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PRICE AND ADVERTISING EFFECTIVENESS OVER THE BUSINESS CYCLE

Abstract

Firms are under increasing pressure to justify their marketing expenditures. This evolution towards greater accountability is reinforced in harsh economic times when marketing budgets are among the first to be reconsidered. Such decisions require information whether, and to what extent, marketing's *effectiveness* varies with the economic tide. However, there is surprisingly little research that addresses this issue. Therefore, we conduct a systematic investigation on the impact of the business cycle on the effectiveness of two important marketing instruments, price and advertising. To do so, we estimate time-varying short- and long-run advertising and price elasticities for 150 brands, across 36 CPG categories, based on 18 years of monthly U.K. data covering 1993-2010. The long-run price sensitivity tends to decrease during economic expansions, while long-run advertising elasticities increase. During contractions, the long-run own- and cross-price elasticities increase. Moreover, across the observation period, the short-run price elasticity has become significantly stronger. Finally, patterns are not the same across categories and brands, which offers opportunities for firms that know how to ride the economic tide.

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

During economic downturns, managers feel the urge to make changes to their marketing mix. Indeed, in a survey among 1,400 managers, 96% indicated to have made changes in the wake of the Global Financial Crisis (*McKinsey* 2009). One of the most common actions is to reduce 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 U.S. -15.8%) (*Advertising Age* 2011), while Marn, Roegner and Zawada (2003) 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 managers' response 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 the question *whether*, *in what direction*, and *how much* the effectiveness of key marketing instruments such as advertising and price is affected by economic conditions. This is an unfortunate state of affairs as knowledge about marketing 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-run 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 UK, across 36 consumer packaged goods (CPG) categories. The single-source data allow 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 et al. 2005, Sethuraman et al. 2011).

PREVIOUS RESEARCH ON BUSINESS CYCLES

In recent years, the link between marketing phenomena and macro-economic fluctuations has received increasing attention. Deleersnyder et al. (2004) study the evolution in the sales of

consumer durables during expansions and contractions, while Lamey et al. (2007) document the effect of the business cycle on the evolution in 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 et al. (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 started to study the implications of pro- versus counter-cyclical 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 pro-cyclically show poorer stock-price performance than companies that set their advertising investments independent of business cycles. Srinivasan et al. (2005) document that firms that rate high on the latent construct of "proactive marketing response in a recession" report a 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, they were all conducted 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 in making their decisions. Especially in firms that are "a house of brands," like most CPG companies (Kapferer 2008), aggregate, firm-level results may be less relevant as the competitive battle is fought at the level of each individual brand. 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). While Steenkamp and Fang (2011) also consider firm market share, this measure is an aggregate across different industries (SIC codes) in which the company is active.

Moreover, the aforementioned studies focus on advertising. While 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 et al. 2005; Sethuraman et al. 2011). This highlights that pricing decisions are arguably even more important for brand performance than advertising decisions.

Gordon, Goldfarb, and Li (2012) analyze how price elasticities vary with the state of the economy based on six years of IRI panel data. They find that the price sensitivity rises when the economy weakens. Their price elasticity measures the current-period (short-run) effect, which leaves open the question what happens to the long-run price elasticity. Also, this study does not look at how the short- and long-run 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 fairly short, both in terms of the number of ups and downs in the economy and in terms of the magnitude of these changes. They also 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*, *short-* as well as *long-run*, evolve over the *business cycle*.   To do so, we employ a dataset 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

The focus of our study is on the effect of the business cycle on the short- and long-run effectiveness of own-brand advertising and price on brand sales. Prior 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, respectively. This also applies to consumers' motivational orientations (Millet et al. 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.

While the primary focus of our paper is on the moderating effect of the business cycle on the brand's own-price and advertising effectiveness, we also consider three other managerially important issues. We investigate whether the effectiveness of advertising or price systematically declines or increases with the passage of time. Further, we examine whether a brand's price elasticity is systematically moderated by its advertising. Third, we will also consider 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.

-- Insert Figure 1 about here --

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, Bijmolt et al. (2005), based on a meta-analysis of 1,851 elasticities, report an average price elasticity of -2.62 (standard deviation 2.21). The latter authors have also documented 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 prior 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, mostly using a promotional offer. In line with these findings, we expect that the magnitude of the price elasticity increases over time (i.e., becomes more negative).

Role of the business cycle. We predict that during economic downturns, the price elasticity becomes stronger (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 the short-run and the long-run price elasticity (more negative value) during economic downturns, and a decrease in magnitude (less negative value) during economic expansions.

Own-Advertising Effectiveness over the Business Cycle

Own-advertising elasticity. Allenby and Hanssens (2004) review advertising-response research of the last 25 years, and find that short-run advertising elasticities for established products are very small, about .01. A recent meta-analysis by Sethuraman et al. (2011) finds a mean long-run elasticity across 402 observations of .24, with 40% of these elasticities between 0 and .1. Srinivasan, Vanhuele, and Pauwels (2010) report an average long-run advertising elasticity of .036 across 74 brands in 4 CPG categories. Sethuraman et al. (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 et al. 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 firms to be noticed by their customers. Also, 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 one's advertising dollars during a contraction.

Conversely, it has been argued that during contractions, consumers become more price conscious and generally tend to ignore image-based advertising (Sethuraman et al. 2011, p. 460). Moreover, in contractions, brands relying heavily on advertising may be seen 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 as opposed to good times.

The net effect of these processes on advertising's short- and long-run sales elasticity is not clear a priori. It is possible that they cancel each other out. This may explain why Sethuraman et al. (2011) find no evidence that advertising elasticity is lower in recessions. On the other hand, 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 need to also consider the sales impact of their *absolute* spending levels. In so doing, not only the *share* of the market captured by their brand matters, but also the *size* of that market, which may shrink/expand considerably because of changes in the economic climate.

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Interaction between Own-Advertising and Own-Price

Over and above the direct effects of advertising on brand sales, it is possible that advertising affects sales through its effect on price sensitivity (e.g., Ataman et al. 2010). There are two alternative predictions. 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 advertising typically consists of brand-differentiating messages, emphasizing non-price 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 et al. 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 our paper, the discussion so far has focused on own effects, i.e., a brand's own price and advertising elasticities. However, to accurately estimate own effects, 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 not only increases own price sensitivity, but also the sensitivity of the focal brand sales to the prices of its competitor (Estelami et al. 2001). As for the cross-advertising effect, a contraction may either lead to 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 consumer packaged goods (CPG) categories in the United Kingdom for 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, 150 national brands were included.[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 covers many well-known household names.

We obtained price information on the 150 brands from Kantar Worldpanel UK, and acquired information on their monthly advertising expenditure from NielsenMedia UK. All marketing-mix series are inflation-adjusted using the UK Consumer Price Index, which was obtained from the OECD.

We use data on real GDP as a proxy for the general economic activity. The cyclical component of the GDP-series has been shown to be a good indicator of the overall economic cycle (Stock and Watson 1999). We obtained GDP data, expressed in constant prices, from the OECD. 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.

-- Insert Table 1 about here --

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[1] The maximum number of brands to be considered in 36*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. Further, of these brands, 13 did not meet the minimum advertising frequency, which leaves us with 150 brands.

METHODOLOGY

Given our research objectives, our modeling approach should address a number of issues. First, our model should provide short- and long-run advertising and price elasticities. Second, it should allow for interactions between these elasticities and the state of the economy. Third, as consumers may react differently to economic contractions and expansions, asymmetric effects should be allowed for. Fourth, as it is unlikely that all brands will be affected in the same way by expansions and contractions, the response parameters should be allowed to vary across brands. Fifth, we need to allow for possible error correlations between brands from the same product category. Sixth, we need to account for possible endogeneity of price and advertising decisions.

Below, we formulate an error-correction model that addresses these six challenges.[2] Before we do that, 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 first have to capture the business cycle itself. To do so, we adopt the Christiano-Fitzgerald (2003) random-walk filter. The CF filter is a band-pass filter built on the same principles as the Baxter and King (BK) filter used in Deleersnyder et al. (2004). However, unlike the BK filter which loses a number of observations at the end of the series, the CF filter is designed to use the entire time series (and thus also uses the information on 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

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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 very large number of 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 (HP) filter (which is a high-pass filter) used in some 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). Band-pass filters can be designed to pass through all components of the time series with a periodicity between 6 and 32 quarters. The HP 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. While 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 (see Deleersnyder et al. 2004, p. 357 for a more in-depth discussion).

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 (see Pauwels et al. 2004 and Srinivasan et al. 2009 for similar practice).[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-run 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 UK economy in 2006 and 2007, followed by the Global Financial Crisis that hit the UK in 2008.[5]

-- Insert Figure 2 about here --

We categorize periods with an increase in the cyclical component as expansions, whereas periods with a decrease are categorized as contractions (Lamey et al. 2007; 2012; Steenkamp and Fang 2011; see also Kontolemis 1997). In Figure 2, white zones represent expansions, grey zones 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 where the month-on-month growth turned from negative to positive.

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[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 (see Stock and Watson 1999 or Lamey et al. 2012 for a detailed discussion).

[5] For a correct assessment of the last peak/trough preceding the 1993-2010 analysis period, the CF filter was applied to a data series including several years before the start of 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 governmental agencies as the NBER Business Cycle Dating Committee (for the U.S). However, their judgment-based procedure has been criticized for a lack of statistical foundation, and for their 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.

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 where the month-on-month growth turned from positive to negative). The peaks and troughs also determine the transition points between the grey and white bars in Figure 2. Formally, we define:

(1)   Expansion$_t$
$$\begin{cases} = \text{gdpc}_t^{\,c} - (\text{prior trough in gdpc}^{\,c}) & \text{if } \Delta\text{gdpc}_t^{\,c} > 0 \\ = 0 & \text{if } \Delta\text{gdpc}_t^{\,c} \leq 0 \end{cases}$$

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 zero values during downturns, whereas Contraction$_t$ takes positive values during downturns and zero during periods of growth. Stronger growth will result in higher values for Expansion$_t$ while 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. Lamey et al. 2012 and Kontolemis 1997), 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. Also many governmental agencies define the depth of a recession relative to the previous trough (Siems 2012).

Model for Assessing Price and Advertising Effectiveness over the Business Cycle

Prior to 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 ($p < 0.10$) in all but 7 (4.6%) instances based on 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 the Levin, Lin and Chu (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. The combined evidence of these tests therefore 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-run effects of advertising and price on brand sales, we adopt the parsimonious error-correction specification (see e.g., Fok et al. 2006; Pauwels et al. 2007; Van Heerde et al. 2007, 2010 for recent marketing applications). For exposition purposes, we start with a model with main effects only, and we later add interactions with the business cycle:

$$
\begin{aligned}
(2) \quad \Delta\ln\text{Sales}_t^{cb} = {} & \beta_0^{cb} + \beta_1^{cb}\Delta\ln\text{Price}_t^{cb} + \beta_2^{cb}\Delta\ln\text{Advertising}_t^{cb} + \\
& \beta_3^{cb}\Delta\ln\text{CompPrice}_t^{cb} + \beta_4^{cb}\Delta\ln\text{CompAdvertising}_t^{cb} + \\
& + \varphi^{cb}\left[\begin{array}{l} \ln\text{Sales}_{t-1}^{cb} - \beta_5^{cb}\ln\text{Price}_{t-1}^{cb} - \beta_6^{cb}\ln\text{Advertising}_{t-1}^{cb} \\ - \beta_7^{cb}\ln\text{CompPrice}_{t-1}^{cb} - \beta_8^{cb}\ln\text{CompAdvertising}_{t-1}^{cb} - \beta_9^{cb}*\text{trend} \end{array} \right] + \varepsilon_t^{cb}
\end{aligned}
$$

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 actions by competing brands 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-run (=same period) own price elasticity, β_2^{cb} the short-run own advertising elasticity, β_3^{cb} the short-run cross-price elasticity, and β_4^{cb} the short-run cross-advertising elasticity; their long-run counterparts (= same period plus future periods) are

β_5^{cb}, β_6^{cb}, β_7^{cb}, and β_8^{cb}, respectively. This long-run impact reflects the cumulative impact of a one-period shock to, respectively, advertising or price. We refer to Fok et al. (2006) for an in-depth discussion of the error-correction model. 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; see also Franses 2001 for a discussion on the role of this trend variable in error-correction specifications). The trend variable runs from -1 in the first observation to +1 in the last. This allows us to interpret the main effect of the elasticity to hold for the middle observation (where the trend variable equals zero) 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 the trend is defined like this or, more traditionally, as running from 1 to T. See Stoolmiller (1994) for a discussion of the interpretational advantages of different coding schemes for trends. The parameter φ^{cb} reflects the speed of adjustment toward the underlying (long-run) equilibrium (Dekimpe and Hanssens 1999, Powers et al. 1991).

Equation (3) expands (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:

$$
\begin{aligned}
(3) \quad \Delta \ln Sales_t^{cb} = {} & \beta_0^{cb} + \beta_1^{cb} Expansion_t + \beta_2^{cb} Contraction_t + \\
& \beta_3^{cb} \Delta \ln Price_t^{cb} + \beta_4^{cb} \Delta \ln Price_t^{cb} * Expansion_t + \beta_5^{cb} \Delta \ln Price_t^{cb} * Contraction_t + \\
& \beta_6^{cb} \Delta \ln Advertising_t^{cb} + \beta_7^{cb} \Delta \ln Advertising_t^{cb} * Expansion_t + \beta_8^{cb} \Delta \ln Advertising_t^{cb} * Contraction_t + \\
& \beta_9^{cb} \Delta \ln CompPrice_t^{cb} + \beta_{10}^{cb} \Delta \ln CompAdvertising_t^{cb} + \\
& + \varphi^{cb} \left[\begin{array}{l} \ln Sales_{t-1}^{cb} - \beta_{11}^{cb} \ln Price_{t-1}^{cb} - \beta_{12}^{cb} \ln Price_{t-1}^{cb} * Expansion_t - \beta_{13}^{cb} \ln Price_{t-1}^{cb} * Contraction_t + \\ + \beta_{14}^{cb} \ln Advertising_{t-1}^{cb} + \beta_{15}^{cb} \ln Advertising_{t-1}^{cb} * Expansion_t + \beta_{16}^{cb} \ln Advertising_{t-1}^{cb} * Contraction_t \\ - \beta_{17}^{cb} \ln CompPrice_{t-1}^{cb} - \beta_{18}^{cb} \ln CompAdvertising_{t-1}^{cb} - \beta_{19}^{cb} * trend \end{array} \right] + \varepsilon_t^{cb}
\end{aligned}
$$

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-run own elasticities to the Base Model: $\Delta \ln \text{Price}_t^{cb} * \text{trend}$, $\Delta \ln \text{Advertising}_t^{cb} * \text{trend}$, $\ln \text{Price}_{t-1}^{cb} * \text{trend}$, $\ln \text{Advertising}_{t-1}^{cb} * \text{trend}$.

Second, we investigate whether advertising moderates the effect of price by adding both the interaction between short-run own-price and short-run own-advertising ($\Delta \ln \text{Price}_t^{cb} * \Delta \ln \text{Advertising}_t^{cb}$) and the interaction between long-run own-price and long-run own-advertising ($\ln \text{Price}_{t-1}^{cb} * \ln \text{Advertising}_{t-1}^{cb}$) to Equation (3).

Third, we consider whether the effects of short- and long-run 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-run cross-price elasticities, we add $\Delta \ln \text{CompPrice}_t^{cb} * \text{Expansion}_t$ and $\Delta \ln \text{CompPrice}_t^{cb} * \text{Contraction}_t$.

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 et al. 2005; Sethuraman et al. 2011). We account for endogeneity by adopting a three stage least squares approach (3SLS). The endogenous variables are $\Delta \text{lnPrice}_t^{cb}$ and $\Delta \text{lnAdvertising}_t^{cb}$, as well as any of the interactions they are part in. The lagged variables are predetermined.

As instrumental variables, we use lagged price and advertising variables *from other product classes* (not from the brand itself). We distinguish between dairy food, non-dairy 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, non-dairy 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. Similar IVs were recently adopted in Lamey et al. (2012) and Ma et al. (2011), among others. Because we also instrument for the interactions involving the first difference of price and advertising (e.g., $\Delta \text{lnPrice}_t^{cb} * \text{Expansion}_t$), the IVs also include the interactions between the original IVs and Expansion and Contraction (Wooldridge 2002, pp. 121-122). Since we have more IVs than endogenous regressors, our model is overidentified.

We formally test for both the strength (through the Angrist-Pischke (2009) multivariate F statistic) and the validity (through 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

To estimate the models, we use 3SLS, which takes into account errors correlations between brands within each category. For 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., $-\varphi^{cb} * \beta_{11}^{cb}$), from which we can derive the estimate for the parameter of interest (e.g., β_{11}^{cb}). The associated standard error is subsequently derived with the Delta method (Greene, 2000, p. 330-331).

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, β can be interpreted as a reliability-weighted mean, where estimates with higher reliability (lower s.e.) 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 retained only those 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% was $\Delta lnPrice_t^{cb} * trend$. When we test the short-run and long-run interactions between price and advertising, only the long-run interaction is significant: $lnPrice_{t-1}^{cb} * lnAdvertising_{t-1}^{cb}$. Finally, of the eight interactions between the various cross effects and the business cycle, only one is significant: $lnCompPrice_{t-1}^{cb} * Contraction_t$. To avoid overspecifying

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

the model, we only retain these three significant interactions (see Bijmolt et al. 2005 and Steenkamp and De Jong 2010 for a similar approach). We label this the "Extended Model."

RESULTS

Overall Descriptive Findings

Table 2 reports some descriptive statistics on the direction and extent to which brand sales are affected by the business cycle. This sets the stage for our main findings concerning the effect of the business cycle on our model parameters. It compares the average monthly sales during expansions (white areas in Figure 2) versus contractions (grey areas in Figure 2). About the same number of CPG brands experienced a significant increase during a contraction as a significant decrease. This may seem counter-intuitive. However, it is consistent with the finding of Du and Kamakura (2008) that as discretionary income decreases, expenditures for essential categories (e.g., food at home) increase relative to nonessential categories (e.g., food outside the home). Such a positive substitution effect was also documented by Gicheva, Hastings, and Villas-Boas (2008). These authors showed that, following an increase in gasoline prices, consumers substitute away from food-away-from-home and towards 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 (restaurant, hairdresser) consumption to more in-home consumption (Cendrowski 2012; Helm 2009; *The Wall Street Journal Europe* 2009). This favors grocery sales in those categories where such a trading-in strategy is feasible, such as for example, cooking sauces, pasta, stout, and hair conditioners (Table 2). Conversely, restored consumer confidence during economic expansions tends to revive out-of-home consumption, which puts pressure on grocery sales (Drake 2009).

-- Insert Tables 2 and 3 about here --

Main Effects of Price and Advertising

Table 3 reports the parameter estimates, both for the Base Model (Equation (3)) and for the Extended Model. Our discussion will focus on the results of the Extended Model. For parameters where 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-run price elasticity ($\beta = -1.4266$, $p<.01$) and long-run price elasticity ($\beta = -.8379$, $p<.01$), which are in the ballpark of the meta-analysis of Bijmolt et al. (2005) for CPG brands. We also find a significant short-run ($\beta = .0021$, $p<.10$) and long-run advertising elasticity ($\beta = .0127$, $p<.01$), both of which are small, but this is not uncommon in CPG categories (Allenby and Hanssens 2004; Sethuraman et al. 2011; Srinivasan et al. 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-run price and advertising elasticities with the trend. We find no evidence that advertising effectiveness declines over time. While the parameter of both interaction terms is negative, indicating a tendency of declining advertising effectiveness over time, neither of the effects 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 et al. 1997; 1998). The short-run price elasticity is becoming increasingly strong over time (more negative), as implied by the significant interaction effect with the trend term ($\beta = -.5716$, $p<.01$). Since the trend variable runs from -1 to + 1, this means that across the 18 years of data (1993-2010), the magnitude of the short-run price elasticity grew by 1.1432 percentage points. Corroborating evidence can be found by comparing our results with the meta-analysis of

Bijmolt et al. (2005). We find that the annual change rate in the short-run price elasticity equals $2*(-.5716/18) = -.0635$, which is close to the annual change rate of -.04 reported by Bijmolt et al. (2005, p. 146).

Interaction between Own-Advertising and Own-Price Effectiveness

We also examine whether price and advertising interact. Based on 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-run and long-run elasticities, respectively) to the Base Model, we find that both interaction terms have the expected positive sign and the term for the long-run interaction is significant at 10%. However, in the Extended Model, which includes other interaction terms, this interaction effect is no longer significant. Hence, 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 on the values of the two economy variables. $Expansion_t$ ($Contraction_t$) shows an average value of 1.39 (1.45), with a minimum of zero 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, as higher economic growth is associated with increased out-of-home consumption (Du and Kamakura 2008). To validate this finding, we calculated the

correlation between (i) the parameter estimate for the main effect of expansion on the intercept in the model [i.e., model-based evidence], and (ii) 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 (more positive) 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 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

While we find no evidence that the business cycle affects short-run elasticities, we find clear evidence that the business cycle affects the long-run impact of both price and advertising. It appears that it takes a while before the full impact of economic ups and downs make themselves felt. Hence, myopic managers may well under-estimate the full impact of economic contractions and expansions on the effectiveness of their marketing instruments. This is especially pertinent in economically difficult times, where managers are already under more stock-market pressure to reach their (quarterly) targets (Deleersnyder et al. 2009; Steenkamp and Fang 2011), and where there is already less room for mistakes/suboptimal decisions.

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

Advertising elasticities increase significantly during expansions ($\beta = .0017$, $p<.10$), 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 being receptive to image advertising and more able to respond to advertising – Ang et al. 2000; Sethuraman et al. 2011) outweigh the negative forces (e.g., more clutter during expansions – Danaher et al. 2008). Finally, advertising effectiveness is lower in bad economic times, though not significantly.

To get a sense for the magnitude of the cyclical swings in adverting and price elasticity, let us consider what is arguably the most important business cycle event in the post-World War II world, viz., the Global Financial Crisis, which hit the UK in 2008 (see Figure 2). Figure 3 displays the long-run elasticities evaluated at (i) the top of the peak in the economic cycle in November 2007 (indicated as "Expansion"), versus (ii) at the bottom of the trough (May 2009) of the Global Financial Crisis (indicated as "Contraction"). The differences are substantial. The average long-run price sensitivity increases by 14% (from -.7863 to -.8956), while the advertising effectiveness drops approximately 60% (from .0218 to .0088).

<center>-- Insert Figure 3 about here --</center>

Cross-Brand Effects

What about the sensitivity of own-brand sales to competitive price and advertising activity? While 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 ($\beta = .4803$, $p<.01$), and the long run ($\beta = .4128$, $p<.01$). Both estimates are close to the meta-analytic average cross-price elasticity of .52 in Sethuraman et al. (1999). When we compare the magnitude of own versus cross-price elasticities for the short-run (-1.4266 versus .4803) and the

long-run (-.8379 versus .4128), it is clear that competitive pricing has a very substantial effect on own brand sales. This is what may be expected in mature markets.[8]

Both the short-run cross-brand advertising elasticity ($\beta = .0012$, $p<.05$) and the long-run cross-brand advertising elasticity ($\beta = .0086$, $p<.01$) are positive and significant. Thus, competitive advertising has a positive effect on own-brand sales. Schultz and Wittink (1976) distinguish between three advertising effects – primary sales effect (a brand's advertising increases own sales without affecting competitive sales), primary demand effect (advertising increases own brand sales and that of its competitors), and competitive advertising (advertising increases own brand sales and decreases sales of its competitors) (See also Hanssens et al. 2001, pp. 322-25). They use these effects to analytically derive six "cases of advertising effect" (pp. 72-73). Given that we find that (i) both own-brand advertising and cross-brand advertising increase sales, and (ii) own advertising elasticities are higher than cross-elasticities, it appears that across all brands and categories, the CPG market (at least in the U.K) can be described by their "Case IV". 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, albeit 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 though of contractions on the long-run competitive price elasticity ($\beta = .0360$,

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[8] Interestingly, Steenkamp et al. (2005) documented relatively *few* significant cross-brand effects. However, our analysis differs from that study on a number of dimensions, such as (i) the time span covered (4 years versus 18 years), (ii) the temporal aggregation level (weekly versus monthly), (iii) model specification (impulse-response functions derived from a VAR model versus specific parameters in an error-correction specification), and (iv) level of entity aggregation (cross effects from individual brands versus 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.

p<.05), implying that markets become more competitive when the going gets tough (Estelami et al. 2001).

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

Hitherto, we have focused on findings aggregated across a large number of brands. These findings provide input for empirical generalizations, which are so 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 in the differences between brands, we categorize brands along two managerially relevant dimensions – their price level and their advertising support. Based on 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, the median split was carried out within each category separately, with "low" < median value, and "high" ≥ median value. We will briefly discuss key differences between the four types of brands. Since the sample size in each cell is modest and differs between cells, we will focus on relative magnitude of effects across the four types of brands rather than on significance levels. Online Appendix B reports detailed results, offering insights into which effects are significant and which ones are insignificant.

We focus on long-run effects to keep the discussion concise, and because we have seen that the business cycle primarily affects long-run 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-run price elasticity and mean long-run advertising elasticity, respectively, for each

type of brands just before the Crisis hit (labeled "Expansion") versus the trough of the business cycle ("Contraction").

-- Insert Figures 4 & 5 about here --

Premium mass brands on average have comparatively high price elasticity and substantial advertising elasticity. However, the business cycle works out quite differently for these two instruments. The direct effect of advertising on sales drops by about two-thirds in a contraction, but interestingly, price sensitivity hardly increases. Further, premium mass brands are the only class of brands for which advertising substantially reduces the long-term price sensitivity through brand differentiation ($\beta = .0122$). Thus, it appears that for this type of brands, 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, price sensitivity in contractions is not buffered by advertising. The interaction between price and advertising is negligible and these brands exhibit the largest absolute increase in price sensitivity in contractions. Figure 4B 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-run 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 as prices of value brands are low to begin with.

Niche brands exhibit lower price sensitivity than mass brands. Being a niche brand has the advantage that their downward potential is dampened because some people prefer their characteristics no matter what. On the downside, their upward potential is also limited as a lot of

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people simply 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 contractions, with a large percentage increase in price elasticity in contractions (31%, albeit from a lower basis). Moreover, the cross-price elasticity increases substantially in contractions ($\beta = .1014$). Advertising cannot be employed to counter price pressure, as in contractions advertising essentially has no effect on sales (Figure 5C). 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, while *value niche brands* do not advertise a lot, when they do, it is rather effective. Advertising effectiveness declines substantially in contractions, but still, it can offer an antidote against the negative effects of increased price sensitivity. Irrespective of the instrument used, however, additional stress will be exercised on an already strained bottom line, as either the margin is reduced more (in case of stronger price reduction) or a higher increase in the fixed costs (in case of advertising hikes) is called for.

Cyclical Sensitivity of Price and Advertising Effectiveness across Product Classes

While the cyclical sensitivity of price and advertising effectiveness are important for brand managers, senior managers (typically (Vice-)Presidents) 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: (i) food, (ii) beverages, (iii) household care, and (iv) personal care. We again focus on the long-run elasticities. In Figures 6 & 7, we show how the effectiveness of advertising and price changes from the high-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), while 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). Further, the long-run cross-price elasticity (β = .6668) is higher than in any other product class. The message is clear: in steep contractions, the beverage brand needs 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.

Food brands are not nearly as much affected by the business cycle as beverage brands. They 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, in contractions, it makes sense to remain price competitive (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 communicate core values.

The business cycle has little effect on the price sensitivity of *household-care* brands, but advertising effectiveness nearly halves, although it remains relatively effective. Further, 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, especially food brands, which have higher price and advertising elasticities in contractions and possibly beverages brands that need more price support in contractions.

Finally, the price sensitivity of *personal care* brands is relatively low, and is hardly affected by the business cycle. In favorable times the direct effect of advertising on sales is low (Figure 7D), but personal care is the only product class where there is an appreciable interaction between advertising and price ($\beta = .0099$). This indicates that advertising has a secondary effect on sales, through reducing price sensitivity. In contractions, the direct effect of advertising turns negative. As discussed earlier, Ang et al. (2000) have argued that in contractions, consumers focus less on image aspects of brands (which are relatively more important in personal care), and moreover that brands relying heavily on advertising may be seen 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 cross-price elasticity increases strongly in contractions (.1379). Thus, in contractions, personal care brands might consider cutting back on advertising and reserve money to respond more vigorously to rival pricing moves.

-- Insert Figures 6 & 7 about here --

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 affect the effectiveness of both brand advertising and brand pricing, using a single-source dedicated data set for a large number of brands over a long period of 18 years, encompassing multiple expansions and contractions, including the Global Financial Crisis. Our single-source data allow 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 et al. 2005, Sethuraman et al. 2011).

We estimate an error-correction model that provides both short- and long-run 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 a 3SLS approach. We investigate the magnitude of short- and long-run price and advertising elasticities, their interaction and evolution over time, and most pertinently, how price and advertising brand elasticities vary across the business cycle. Further, 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, value niche brands) and four product classes (food, beverages, household care, personal care).

Our findings show that while the short-run price and advertising elasticities do not change with the business cycle, the long-run elasticities do. The long-run price sensitivity decreases during expansions whereas it increases during economic downturns. Contractions also make the long-run competitive price effects stronger. The long-run 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-run price elasticity has gradually grown in magnitude, while 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 on marketing investments across the business cycle in order to build

brand sales. Especially during contractions, managers are under close scrutiny as to how they allocate their budgets over price reductions (by lowering the margins) and advertising. Some answers to this question can be found in our work. Compared to expansions, during contractions, consumers are less responsive to advertising; at the same time, they react stronger to price reductions. Application of the Dorfman-Steiner (1954) rule leads us to recommend reallocation of budgets from advertising to price discounts in tough times.

However, this recommendation is not without several caveats. First, this recommendation 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-run 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. While the direct effect of advertising on sales declines dramatically in contractions, advertising has an important indirect effect by reducing price sensitivity. Therefore, in these cases there is less reason to follow a pro-cyclical advertising strategy and lower prices during downturns than for other brands. As such, we identify another way through which advertising may enhance brand performance: not only does it increase the willingness to pay (Steenkamp, van Heerde, and Geyskens 2010) and lower the price sensitivity (Ataman et al. 2010), it also insulates a brand's marketing effectiveness from the impact of the business cycle (this study).

An important question is how our finding that the long run-advertising elasticity evolves in a procyclical way can be reconciled 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 counter-cyclically. When the economy is expanding, CPG sales tend to suffer because consumers engage in more out-of-home consumption. Thus, while the long-run advertising elasticity moves procyclically relative to the overall economy, it moves in a countercyclical way compared to CPG sales. So 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 which were among the top three in their industry had rising profits in 2008, and only 30% saw their profits decline (*The Economist* 2009). Although during economic downturns danger signs are all around, 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 the own instruments, indicate that economic downturns are no easy ride either for those managers.   Depending on the product class one is operating in, and depending on the relative positioning within that product class, opportunities exist to profitably ride the economic tides. Our results help identify what strategic adjustments are more or less opportune for different brands and for different product classes.

Directions for Future Research

Our study has several limitations that offer opportunities for future research. First, we exclude private labels, as their marketing support is typically governed by very different decision processes than national brands. Even though some retailers have recently started to advertise their

private labels, the intensity of this is minor compared to national brands, and 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 future research, especially given their remarkable and persistent market-share gains during contractions (Lamey et al. 2007).

Second, our analyses are based on relatively mature CPG categories. Such products are characterized by very small advertising elasticities. Less mature categories, on the other hand, can be expected to show stronger advertising sensitivity (Allenby and Hanssens 2004). In addition, this sensitivity may also vary more with the overall economic sentiment. Future research could include such products. Also, new products are known to have higher advertising effectiveness. While we focused on major brands that had been in the market for a long time, the question remains whether recent brands are equally affected when the economy goes down.

Third, the products in our dataset are mainly every-day consumables. Purchases cannot really be postponed until the economy recovers. This is not the case for durables. Consumers can and do wait until the economic conditions improve and the uncertainty diminishes (Deleersnyder et al. 2004). This could result in even stronger business-cycle effects on marketing-mix effectiveness. A deeper investigation into this issue is hence called for.

Finally, given the nature of our data, we estimated an aggregate response model. While 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 et al. (1999) is likely to result in additional insights. Indeed, this would allow studying how consumers (segments) react differently, in terms of changes in their advertising and price responsiveness, to changing economic conditions.

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

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TABLE 1. DATA COVERAGE

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

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		

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		$\neq 0$	0.0747 ***	2.6715	0.0076	0.0835 **	2.4704	0.0135
Expansion_t	Main effect expansion on sales	$\neq 0$	-0.0103 ***	-4.8699	0.0000	-0.0103***	-4.4726	0.0000
Contraction_t	Main effect contraction on sales	$\neq 0$	0.0004	0.2346	0.8146	-0.0004	-0.0677	0.9460
$\Delta \ln\text{Price}_t^{cb}$	Short-run price elasticity	< 0	-1.4355 ***	-20.9974	0.0000	-1.4266***	-18.4458	0.0000
$\Delta \ln\text{Price}_t^{cb} * \text{Expansion}_t$	Impact of expansion on SR price elasticity	> 0	-0.0284	-0.7907	0.7854	0.0422	1.0014	0.1583
$\Delta \ln\text{Price}_t^{cb} * \text{Contraction}_t$	Impact of contraction on SR price elasticity	< 0	-0.0435 **	-2.0143	0.0220	0.0169	0.6012	0.7262
$\Delta \ln\text{Advertising}_t^{cb}$	Short-run advertising elasticity	> 0	0.0017 *	1.4517	0.0733	0.0021*	1.6015	0.0546
$\Delta \ln\text{Advertising}_t^{cb} * \text{Expansion}_t$	Impact of expansion on SR adv. elasticity	$\neq 0$	0.0006	0.8460	0.3976	0.0004	0.5996	0.5487
$\Delta \ln\text{Advertising}_t^{cb} * \text{Contraction}_t$	Impact of contraction on SR adv. elasticity	$\neq 0$	-0.0003	-0.7113	0.4769	-0.0004	-0.8252	0.4092
$\Delta \ln\text{CompAdvertising}_t^{cb}$	Short-run cross adv. elasticity	$\neq 0$	0.0011 **	2.2799	0.0226	0.0012**	2.4836	0.0130
$\Delta \ln\text{CompPrice}_t^{cb}$	Short-run cross price elasticity	> 0	0.5902 ***	20.2601	0.0000	0.4803***	14.9085	0.0000
$\ln\text{Price}_{t-1}^{cb}$	Long-run price elasticity	< 0	-0.8117 ***	-18.1477	0.0000	-0.8379***	-13.6927	0.0000
$\ln\text{Price}_{t-1}^{cb} * \text{Expansion}_t$	Impact of expansion on LR price elasticity	> 0	0.0072 *	1.3204	0.0934	0.0097*	1.6338	0.0512
$\ln\text{Price}_{t-1}^{cb} * \text{Contraction}_t$	Impact of contraction on LR price elasticity	< 0	-0.0048	-0.9751	0.1647	-0.0084*	-1.4800	0.0694
$\ln\text{Advertising}_{t-1}^{cb}$	Long-run advertising elasticity	> 0	0.0121 ***	6.8236	0.0000	0.0127***	2.4222	0.0077
$\ln\text{Advertising}_{t-1}^{cb} * \text{Expansion}_t$	Impact of expansion on LR advertising elast.	$\neq 0$	0.0018 **	2.1602	0.0308	0.0017*	1.9076	0.0564
$\ln\text{Advertising}_{t-1}^{cb} * \text{Contraction}_t$	Impact of contraction on LR adv. elasticity	$\neq 0$	-0.0003	-0.4485	0.6538	-0.0006	-0.6042	0.5457
$\ln\text{CompAdvertising}_{t-1}^{cb}$	Long-run cross advertising elasticity	$\neq 0$	0.0085 ***	7.0154	0.0000	0.0086***	6.5488	0.0000
$\ln\text{CompPrice}_{t-1}^{cb}$	Long-run cross price elasticity	> 0	0.4569 ***	9.5098	0.0000	0.4128***	7.8211	0.0000
$\ln\text{Sales}_{t-1}^{cb}$	Speed of adjustment parameter	< 0	-0.3905 ***	-72.1529	0.0000	-0.3880***	-66.1678	0.0000
trend	Main effect trend	$\neq 0$	0.1195 ***	11.2935	0.0000	0.1137***	10.0474	0.0000
$\Delta \ln\text{Price}_t^{cb} * \text{trend}$	Impact of trend on SR price elasticity	< 0				-0.5716***	-4.5521	0.0000
$\ln\text{Price}_{t-1}^{cb} * \ln\text{Advertising}_{t-1}^{cb}$	LR Interaction advertising and price	> 0				0.0053	1.0897	0.1380
$\ln\text{CompPrice}_{t-1}^{cb} * \text{Contraction}_t$	Impact of contraction on LR cross price elast.	> 0				0.0360**	1.8148	0.0348

***: $p<.01$;**: $p<0.05$; *: $p<0.10$; p-values are 1-sided for directional hypotheses, and 2-sided otherwise; weight for β is inverse of its standard error, normalized to 1.

FIGURE 1.
RESEARCH FRAMEWORK
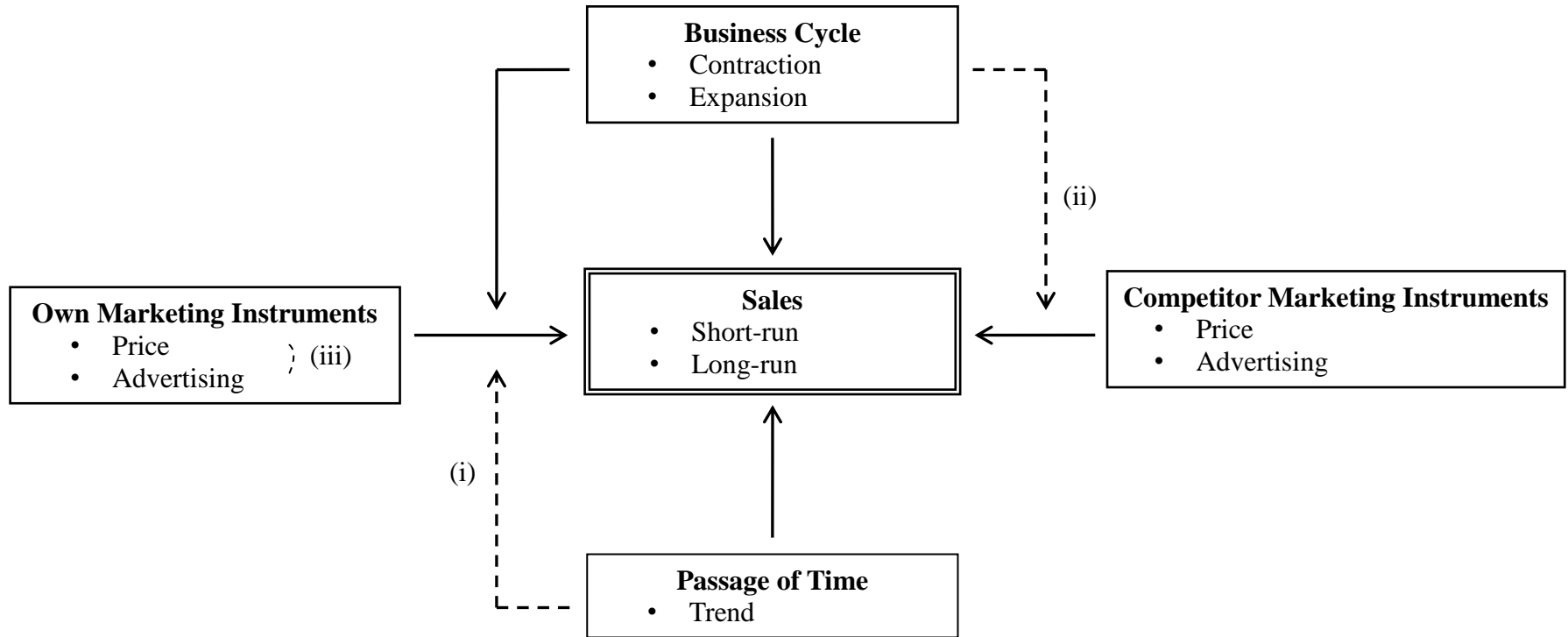
Key:

⟶ Focal Model

- - -> Model Extensions:
       (i) Trend in short- and long-run own elasticities
       (ii) Moderating impact of business cycle on cross-elasticities
       (iii) Interaction between price and advertising

FIGURE 2.
CYCLICAL DEVIATIONS FROM THE LONG-RUN TREND IN THE LOG-TRANSFORMED
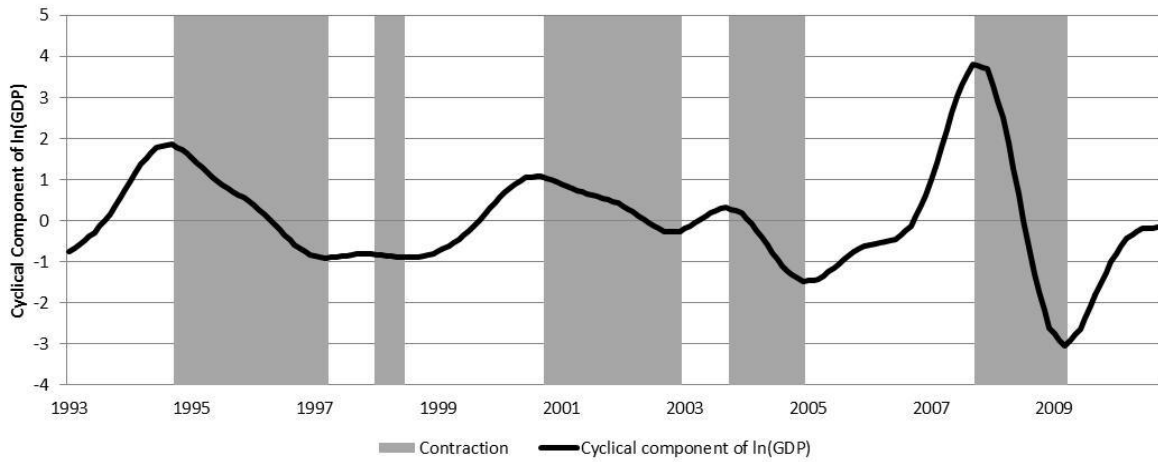GDP SERIES FOR THE UK ECONOMY (1993-2010)

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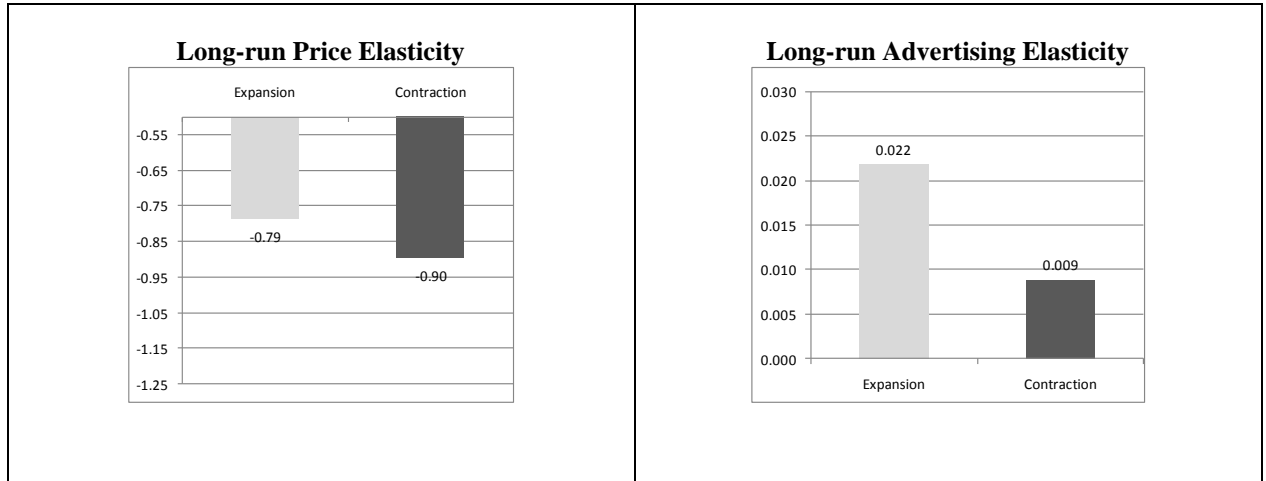ECONOMY AND AT ITS NADIR

FIGURE 4.
THE EFFECT OF THE GLOBAL FINANCIAL CRISIS:
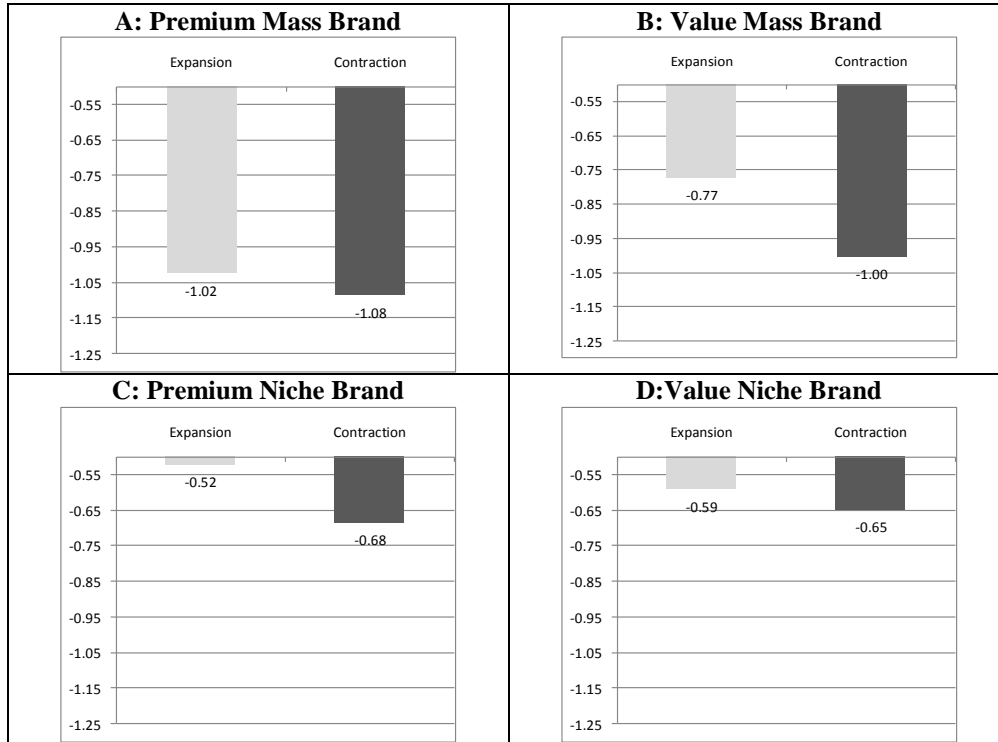LONG-TERM PRICE ELASTICITY FOR FOUR TYPES OF BRANDS

A: Premium Mass Brand — Expansion: -1.02, Contraction: -1.08
B: Value Mass Brand — Expansion: -0.77, Contraction: -1.00
C: Premium Niche Brand — Expansion: -0.52, Contraction: -0.68
D: Value Niche Brand — Expansion: -0.59, Contraction: -0.65

FIGURE 5.
THE EFFECT OF THE GLOBAL FINANCIAL CRISIS:
LONG-TERM ADVERTISING ELASTICITY FOR FOUR TYPES OF BRANDS

A: Premium Mass Brand — Expansion: 0.020, Contraction: 0.006
B: Value Mass Brand — Expansion: 0.009, Contraction: 0.005
C: Premium Niche Brand — Expansion: 0.003, Contraction: 0.000
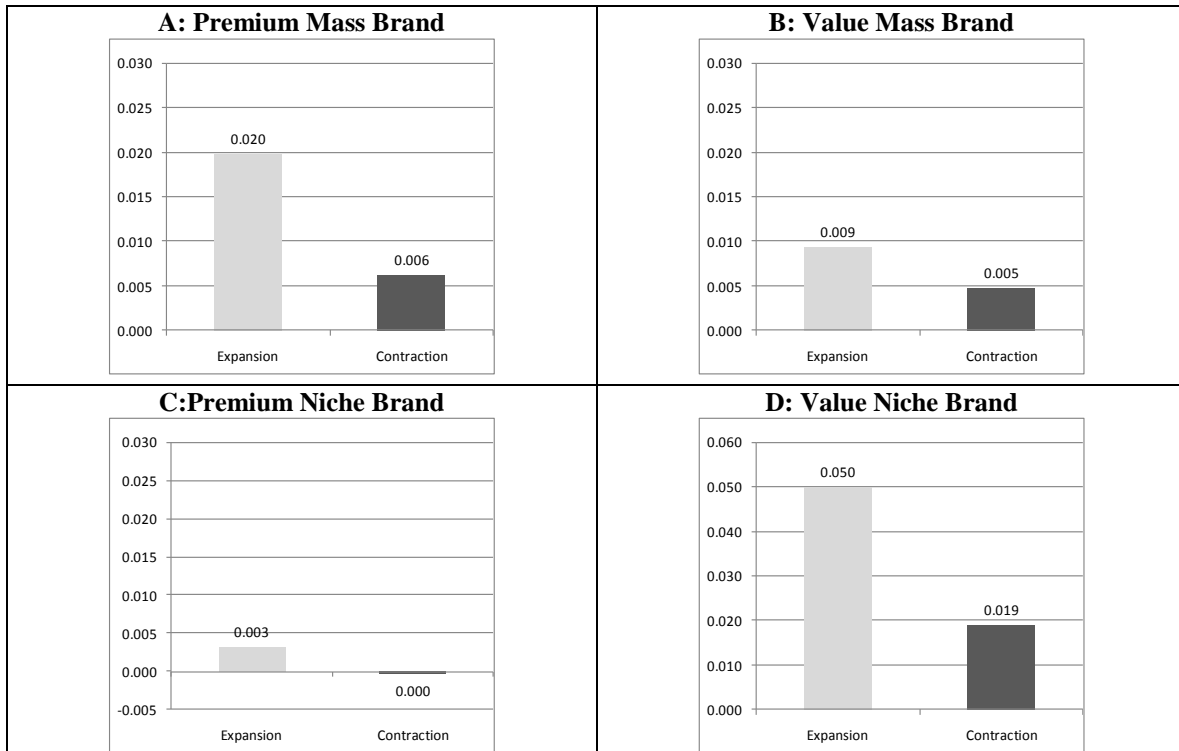D: Value Niche Brand — Expansion: 0.050, Contraction: 0.019

FIGURE 6.
THE EFFECT OF THE GLOBAL FINANCIAL CRISIS:
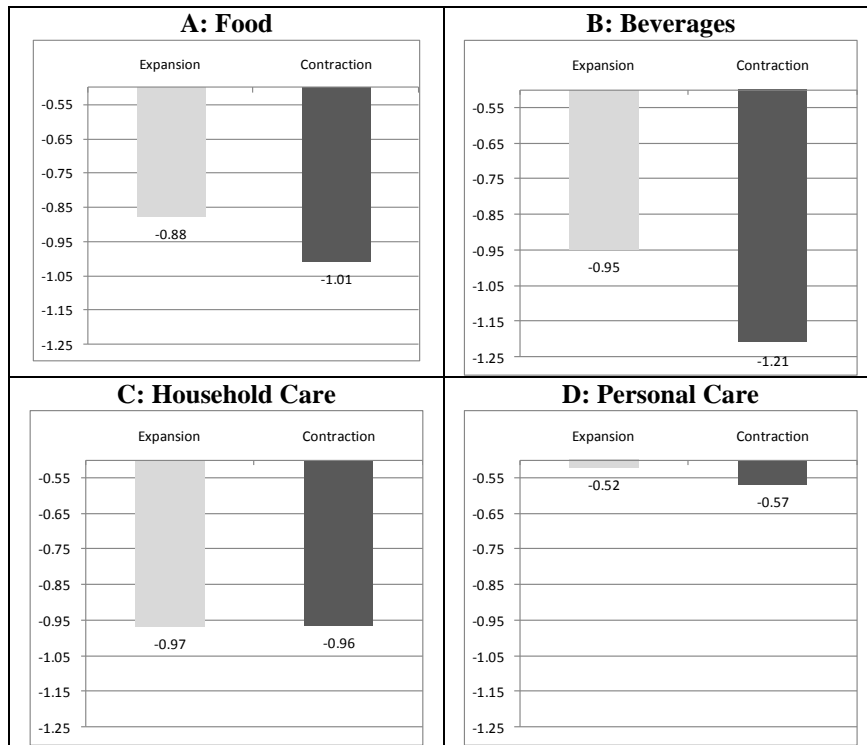LONG-TERM PRICE ELASTICITY FOR FOUR PRODUCT CLASSES

FIGURE 7.
THE EFFECT OF THE GLOBAL FINANCIAL CRISIS:
LONG-TERM ADVERTISING ELASTICITY FOR FOUR PRODUCT CLASSES