, and Mela 2010), it also insulates a brand's marketing effectiveness from the impact of the business cycle (as we illustrate in this study).

We now encounter an important question: how can we reconcile our finding that the long run-advertising elasticity evolves in a procyclical way with observations that companies spending relatively more on advertising during economic downturns have better financial performance (Deleersnyder et al. 2009; Steenkamp and Fang 2011)? We believe the answer lies in the nature of CPG products. We find that, across the board, CPG sales move countercyclically. When the economy is expanding, CPG sales tend to suffer because consumers engage in more out-of-home consumption. Thus, while the long-term advertising elasticity moves procyclically relative to the overall economy, it moves in a countercyclical way compared with CPG sales. Therefore, an expansion means relatively bad times for CPG sales, and it is then that advertising becomes more effective in the long run. This is consistent with the idea that spending during hard times (for the focal industry) is beneficial.

Our results show that economic downturns should not necessarily be detrimental for CPG companies, given the insignificant effect of contractions on base sales. The Boston Consulting Group provides additional evidence for these findings, noting that 58% of companies that were among the top three in their industry had rising profits in 2008, and only 30% saw their profits decline (*The Economist* 2009). Although danger signs are all around during economic downturns, CPG companies should grasp the opportunities they represent as well. In terms of their base sales, CPG companies may be able to capitalize on the positive substitution effect from out-of-home consumption during economic downturns. However, their higher vulnerability to competitive price attacks and the reduced effectiveness of some of their own instruments indicate that economic downturns are no easy ride for those managers. Depending on a company's product class and its relative positioning within that class, opportunities exist to ride the economic tides profitably. Our results help identify which strategic adjustments are more or less opportune for different brands and product classes.

Directions for Further Research

Our study has several limitations that offer opportunities for further research. First, we excluded private labels, because their marketing support is typically governed by very different decision processes than national brands. Even though some retailers have recently begun to advertise their private labels, their ad intensity is minor compared with national brands—if present, it is almost never product specific (Corstjens and Steele 2008; Lamey et al. 2012). However, examining to what extent marketing-mix effectiveness varies over the business cycle for private labels is an interesting avenue for further research, especially given these labels' remarkable and persistent market-share gains during contractions (Lamey et al. 2007).

Second, we based our analyses on relatively mature CPG categories. Such products are characterized by very small advertising elasticities. Conversely, we expect less mature categories to show stronger advertising sensitivity (Allenby and Hanssens 2004). In addition, this sensitivity may also vary more with the overall economic sentiment. Future studies could include such products. In addition, new products are known to have higher advertising effectiveness. Because we focused on major brands that had been in the market for a long time, the question remains whether economic downturns equally affect more recent brands.

Third, the products in our data set are mainly everyday consumables, purchases that cannot really be postponed until the economy recovers. This is not the case for durables: consumers can and do wait to purchase until economic conditions improve and uncertainty diminishes (Deleersnyder et al. 2004). This could result in even stronger business-cycle influences on marketing-mix effectiveness. Therefore, we call for a deeper investigation into this issue.

Finally, given the nature of our data, we estimated an aggregate response model. Although it would be difficult to obtain individual-level data from a representative panel across multiple business cycles, estimating brand-choice models in the tradition of Seetharaman, Ainslie, and Chintagunta (1999) is likely to result in additional insights. Indeed, this would enable studying how consumers (segments) react differently, in terms of changes in their advertising and price responsiveness, to changing economic conditions.

In summary, this study provides insights on the evolution of price and advertising effectiveness across the business cycle over a large set of CPG brands. We hope that this research inspire additional studies that will help brand managers to better ride the economic tides.

REFERENCES

Advertising Age (2011), "Advertising Spending," (December 19), (accessed January 21, 2013), [available at http://adage.coverleaf.com/advertisingage/20111219?pg=4#pg4].

Allenby, Greg M. and Dominique M. Hanssens (2004), "Advertising Response," MSI Special Report 05-200a. Cambridge, MA: Marketing Science Institute.

Ang, Swee H., Siew M. Leong, and Philip Kotler (2000), "The Asian Apocalypse: Crisis Marketing for Consumers and Businesses," *Long Range Planning*, 33 (1), 97–119.

Angrist, Joshua D. and Jörn-Steffen Pischke (2009), *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton, NJ: Princeton University Press.

Ataman, M. Berk, Harald J. van Heerde, and Carl F. Mela (2010), "The Long-Term Effect of Marketing Strategy on Brand Sales," *Journal of Marketing Research,* 47 (October), 866–82.

Beaudry, Paul and Gary Koop (1993), "Do Recessions Permanently Change Output?" *Journal of Monetary Economics*, 31 (2), 149–63.

Bijmolt, Tammo H.A., Harald J. van Heerde, and Rik G.M. Pieters (2005), "New Empirical Generalizations on the Determinants of Price Elasticity," *Journal of Marketing Research*, 42 (May), 141–56.

Boulding, William, Eunkyu Lee, and Richard Staelin (1994), "Mastering the Mix: Do Advertising, Promotion, and Sales Force Activities Lead to Differentiation?" *Journal of Marketing Research*, 31 (May), 159–72.

Cendrowski, Scott (2012), "Bet on the Brands," *Fortune*, (July 2), 73–76.

Chib, Siddhartha and Edward Greenberg (1995), "Hierarchical Analysis of SUR Models with Extensions to Correlated Serial Errors and Time-Varying Parameter Models," *Journal of Econometrics*, 68 (2), 339–60.

Christen, Markus, Sachin Gupta, John C. Porter, Richard Staelin, and Dick Wittink (1997), "Using Market-Level Data to Understand Promotion Effects in a Nonlinear Model," *Journal of Marketing Research*, 34 (August), 322–34.

Christiano, Lawrence J. and Terry J. Fitzgerald (2003), "The Band Pass Filter," *International Economic Review*, 44 (2), 435–65.

Cohen, Jacob, Patricia Cohen, Stephen G. West, and Leona S. Aiken (2003), *Applied Multiple Regression/Correlation Analysis for the Behavioral Sciences*, 3d ed. Mahwah, NJ: Lawrence Erlbaum Associates.

Corstjens, Marcel and Richard Steele (2008), "An International Empirical Analysis of the Performance of Manufacturers and Retailers," *Journal of Retailing and Consumer Services*, 15 (3), 224–36.

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 (1995a), "Empirical Generalizations About Market Evolution and Stationarity," *Marketing Science*, 14 (3), G109–121.

——— and ——— (1995b), "The Persistence of Marketing Effects on Sales," *Marketing Science*, 14 (1), 1–21.

——— and ——— (1999), "Sustained Spending and Persistent Response: A New Look at Long-Term Marketing Profitability," *Journal of Marketing Research*, 36 (November), 397–412.

Deleersnyder, Barbara, Geyskens Inge, Katrijn Gielens, and Marnik G. Dekimpe (2002), "How Cannibalistic Is the Internet Channel? A Study of the Newspaper Industry in the United Kingdom and the Netherlands," *International Journal of Research in Marketing*, 19 (4), 337–48.

———, 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.

———, ———, 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.

Dorfman, Robert and Peter O. Steiner (1954), "Optimal Advertising and Optimal Quality," *American Economic Review*, 44 (5), 826–36.

Drake, Isobel (2009), "Food Retail Sales Fall but Restaurants Get a Boost," *Australian Food News*, (September 9), (accessed September 9, 2009), [available at http://www.ausfoodnews.com.au/2009/09/09/food-retail-sales-fall-but-restaurants-get-a-boost.html].

Du, Rex Y. and Wagner A. Kamakura (2008), "Where Did All That Money Go? Understanding How Consumers Allocate Their Consumption Budget," *Journal of Marketing*, 72 (November), 109–131.

The Economist (2009), "Thriving on Adversity," (October 3), (accessed January 21, 2012), [available at http://www.economist.com/node/14540023].

Estelami, Hooman, Donald R. Lehmann, and Alfred C. Holden (2001), "Macro-Economic Determinants of Consumer Price Knowledge: A Meta-Analysis of Four Decades of Research," *International Journal of Research in Marketing*, 18 (4), 341–55.

Fok, Dennis, Csilla Horváth, Richard Paap, and Philip Hans Franses (2006), "A Hierarchical Bayes Error Correction Model to Explain Dynamic Effects of Price Changes," *Journal of Marketing Research,* 43 (August), 443–62.

Frankenberger, Kristina D. and Roger G. Graham (2003), "Should Firms Increase Advertising Expenditures During Recessions?" MSI Working Paper 03-115. Cambridge, MA: Marketing Science Institute.

Franses, Philip Hans (2001), "How to Deal with Intercept and Trend in Practical Cointegration Analysis," *Applied Economics*, 33 (5), 577–79.

Gicheva, Dora, Justine S. Hastings, and Sofia B. Villas-Boas (2008), "Revisiting the Income Effect: Gasoline Prices and Grocery Purchases," CUDARE Working Paper 1044R, University of California, Berkeley.

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 (February), 4–23.

Greene, William H. (2000), *Econometric Analysis*. Upper Saddle River, NJ: Prentice Hall.

Hanssens, Dominique M., ed. (2009), *Empirical Generalizations About Marketing Impact*. Cambridge MA: Marketing Science Institute.

———, Leonard J. Parsons, and Randall L. Schultz (2001), *Market Response Models: Econometric and Time Series Analysis*. Dordrecht, the Netherlands: Kluwer Academic Publishers.

Helm, Burt (2009), "100 Best Global Brands 2009: Turmoil in the Rankings," *Businessweek*, (September 16), (accessed September 28, 2009), [available at http://www.businessweek.com/stories/2009-09-16/turmoil-in-the-rankings].

Kapferer, Jean-Noël (2008), *The New Strategic Brand Management*. London: Kogan Page.

Kaul, Anil and Dick R. Wittink (1995), "Empirical Generalizations About the Impact of Advertising on Price Sensitivity and Price," *Marketing Science*, 14 (3, Part 2), G151–60.

Kontolemis, Zenon G. (1997), "Does Growth Vary over the Business Cycle? Some Evidence from the G7 Countries," *Economica*, 64 (August), 441–60.

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.

———, ———, 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.

Ma, Yu, Kusum L. Ailawadi, Dinesh K. Gauri, and Dhruv Grewal (2011), "An Empirical Investigation of the Impact of Gasoline Prices on Grocery Shopping Behavior," *Journal of Marketing*, 75 (March), 18–35.

Marn, Michael V., Eric V. Roegner, and Craig C. Zawada (2003), "The Power of Pricing," *McKinsey Quarterly*, 39 (1), 26–40.

McKinsey & Company (2009), "The Crisis: A New Era in Management," *McKinsey Quarterly*, 45 (1), 1–156.

Mela, Carl F., Sunil Gupta, and Kamel Jedidi (1998), "Assessing Long-Term Promotional Influences on Market Structure," *International Journal of Research in Marketing*, 15 (2), 89–107.

——, ——, 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.

——, Kamel Jedidi, and Douglas Bowman (1998), "The Long-Term Impact of Promotions on Consumer Stockpiling Behavior," *Journal of Marketing Research*, 35 (May), 250–62.

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.

Mitra, Anusree and John G. Lynch (1995), "Toward a Reconciliation of Market Power and Information Theories of Advertising Effects on Price Elasticity," *Journal of Consumer Research*, 21 (4), 644–59.

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.

Nilsson, Ronny and Gyorgy Gyomai (2011), "Cycle Extraction: A Comparison of the Phase-Average Trend Method, the Hodrick-Prescott and Christiano-Fitzgerald Filters," Organisation for Economic Co-operation and Development, (accessed December 10, 2012), [available at http://www.oecd.org/std/leadingindicatorsandtendencysurveys/41520591.pdf].

Parekh, Rupal (2009), "When Will This End?" *Advertising Age*, (February 16), (accessed February 22, 2009), [available at http://adage.com/article/news/p-g-unilever-colgate-coke-a-b-cutting-budgets/134634/].

Pauwels, Koen, Jorge Silva-Risso, Shuba Srinivasan, and Dominique M. Hanssens (2004), "New Products, Sales Promotions, and Firm Value, with Application to the Automobile Industry," *Journal of Marketing*, 68 (October), 142–56.

——, Shuba Srinivasan, and Philip Hans Franses (2007), "When Do Price Thresholds Matter in Retail Categories?" *Marketing Science*, 26 (1), 83–100.

Phillips, Peter C.B. and Pierre Perron (1988), "Testing for a Unit Root in Time Series Regression," *Biometrika*, 75 (2), 335–46.

Powers, Keiko I., Dominique M. Hanssens, Yih-Ing Hser, and M. Douglas Anglin (1991), "Measuring the Long-Term Effects of Public Policy: The Case of Narcotics Use and Property Crime," *Management Science*, 37 (6), 627–44.

Quelch, John A. (2008), "Family First in Tough Marketing Times," *Financial Times*, (February 17), (accessed December 17, 2009), [available at http://www.ft.com/cms/s/ab648a44-dbf3-11dc-bc82-0000779fd2ac.html].

Rosenthal, Robert (1991), *Meta-Analytic Procedures for Social Research*. Newbury Park, CA: Sage Publications.

Schultz, Randall L. and Dick R. Wittink (1976), "The Measurement of Industry Advertising Effects," *Journal of Marketing Research*, 13 (February), 71–75.

Seetharaman, P.B., Andrew Ainslie, and Pradeep K. Chintagunta (1999), "Investigating Household State Dependence Effects Across Categories," *Journal of Marketing Research*, 36 (November), 488–500.

Sethuraman, Raj, V. Srinivasan, and Doyle Kim (1999), "Asymmetric and Neighborhood Cross-Price Effects: Some Empirical Generalizations," *Marketing Science*, 18 (1), 23–41.

——, Gerard J. Tellis, and Richard A. Briesch (2011), "How Well Does Advertising Work? Generalizations from Meta-Analysis of Brand Advertising Elasticities," *Journal of Marketing Research*, 48 (June), 457–71.

Siems, Thomas M. (2012), "Branding the Great Recession," *Financial Insights*, Federal Reserve Bank of Dallas, 1 (1), 1–3.

Srinivasan, Raji, Arvind Rangaswamy, and Gary L. Lilien (2005), "Turning Adversity into Advantage: Does Proactive Marketing during a Recession Pay Off?" *International Journal of Research in Marketing*, 22 (2), 109–125.

Srinivasan, Shuba, Koen Pauwels, Jorge Silva-Risso, and Dominique M. Hanssens (2009), "Product Innovations, Advertising, and Stock Returns," *Journal of Marketing*, 73 (January), 24–43.

——, Marc Vanhuele, and Koen Pauwels (2010), "Mind-Set Metrics in Market Response Models: An Integrative Approach," *Journal of Marketing Research*, 47 (August), 672–84.

Steenkamp, Jan-Benedict E.M. and Martijn G. de Jong (2010), "A Global Investigation into the Constellation of Consumer Attitudes Toward Global and Local Products," *Journal of Marketing*, 74 (November), 18–40.

—— 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.

——, Vincent R. Nijs, Dominique M. Hanssens, and Marnik G. Dekimpe (2005), "Competitive Reactions to Advertising and Promotion Attacks," *Marketing Science*, 24 (1), 35–54.

——, Harald J. van Heerde, and Inge Geyskens (2010), "What Makes Consumers Willing to Pay a Price Premium for National Brands over Private Labels?" *Journal of Marketing Research*, 47 (December), 1011–24.

Stock, James H. and Mark W. Watson (1999), "Business Cycle Fluctuations in US Macroeconomic Time Series," in *Handbook of Macroeconomics*, John B. Taylor and Michael Woodford, eds. Amsterdam: Elsevier Science BV, 3–64.

Stoolmiller, Mike (1994), "Antisocial Behavior, Delinquent Peer Association, and Unsupervised Wandering for Boys: Growth and Change from Childhood to Early Adolescence," *Multivariate Behavioral Research*, 29 (3), 263–88.

Tellis, Gerard J. (1988), "The Price Elasticity of Selective Demand: A Meta-Analysis of Econometric Models of Sales," *Journal of Marketing Research,* 25 (November), 331–41.

Van Heerde, Harald J., Kristiaan Helsen, and Marnik G. Dekimpe (2007), "The Impact of a Product-Harm Crisis on Marketing Effectiveness," *Marketing Science*, 26 (2), 230–45.

——, Shuba Srinivasan, and Marnik G. Dekimpe (2010), "Estimating Cannibalization Rates for a Pioneering Innovation," *Marketing Science*, 29 (6), 1024–39.

The Wall Street Journal Europe (2009), "U.K. Supermarkets Find Value in Crisis," (August 10), 1.

Wooldridge, Jeffrey M. (2002), *Econometric Analysis of Cross Section and Panel Data*, Cambridge: Massachusetts Institute of Technology Press.