Brand Equity in Good and Bad Times:

What Distinguishes Winners from Losers in CPG Industries?

Koushyar Rajavi

Tarun Kushwaha

Jan-Benedict E.M. Steenkamp

Koushyar Rajavi (Email: koushyar.rajavi@scheller.gatech.edu; Voice: 404-894-7773) is an Assistant Professor of Marketing at Scheller College of Business at Georgia Institute of Technology. Tarun Kushwaha (Email: tkushwah@gmu.edu; Voice: 979-422-9710) is Professor of Marketing at School of Business at George Mason University, and Jan-Benedict E.M. Steenkamp (Email: jbs@unc.edu; Voice: 919-962-9579) is C. Knox Massey Distinguished Professor of Marketing at the Kenan-Flagler Business School of the University of North Carolina.

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Abstract

We examine why some brands are able to ride the wave of macroeconomic expansions, while other brands are better able to successfully weather contractions. Using a utility-based framework, we develop hypotheses how the impact of these shocks on brand equity is moderated by six strategic brand factors—price positioning, advertising spending, product line length, distribution breadth, brand architecture, and market position. We utilize monthly data on 325 CPG national brands in 35 categories across 17 years from the United Kingdom to obtain quarterly sales-based brand equity estimates. The two pre-eminent brand factors are distribution and assortment. Distribution is by far the most important factor in contractions. It is also the most important factor in expansions. In short, in good times and bad times, extensively distributed brands win. In expansions, a wide assortment is also a very strong contributor to brand equity, while it does not destroy brand equity in contractions. We further find that advertising spending, premium price positioning, umbrella branding structure, and market leadership matter in either expansions and/or contractions, the magnitude of their effects on brand equity is relatively modest. We conclude with managerial implications.

Keywords: Brand Management, Brand Equity, Sales-Based Brand Equity, Macroeconomic Fluctuations, Brand Positioning, Contractions, Expansions

The ups and downs of macroeconomic cycles provide brand managers with opportunities to grow their brand or insulate it from harm. In economic contractions, consumers have lower disposable incomes and hence face tighter budgets. This makes them more price sensitive (Gordon, Goldfarb, and Li 2013; van Heerde et al. 2013), less brand loyal (Pointer Media Network 2009), and more inclined to shift their purchases to (cheaper) private labels (Lamey et al. 2007, 2012; Scholdra et al. 2022). The opposite effects occur in good times. Consumers change their cross-category consumption behavior across the business cycle (e.g., Deleersnyder et al. 2004; Du and Kamakura 2008), but we know little about how do business cycles affect different brands within a category? Dekimpe and Deleersnyder (2018, p. 54) raise this issue as an important research question: “Are all brands equally affected?” We examine this issue for brand equity, regarded by academics and practitioners alike as a key performance metric of a brand (Aaker 1991; Datta, Ailawadi, and van Heerde 2017; Millward Brown 2017).

There is a rich literature on the effects of various marketing mix instruments on brand equity (e.g., Ailawadi, Lehmann, and Neslin 2003; Sriram, Balachander, and Kalwani 2007; Yoo, Donthu, and Lee 2000). This important work is short-term, tactical in scope. Academics recommend that brand equity be built and maintained for the long run, using the various elements of the marketing mix (Aaker 1991; Lodish and Mela 2007). In this paper we complement previous work by adopting a strategic perspective. Our perspective is that of the firm – and in particular brand management – that uses the marketing mix not only tactically, but also strategically to position the brand vis-à-vis its competitors. We examine six strategic brand factors: price positioning, advertising spending, line length, distribution breadth, brand architecture, and market position.

The purpose of this paper is to examine how brands with different positioning along these six strategic brand factors are more or less able to weather economic shocks. Our research straddles two important research streams—drivers of brand equity and the effects of macroeconomic conditions. Our contribution is twofold. First, we adopt a strategic view on the effect of managerial decisions on brand equity, by focusing on the role of strategic brand factors. Second, we examine how and to what extent the effects of these strategic brand factors differs systematically between expansions and contractions. The context in which we test our hypotheses is consumer packaged goods (CPG) in the United Kingdom. We estimate the effect of business cycles on brand equity of brands with different characteristics utilizing data on 325 CPG national brands in 35 categories across 17 years.

Background Literature

Macroeconomic Fluctuations

There is a rich and growing marketing literature on the effects of macroeconomic fluctuations on marketing-related phenomena. Past research (see Web Appendix A for a summary) shows that macroeconomic fluctuations influence consumers' category preferences (Kamakura and Du 2012), budget allocation (Du and Kamakura 2008), purchase of durable goods (Deleersnyder et al. 2004), shopping frequency, and purchase volume (Ma et al. 2011; Scholdra et al. 2022). They also affect brands' price elasticity (Gordon, Goldfarb, and Li 2013; van Heerde et al. 2013), advertising effectiveness (e.g., Srinivasan, Lilien, and Sridhar 2011; Steenkamp and Fang 2011; van Heerde et al. 2013), R&D effectiveness (Srinivasan, Lilien, and Sridhar 2011; Steenkamp and Fang 2011), and marketing conduct over the macroeconomic fluctuations (Lamey et al. 2012). Consumers switch more frequently to private labels in downturns (Lamey et al. 2007, 2012; Scholdra et al. 2022). For the most part, past research did not focus on examining customers' heterogeneous behaviour across different types of brands and investigating why some brands fare better than others during different economic conditions. We extend this body of research by considering the link between strategic brand factors and brand equity during expansions and contractions.

Brand Equity

A widely used definition of brand equity is the value added by the brand name to a product (Farquhar 1989). The two basic approaches to operationalizing the value added to the products by its brand name are consumer mindset metrics and market outcomes (Datta, Ailawadi, and van Heerde 2017). The first approach is known as consumer-based brand equity (CBBE) and is grounded in metrics such as awareness, attachment, and attitudes towards the brand. The second approach, sales-based brand equity (SBBE), is based on market outcomes that can be attributed to the brand, such as price, volume, or revenue premia (Ailawadi, Lehmann, and Neslin 2003; Datta, Ailawadi, and van Heerde 2017; Sriram, Balachander, and Kalwani 2007). Extant research has shown that SBBE and CBBE are positively related, but that the magnitude of the correlation is modest, around .3 (Datta, Ailawadi, and van Heerde 2017), because what consumers think and feel is far from perfectly aligned with what they actually do (Sheppard, Hartwick, and Warshaw 1988). Our interest is in SBBE, as it is the ability of managers to generate superior market performance that provides the ultimate justification for spending money on branding activities.

Past research has examined the effect of marketing mix activities on SBBE. Ailawadi, Lehmann, and Neslin (2003) and Sririam, Balachander, and Kalwani (2007) found that advertising had a positive effect on brand equity while promotion had no effect. Sriram and colleagues further found that innovation activity increased the equity of toothpaste brands, but not for dish detergent brands. Previous research did not examine the heterogeneity in SBBE across brand characteristics in different economic conditions. We extend research on SBBE by examining how equity of different types of brands are affected during the business cycles.

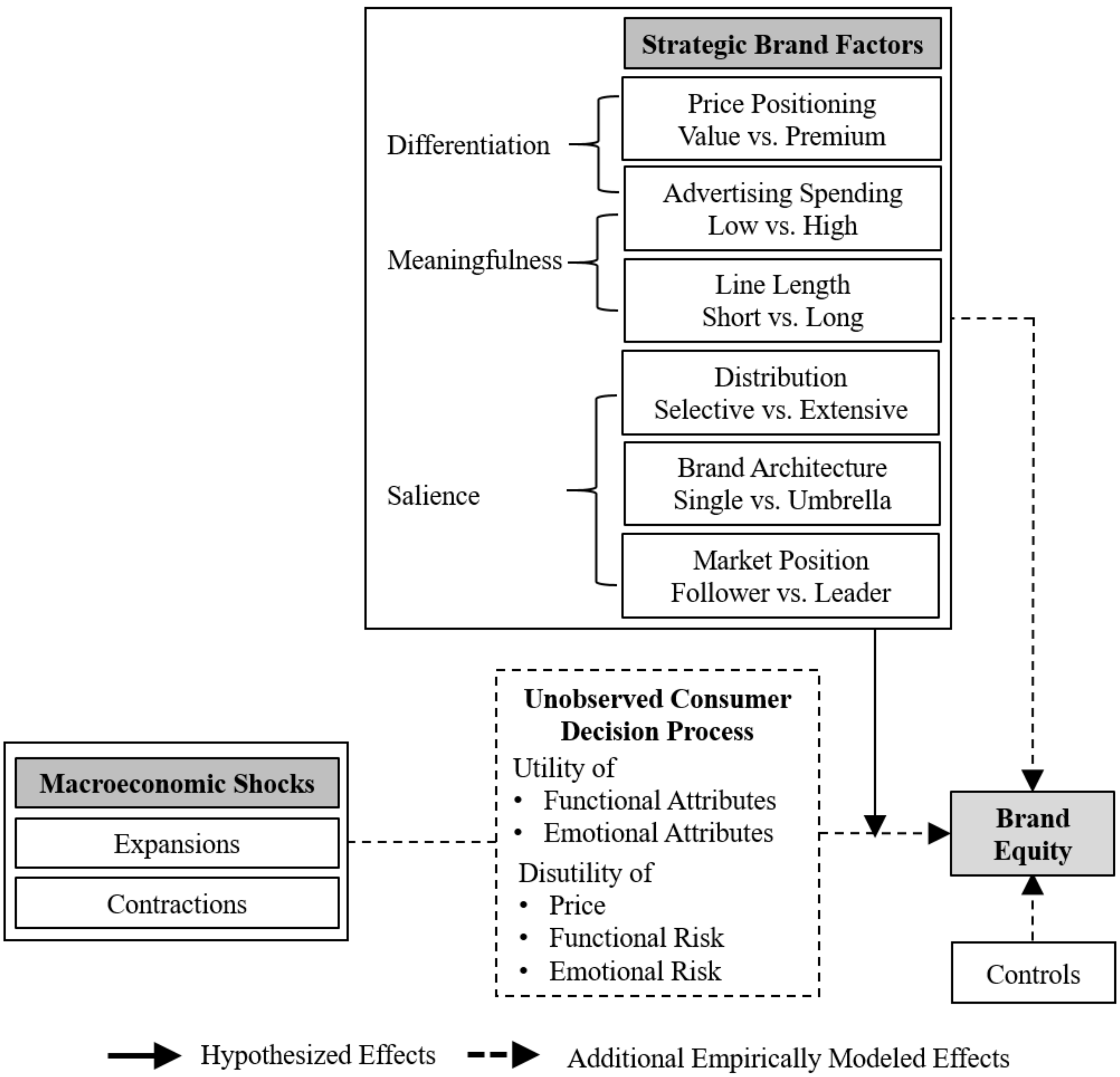
Research Framework and Hypotheses

Overview of Theoretical Framework

Figure 1 presents the research framework that guided our study. In our framework, we include six strategic brand factors: price positioning (value vs. premium), advertising spending (low vs. high), line length (short vs. long), distribution breadth (selective vs. extensive), brand architecture (single-category vs. umbrella-category branding strategy), and market position (follower vs. leader). Strategic brand factors are sticky but not fixed over time. For example, it is possible to change the price positioning of the brand, if desired, but such a change should only be executed gradually. You cannot change a value brand to a premium brand in the short run. The same applies to the other strategic brand factors.

These six factors tap into the three components of brand image as identified by Keller (1993). In Keller's theory of customer-based brand equity, strong brands elicit strong, favorable associations that are unique. Keller's work has inspired various brand consultancies to propose their own branding models. These models share broadly speaking the same components, albeit they use different labels. In our work, we adopt Kantar's BrandZ model because it is closest to Keller's original work. Kantar (2021) identifies three pillars of strong brands– differentiation (akin to Keller's uniqueness), meaningfulness (favorability), and salience (strength). According to Kantar (2021, p. 13), differentiation refers to the brand being distinct from others. Price and advertising are among the key strategic factors contributing to brand differentiation (Mela, Gupta, and Jedidi 1998). Meaningful brands meet people's heterogeneous needs and make people feel emotionally connected to the brand. Line length (multiple SKUs to meet varying consumer needs; Ataman, Mela, and van Heerde 2008) and advertising (to create emotional connections; Aaker 1991) are strategic brand factors that contribute to meaningfulness. Finally, salient brands are brands that come to mind quickly in purchase situations. Distribution and market position contribute to brand salience, as does ubiquity across product categories (umbrella brand) (Bronnenberg, Mahajan, and Vanhonacker 2000; Sharp 2010).

Figure 1: Research Framework



Brand Utility Framework

We examine whether and how the effect of macroeconomic conditions on brand equity plays out differently depending on these six strategic brand factors through the lens of multiattribute decision making under uncertainty and informational constraints (Meyer 1981; Pras and Summers 1978). We draw upon Pras and Summers (1978), Erdem and Keane (1996), and Erdem, Zhao, and Valenzuela (2004) and propose that the utility consumers derive from a brand attribute l (U_l) depends on the brand's perceived score on attribute l (X_l) and the importance of attribute l to consumers (ω_l), as well as the uncertainty about the ability of the brand to deliver attribute l (σ_l), weighed by consumers' tolerance for risk for that attribute l (r_l): $U_l = \omega_l X_l - r_l\sigma_l$.[1] We assume that consumers on average are risk averse (Erdem, Zhao, and Valenzuela 2004; van Ewijk, Gijsbrechts, and Steenkamp 2022), and thus $r_l\sigma_l$ captures the disutility from risk associated with uncertainty in attribute delivery.

We distinguish between functional (tangible) and emotional/self-expressive (intangible) attributes (Aaker 1996; Erdem, Zhao, and Valenzuela 2004; Myers and Shocker 1981). Functional attributes refer are related to the tangible functions performed by the brand. Emotional/self-expressive attributes refer to the intangible feelings the brand provides to consumers and what the consumption of the brand tells others about the kind of person I am. We aggregate across functional and emotional attributes and risks, and include the disutility of price. Thus, the utility brand i provides can be expressed as a function of five elements:

$$U_i = \underbrace{-\alpha P_i}_{\substack{\text{Disutility}\\ \text{of price}}} + \underbrace{\boldsymbol{\omega}_f \boldsymbol{X}_{f,i}}_{\substack{\text{Utility}\\ \text{from}\\ \text{functional}\\ \text{attributes}}} - \underbrace{\boldsymbol{r}_f \boldsymbol{\sigma}_{f,i}}_{\substack{\text{Disutility}\\ \text{from}\\ \text{functional}\\ \text{risk}}} + \underbrace{\boldsymbol{\omega}_e \boldsymbol{X}_{e,i}}_{\substack{\text{Utility}\\ \text{from}\\ \text{emotional}\\ \text{attributes}}} - \underbrace{\boldsymbol{r}_e \boldsymbol{\sigma}_{e,i}}_{\substack{\text{Disutility}\\ \text{from}\\ \text{emotional}\\ \text{risk}}}$$

[1] Our development is for the aggregate consumer; hence we do not have a consumer subscript.

where α is the price sensitivity, $\boldsymbol{\omega}_f$ and $\boldsymbol{\omega}_e$ are the importance attached to functional and emotional attributes, $\boldsymbol{r}_f$ and $\boldsymbol{r}_e$ denote the risk aversion for functional and emotional attributes, $\boldsymbol{X}_{f,i}$ and $\boldsymbol{X}_{e,i}$ represent the vector of brand i's perceived scores on the functional and emotional attributes, respectively, and $\boldsymbol{\sigma}_{f,i}$ and $\boldsymbol{\sigma}_{e,i}$ indicate uncertainty about attribute delivery. We neither claim to break new ground in utility theory nor will we estimate the different components specified in the utility equation. Rather, we use this utility framework as a heuristic for hypotheses development.

We propose that the relative importance of price, functional attributes and risks, and emotional attributes and risks vary across the business cycle (i.e., change in magnitudes of α, $\boldsymbol{\omega}$, and $\boldsymbol{r}$'s during the business cycle). In contractions, with tight budgets, consumers have lower willingness to pay, hence $\alpha_{CON} > \alpha_{EXP}$, and thus the disutility for a given level of price will be greater during contractions (Lamey et al. 2007; van Heerde et al. 2013). During contractions, different motivational orientations are triggered than during expansions (Scholdra et al. 2022). Contractions induce avoidance motivation and negative economic sentiments, while expansions trigger approach motivation and positive economic sentiment (Millet, Lamey, and Van den Bergh 2012). Hedonic attributes which trigger approach motivation are associated with emotional attributes, while utilitarian attributes which trigger avoidance motivation are associated with functional attributes (Higgins 2006; Tamir, Chiu, and Gross 2007). Conversely, in expansions, incomes are on the rise and budgetary restrictions are less tight. Now, the consumer has the opportunity to focus more on relevant emotional attributes (Lamey et al. 2012). Relatedly, Kamakura and Du (2012) find that consumers' share of expenditures on positional goods (i.e., goods that people use to convey their relative standing within society) increases in expansions. This is in line with "hierarchy of needs" (Maslow 1943); with more budgetary restrictions in economic contractions, consumers are expected to prioritize their basic physiological attributes over their social and self-actualization needs (Kamakura and Du 2012). Thus, we expect the utility weights associated with functional attributes and risks to be greater during contractions ($\boldsymbol{\omega}_{f,CON} > \boldsymbol{\omega}_{f,EXP}$ and $\boldsymbol{r}_{f,CON} > \boldsymbol{r}_{f,EXP}$) and those associated with emotional attributes and risks to be greater during expansions ($\boldsymbol{\omega}_{e,EXP} > \boldsymbol{\omega}_{e,CON}$ and $\boldsymbol{r}_{e,EXP} > \boldsymbol{r}_{e,CON}$).

Predictions

We use these insights to develop hypotheses about the role of the six strategic brand factors in moderating the effect of the business cycle on brand equity.

Price Positioning. Following van Heerde et al. (2013), we distinguish between value brands and premium brands. Value brands are lower priced and utilitarian in scope (Steenkamp 2014). They are positioned on tangible attributes, providing high value because they offer reasonable quality for a low price. Premium brands cost more and offer better quality and excel on emotional attributes (Aaker and Joachimsthaler 2000). Premium brands cost more ($P_{PRM} > P_{VAL}$), but are also higher on functional and emotional attributes vis-à-vis value brands ($\boldsymbol{X}_{f,PRM} > \boldsymbol{X}_{f,VAL}$ and $\boldsymbol{X}_{e,PRM} > \boldsymbol{X}_{e,VAL}$; Steenkamp 2014). Premium brands also reduce consumers' purchase risk. Price premium is associated with reduction in uncertainty and greater trust (Ba and Pavlou 2002) and higher incentives to provide consistent quality (Klein and Leffler 1981). Thus, premium brands will have lower functional risk than value brands ($\boldsymbol{\sigma}_{f,PRM} < \boldsymbol{\sigma}_{f,VAL}$). In expansions, emotional considerations gain importance ($\boldsymbol{\omega}_{e,EXP} > \boldsymbol{\omega}_{e,CON}$) (Millet, Lamey, and Van den Bergh 2012), which benefits premium brands. Therefore:

> **$\mathbf{H_{1EXP}}$**: In expansions, premium brands perform better on brand equity than value brands.

In contractions, both price ($\alpha_{CON} > \alpha_{EXP}$; Lamey et al. 2007; van Heerde et al. 2013) and functional utility ($\boldsymbol{\omega}_{f,CON} > \boldsymbol{\omega}_{f,EXP}$) attain greater importance, while functional risk aversion increases as well ($\boldsymbol{r}_{f,CON} > \boldsymbol{r}_{f,EXP}$) (Millet, Lamey, and Van den Bergh 2012). These forces are contradictory. Value brands benefit from lower disutility of price but are hurt by lower functional utility and higher functional risk. Because of the opposing forces, we refrain from proposing a formal hypothesis for price positioning's role in contractions.[2]

Advertising Spending. We distinguish between low and high advertising spender brands. Economists (e.g., Klein and Leffler 1981; Kihlstrom and Riordan 1984) derived analytically that advertising expenditure is positively related to product quality. This confirms the old dictum that it does not make sense to advertise a bad product. Kirmani and Wright (1989) showed empirically that high advertising expenditure is perceived by consumers as an indicator of marketing effort, which is a clue to the marketer's confidence in product quality. Consequently, high advertising spender brands should be perceived by consumers as being higher on functional utility ($\boldsymbol{X}_{f,HI\text{-}AD} > \boldsymbol{X}_{f,LO\text{-}AD}$), which suggests that in contractions, they fare better on brand equity than low advertising spender brands, given that functional attributes weigh more heavily in bad times ($\boldsymbol{\omega}_{f,CON} > \boldsymbol{\omega}_{f,EXP}$). Advertising is a major marketing instrument to imbue a brand with emotions and to communicate the emotional attributes to consumers (Aaker 1996). Thus, we expect that the high advertising spender brands deliver more emotional utility ($\boldsymbol{X}_{e,HI\text{-}AD} > \boldsymbol{X}_{e,LO\text{-}AD}$) and that consumers have a clearer idea about the emotional attributes delivered by high advertising spender brands ($\boldsymbol{\sigma}_{e,HI\text{-}AD} < \boldsymbol{\sigma}_{e,LO\text{-}AD}$). This suggests that in economic expansions, when the emotional attributes ($\boldsymbol{\omega}_{e,EXP} > \boldsymbol{\omega}_{e,CON}$) and disutility from emotional risks are higher ($\boldsymbol{r}_{e,EXP} > \boldsymbol{r}_{e,CON}$), high ad spender brands do better on brand equity than low advertising spender brands.

H2EXP: In expansions, high advertising spender brands perform better on brand equity than low advertising spender brands.

H2CON: In contractions, high advertising spender brands perform better on brand equity than low advertising spender brands.

[2] Web Appendix B reports the impact of each affected component on the utility function.

Line Length. Line length refers to the number of SKUs offered by a brand in a category. The more SKUs a brand carries, the more difficult it is for consumers to accurately gauge their respective qualities. Consumers may be exposed to varieties (e.g., taste) about which they have little idea. In a recent study, van Ewijk, Gijsbrechts, and Steenkamp (2022) document that adding new SKUs has a 'dark side' as it increases consumer uncertainty about quality of the brand. This suggests that longer line length is associated with higher functional risk: $\boldsymbol{\sigma}_{f,LNG} > \boldsymbol{\sigma}_{f,SHR}$. This means that in contractions, when risk aversion is higher ($\boldsymbol{r}_{f,CON} > \boldsymbol{r}_{f,EXP}$), the higher disutility from functional risk disadvantages longer line length brands versus shorter line length brands.

Brands that carry a wider assortment are able to more closely meet the heterogeneous needs of consumers (Nevo 2001) and allow consumers to choose the product that aligns best with their psycho-social values. This is likely to lead increase consumer perceptions of emotional attributes ($\boldsymbol{X}_{e,LNG} > \boldsymbol{X}_{e,SHR}$), which is more highly valued in expansions ($\boldsymbol{\omega}_{e,EXP} > \boldsymbol{\omega}_{e,CON}$), leading to higher emotional utility for brands with a longer line length. Thus, we propose:

$\mathbf{H}_{3\mathbf{EXP}}$: In expansions, brands with longer line length perform better on brand equity than brands with shorter line length.

$\mathbf{H}_{3\mathbf{CON}}$: In contractions, brands with shorter line length perform better on brand equity than brands with longer line length.

Distribution. Wider distribution is a key factor to market success of CPG brands (Ataman, van Heerde, and Mela 2010; Srinivasan, Vanhuele, and Pauwels 2010). Although Klein and Leffler (1981) focus on advertising as brand-specific marketing program investment, their analytical conclusions apply to any kind of observable brand-name expenditures (Milgrom and Roberts 1986, pp. 799-800), including distribution (Rao and Mahi 2003). Consumers interpret a brand's ubiquitous presence as a sign of its consistent performance across different markets.

Extensive distribution costs, associated with high expenditures on slotting allowances, in-store promotion material, and other expensive retail investments would be lost if the brand does not deliver on its promises (Rao and Mahi 2003). Thus, extensively distributed brands score higher on functional attributes than selectively distributed brands ($\boldsymbol{X}_{f,EXT} > \boldsymbol{X}_{f,SEL}$). Additionally, there are more stores where the brand can be bought, which offers opportunities to buy the brand for a lower price, which suggests that the disutility of price is lower for extensively distributed brands ($P_{EXT} < P_{SEL}$). This suggests that extensively distributed brands should perform better in contractions than selectively distributed brands. Extensive distribution further contributes to brand trust (Rajavi, Kushwaha, and Steenkamp 2019), which has been shown to correlate with brand affect (Chaudhuri and Holbrook 2001, p. 89). Brand affect is brand's potential to elicit positive emotional response. This suggests that extensively distributed brands perform better on emotional attributes in the minds of consumers than selectively distributed brands ($\boldsymbol{X}_{e,EXT} > \boldsymbol{X}_{e,SEL}$), and as such, are valued more during expansions. Thus:

> **H$_{4EXP}$**: In expansions, brands with extensive distribution breadth perform better on brand equity than brands with selective distribution breadth.
>
> **H$_{4CON}$**: In contractions, brands with extensive distribution breadth perform better on brand equity than brands with selective distribution breadth.

Brand Architecture. We distinguish between umbrella brands and single-category brands (Erdem 1998; Erdem and Sun 2002). Umbrella branding helps consumers in cross-category learning which helps the umbrella brand in transferring favorable brand associations from one category to another (Erdem and Chang 2012). Firms that adopt umbrella branding have more incentives (vis-à-vis single category brands) to maintain and improve quality of their offerings as they face greater risk of poor-quality attribution (Montgomery and Wernerfelt 1992; Erdem 1998; Miklós-Thal 2012): $\boldsymbol{X}_{f,UMB} > \boldsymbol{X}_{f,SIN}$ and $\boldsymbol{\sigma}_{f,UMB} < \boldsymbol{\sigma}_{f,SIN}$. As functional considerations weigh heavily in contractions, we expect umbrella brands to perform better in bad times than single-category brands. However, umbrella branding strategy also has risks associated with it. Umbrella brands may be forced to adopt a uniform brand positioning strategy across many categories, while relevant emotional associations may differ across categories. This suggests that emotional risks are higher for umbrella brands: $\boldsymbol{\sigma}_{e,UMB} > \boldsymbol{\sigma}_{e,SIN}$. As emotional aspects matter more in expansions (Millet, Lamey, and Van den Bergh 2012), the negative impact of emotional risk will reduce utility for umbrella brands more than single-category brands:

H_{5EXP}: In economic expansions, single-category brands perform better on brand equity than umbrella brands.
H_{5CON}: In economic contractions, umbrella brands perform better on brand equity than single-category brands.

Market Position. Here we distinguish between whether the brand is a leader versus a follower in the category. Aaker (2007, p. 17) maintains that "the most influential exemplars [of leader brands] will be those that are perceived to be superior in terms of quality, performance, and reliability." Market leader brands have greater incentives to maintain higher quality and meet the brand's promise as financial consequences of failure are much larger for them (Milgrom and Roberts 1986): $\boldsymbol{X}_{f,LEA} > \boldsymbol{X}_{f,FOL}$, which benefits leader brands especially in contractions.

What about emotional payoff ? On the one hand, it has been argued that brands with dominant market position might generate more positive emotions because of the bandwagon effect – the pleasure that consumers have from using a product when more people are using it (Hellofs and Jacobson 1999; Edeling and Himme 2018), and the "fitting in" effect that enhances consumers' sense of belonging to a larger social group (van Herpen, Pieters, and Zeelenberg 2009). On the other hand, it has been argued that using popular and well-known brands might decrease consumers' emotional utility because of the loss of exclusivity effect: "consumers feel worse about the product and perhaps even themselves (through loss of image) when the brand they are using is popular" (Hellofs and Jacobson 1999, p. 18). Thus, leading brands may or may not be more favorably perceived on emotional attributes than their follower counterparts. Given the competing theoretical arguments, we refrain from hypothesizing for market position's effect during expansions:

H_{6CON}: In contractions, market leader brands perform better on brand equity than follower brands.

Method

Our empirical strategy consists of two general steps: 1) estimating brand equity using the sales-based brand equity (SBBE) approach, and 2) explaining heterogeneity in the SBBE estimates using strategic brand factors (SBFs) and their interactions with macroeconomic expansions and contractions. Following Datta, Ailawadi, and van Heerde (2017) and Sriram, Balachander, and Kalwani (2007), we operationalize SBBE using the brand intercept method, where, after accounting for marketing mix investments and tangible product characteristics, what is left in the brand intercept is a measure of the ability to leverage the brand to generate sales. In the first step, we follow Datta, Ailawadi, and van Heerde (2017), and estimate quarterly brand intercepts using a model with marketing activities and product attributes of the focal brands, and other control variables as predictors, and brand volume market share as the dependent variable. In Step 2, we use six SBFs (i.e., Price Positioning, Ad Spending, Distribution Breadth, Line Length, Brand Architecture, and Market Position), as well as their interactions with the magnitude of macroeconomic expansions and contractions to explain the variation in the quarterly brand intercepts, i.e., brand equity estimates.[3]

We investigate our hypotheses in the context of CPG categories in the UK. We acquired UK household scanner panel data from Kantar Worldpanel for 35 CPG categories. The monthly

[3] We acknowledge that the estimation can alternatively be done in one stage. However, the shared variance between marketing mix instruments and strategic brand factors is likely to lead to severe collinearity issues.

brand-level data covers 17 years from January-1994 to November-2010 (203 months) and includes information on marketing conduct and performance of national brands in each CPG category. We retained all brands that satisfied the following two conditions: a) non-zero sales in at least 95% of the months during the data window, and b) average monthly volume market share exceeding 0.1%. Our resulting sample consists of 325 national brands. We complement our data with monthly ad expenditures for brands in our sample which we get from Nielsen Media UK.[4]

Step 1: Estimating SBBE

We follow Datta, Ailawadi, and van Heerde (2017) and use market share attraction model (Cooper and Nakanishi 1988) at the monthly level to estimate SBBE at brand-quarter level. We specify a model that allows for heterogeneous brand-specific coefficients (Gielens 2012; Datta, Ailawadi, and van Heerde 2017). Market share of brand *i* in category *j* during month *t* is expressed as the attraction of that brand (A_{ijt}) relative to the aggregate attractions of the I_j brands in category *j* during month *t* (I_j represents number of brands in product category *j*):

$$(1) \qquad MS_{ijt} = \frac{A_{ijt}}{\sum_{k=1}^{I_j} A_{kjt}}$$

where MS_{ijt} is the market share of brand *i* in category *j* during month *t*. We specify attraction of each brand as a function of brand-quarter dummies (i.e., SBBE estimates), marketing mix instruments (advertising stock, regular price, price promotion depth, product line length, and distribution intensity), and product attributes.[5] To control for state dependence in market share, we also include lagged market share as a regressor in the model (Gielens 2012). By including

[4] Our dataset is similar to the data used by van Heerde et al. (2013). Two notable differences are: 1) whereas van Heerde et al. (2013) examine leading national brands (average of 4.1 brands in a category), our analysis covers a broader set of national brands, with an average of 9.3 brands in each category, and 2) we had to drop two product categories (dry soup and peanut butter) because we could only identify two national brands that satisfied our selection criteria and with only two brands it was not possible to estimate the market share attraction model.
[5] We provide category-specific summary of market shares in Web Appendix C, marketing mix instruments in Web Appendix D, and product attributes in Web Appendix E.

Gaussian copulas, we account for potential endogeneity of marketing mix variables that might arise due to unobservables that are not accounted for in our model (Park and Gupta 2012; Datta, Ailawadi, and van Heerde 2017; Datta et al. 2022; Papies, Ebbes, and van Heerde 2017):[6,7]

$$(2) \qquad A_{ijt} = \exp\Big(\sum_{q=1}^{Q} \alpha_{ijq} * DUMQTR_{tq} + \beta_{ij1} lnADSTOCK_{ijt} + \beta_{ij2} lnPRICE_{ijt} + \beta_{ij3} lnPROMO_{ijt} + \beta_{ij4} lnLL_{ijt} + \beta_{ij5} lnDIST_{ijt} + \beta_{ij6} lnMS_{ijt-1} + \sum_{a=1}^{n_j} \gamma_{aij} ATTR_{aijt} + \sum_{c=1}^{5} \delta_{cij} COPULA_{cijt} + \varepsilon_{ijt}\Big)$$

where q denotes quarters and $DUMQTR_{tq}$ represents quarterly dummies and hence its coefficient (α_{ijq}) holds brand- and quarter-specific intercepts. $ADSTOCK_{ijt}$, $PRICE_{ijt}$, $PROMO_{ijt}$, LL_{ijt}, and $DIST_{ijt}$ represent advertising stock, regular price, price promotion depth, product line length, and distribution by brand i in category j during month t, respectively, and $ATTR_{aijt}$ ($a=1\ldots n_j$) represents different product attributes, which are defined separately for each category (see Web Appendix E). Operationalization of the variables used in the first stage are presented in Table 1.[8]

Model Estimation. The attraction model for each product category j can be written as a system of I_j equations that is estimated simultaneously using seemingly unrelated regression (SUR). After substituting Equation (2) into Equation (1), the system of equations can be linearized and normalized by first taking its logarithm, followed by using either of the two approaches discussed by Cooper and Nakanishi (1988): 1) normalizing with respect to a base brand (base-brand approach), or 2) normalizing by centering (log-centering approach). The two approaches are equivalent (Cooper and Nakanishi 1988) and we use the latter. Finally, we

[6] For example, our model does not account for feature/display activity of brands or their slotting allowances. In case such variables that are not observed in our model are correlated with the predictors in the model, if we do not account for endogeneity, our estimates might be biased.

[7] A necessary identification requirement for the Gaussian copula approach is non-normality of the endogenous regressors. Using Shapiro-Wilk tests, normality of all five log-transformed marketing mix instruments were strongly rejected at .01 level, hence allowing us to specify Gaussian copulas.

[8] We tested the stationarity of the variables included in our first-stage model using Levin-Lin-Chu and Fisher-type panel unit root tests. Across both tests, the null of presence of unit root was strongly rejected ($p<.001$).

Table 1: Variables in Step 1

Construct	Var. Name	Operationalization
Volume Market Share	MS_{ijt}	Monthly brand volume market share for brand *i* in category *j* at month *t*.
Brand Attraction	A_{ijt}	Attraction of brand *i* in category *j* in month *t*
Sales-based Brand Equity (SBBE)	α_{ijq}	Brand- and quarter- specific intercepts for brand *i* in category *j* at quarter *q*.
Quarter Dummies	$DUMQTR_{tq}$	Quarterly time indicator which gets a value of 1 if month *t* is in quarter *q* and 0 otherwise.
Advertising Stock	$ADSTOCK_{ijt}$	Advertising stock of brand *i* in category *j* in month *t*, where $ADSTOCK_{ijt} = \lambda_j ADSTOCK_{ijt-1} + (1-\lambda_j)AD_{ijt}$ and AD_{ijt} is monthly advertising expenditures, adjusted by yearly consumer price index in the UK, by brand *i* in category *j* in month *t*. The smoothing parameter (λ_j) is determined separately for each product category based on a grid search on the interval of [0,.9] in increments of .1 (we report smoothing parameters [λ_j] of different categories in Web Appendix F).
Regular Price	$PRICE_{ijt}$	Regular price of brand *i* in category *j* at month *t*, adjusted by yearly consumer price index in the UK. Regular price operationalized based on average price of a brand over a six-month moving window (Gielens 2012).
Price Promotion	$PROMO_{ijt}$	1 – (average paid price by consumers for brand *i* in category *j* in month *t* / regular price of brand *i* in category *j* in month *t*); higher values indicate deeper price discounts offered by the brand.[9]
Product Line Length	LL_{ijt}	the number of stock-keeping units (SKUs) offered by brand *i* in category *j* at month *t*.
Distribution	$DIST_{ijt}$	Percentage of UK retailers that sold brand *i*'s SKUs during month *t*, weighted by retailer's volume market share in the category *j* in month *t*.
Product Attributes	$ATTR_{aijt}$ ($a=1\ldots n_j$)	Fraction of SKUs of brand *i* in category *j* that have a certain product attribute at month *t* of year *y*. Quantity and nature of product attributes vary across the 35 product categories. n_j represents the number of attributes in category *j*; at most 9 attributes are defined for a category. Attributes for different categories are listed in Web Appendix E.
Gaussian Copula Control Functions	$COPULA_{cijt}$ (c=$1\ldots5$)	Five control functions based on the method proposed by Park and Gupta (2012) for the five potentially endogenous marketing mix instruments.

[9] In our data, we only observe paid price. Using Gielens' (2012, p. 412) approach, we decomposed paid price into regular price (average price level of a brand defined over a six-month moving window) and price promotion depth (the same approach has also been used in Geyskens, Gielens, and Gijsbrechts 2010). We thank an anonymous reviewer for this suggestion.

estimate this system of seemingly unrelated equations using Feasible Generalized Least Square:

$$(3) \qquad ln\left(\frac{MS_{ijt}}{\widetilde{MS_{Jt}}}\right) = \sum_{q=1}^{Q}(\alpha'_{ijq}) * DUMQTR_{tq} + \beta_{ij1}(lnADSTOCK_{ijt} - \overline{lnADSTOCK_{Jt}})$$
$$+\beta_{ij2}(lnPRICE_{ijt} - \overline{lnPRICE_{Jt}}) + \beta_{ij3}(lnPROMO_{ijt} - \overline{lnPROMO_{Jt}})$$
$$+\beta_{ij4}(lnLL_{ijt} - \overline{lnLL_{Jt}}) + \beta_{ij5}(lnDIST_{ijt} - \overline{lnDIST_{Jt}})$$
$$+\beta_{ij6}(lnMS_{ijt-1} - \overline{lnMS_{Jt-1}}) + \sum_{a=1}^{n_j}\gamma_{aij}(ATTR_{aijt} - \overline{ATTR_{aJt}})$$
$$+\sum_{c=1}^{5}\delta_{cij}(COPULA_{cijt} - \overline{COPULA_{cJt}}) + \varepsilon'_{ijq}$$ [10]

In the above equation, α'_{ijq} is our brand- and quarter-specific equity estimates that we will use in the second stage (hereinafter, we refer to α'_{ijq} as $SBBE_{ijq}$).[11]

Estimation Results. Table 2 reports the weighted mean marketing mix elasticities across all 325 brands (for category-specific results see Web Appendix F). All elasticities have the expected sign and their meta-analytic Z-statistics (Rosenthal 1991) are significant. We find a small but significant mean advertising elasticity (.0149), close to .0021 in van Heerde et al. (2013). Our mean price elasticity (-.8895) is smaller in magnitude than the -1.4266 reported by van Heerde et al. (2013). However, van Heerde et al.'s (2013) elasticities are based on absolute sales rather than market share.[12] Bijmolt, van Heerde, and Pieters (2005, Table 2) report that price elasticities based on market share are on average .32 smaller in absolute magnitude than price elasticities based on sales. The weighted average price promotion elasticity of .1966 is in line with .146 reported by Srinivasan, Vanhuele, and Pauwels (2010). Mean distribution elasticity of .3392 is consistent with .40 of Datta, Ailawadi, and van Heerde (2017) and .368 of Datta et al. (2022). Finally, our mean elasticity for line length (.6396) is in the range of values (from .348 to 1.511) reported by Jindal et al. (2020) and comparable with .459 reported by Datta et al. (2022).

[10] Our exposition follows Cooper and Nakanishi's (1988) Equation (2.13). $\widetilde{MS_{Jt}}$ is the geometric mean of MS_{Jt}. The bar operator ($\bar{X}$) represents arithmetic mean.
[11] α'_{ijq} is technically $\alpha_{ijq} - \overline{\alpha_{Jq}}$. Thus, our brand- and quarter-specific SBBE estimates are relative to the category's average SBBE. Similarly, ε'_{ijq} is $\varepsilon_{ijq} - \overline{\varepsilon_{Jq}}$.
[12] Our analysis also covers more brands in each product category.

Table 2: Marketing Mix Elasticities Estimates

Marketing Instrument Elasticities	Mean[a]
Brand Advertising (Ad Stock)	.0149**
Brand Regular Price	-.8895***
Brand Price Promotion Depth	.1966***
Brand Line Length	.6396***
Brand Distribution	.3392***

p* <.10; ** *p* <.05; * *p* <.01. [a] Weighted means across 325 brands in 35 categories, with weights being the inverse of the estimated standard errors. Significance tests are based on meta-analytic Z-values.

We illustrate quarterly SBBE estimates for some brands across four product categories (Figure 2). As it can be seen, Mr Muscle, Lavazza, and Wilkinson are consistently valuable brands in the UK. Some brands (e.g., Sensodyne) have experienced considerable growth over years, while other brands have declined over time (e.g., Ajax, Mentadent), and others remained fairly stable (e.g., Douwe Egberts, Cif). We report category-specific statistics on SBBE scores in Web Appendix G.

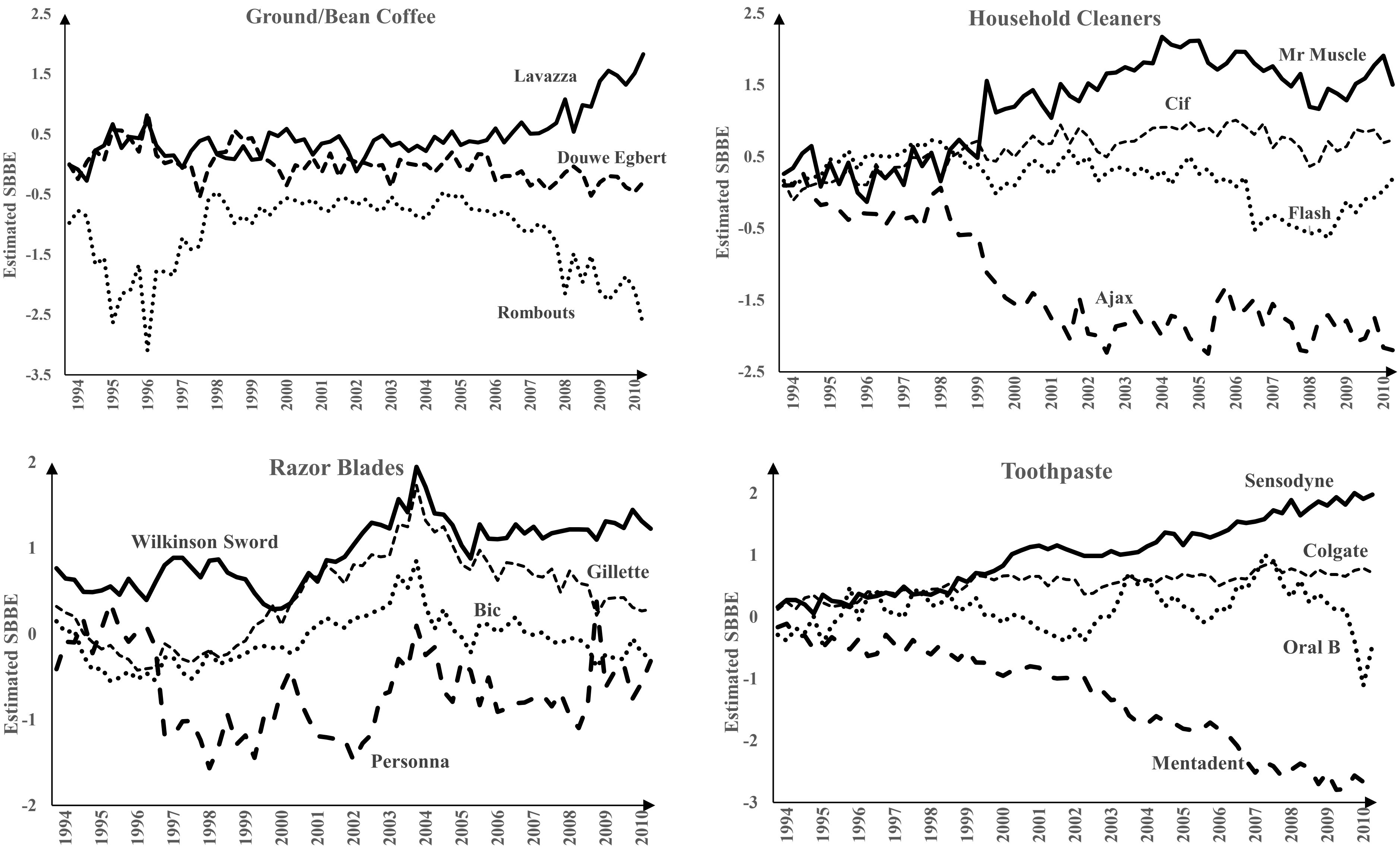
Step 2: Explaining the Dynamics of Brand Equity

Operationalizing Business Cycles. We use quarterly data on inflation-adjusted gross domestic product per capita (GDPPC) from UK's Office for National Statistics to extract macroeconomic fluctuations. We follow past research (e.g., Lamey et al. 2007, 2012) and adopt time-series filtering to extract the cyclical component of (log-transformed) macroeconomic fluctuations ($lnGDPPC_q^{cyc}$; see Web Appendix H for details). Following van Heerde et al. (2013), we use $lnGDPPC_q^{cyc}$ and define the magnitude of expansions (contractions) as the difference between the actual level of the cyclical component of the macroeconomic fluctuations at quarter q and the prior trough (peak):

$$(4)\quad EXP_q = \begin{cases} lnGDPPC_q^{cyc} - \left(prior\ trough\ in\ lnGDPPC_q^{cyc}\right) & ;if\ \Delta lnGDPPC_q^{cyc} > 0 \\ 0 & ;if\ \Delta lnGDPPC_q^{cyc} \leq 0 \end{cases}$$

$$(5)\quad CON_q = \begin{cases} 0 & ;if\ \Delta lnGDPPC_q^{cyc} > 0 \\ \left(prior\ peak\ in\ lnGDPPC_q^{cyc}\right) - lnGDPPC_q^{cyc} & ;if\ \Delta lnGDPPC_q^{cyc} \leq 0 \end{cases}$$

Figure 2: Sales-Based Brand Equity Estimates in Four Product Categories



* To avoid overcrowding the plots, we focus on a sample of 3-4 brands in each category.

EXP_q (CON_q) takes positive values during economic upturns (downturns) and 0 during downturns (upturns). This operationalization allows us to capture the magnitude of expansions and slowdowns, with the value of EXP_q (CON_q) capturing the *percentage* improvement (decline) in the economy during expansions (contractions).

Model Specification. To examine how different strategic brand factors help (or hurt) brands during expansions and contractions, we use the following model:

$$(6) \quad SBBE_{ijq} = \alpha_0 + \alpha_1 SBBE_{ijq-1} + \sum_{m=2}^{m=7} \alpha_m SBF_{ijq}^k + \alpha_8 EXP_q + \sum_{m=9}^{m=14} \alpha_m EXP_q * SBF_{ijq}^k$$
$$+ \alpha_{15} CON_q + \sum_{m=16}^{m=21} \alpha_m CON_q * SBF_{ijq}^k + \sum_{m=22}^{m=26} \alpha_m CONTROLS_{ijq}^l$$
$$+ \sum_1^B \tau_b\, BRAND_b + \sum_1^Q \delta_q\, QUARTER_q + \sum_1^Y \gamma_y\, YEAR_y + \varepsilon_{ijq}$$ [13]

where *i* represents brands, *j* represents categories, and *q* represents quarters. We include lagged brand equity ($SBBE_{ijq-1}$) as an independent variable to allow for inertia in brand equity (Sriram, Balachander, and Kalwani 2007). SBF_{ijq}^k (*k=1…6*) represents the six strategic brand factors: Price Positioning (value vs. premium; $PRICE_{ijq}$), Ad Spending (low vs. high; AD_{ijq}), Line Length (short vs. long; LL_{ijq}), Distribution Breadth (selective vs. extensive; $DIST_{ijq}$), Brand Architecture (single- vs. umbrella-category branding; $ARCH_{ij}$), and Market Position (follower vs. leader; POS_{ijq}). The operationalization for the six SBFs, five control ($CONTROLS_{ijq}^l$, *l= 1…5*)*,* as well as other variables used in Step 2 are presented in Table 3. In operationalizing the first four SBF variables we use marketing mix activities of brands in the four quarters preceding the current time period. Using a four-quarter rolling window increases the stability of our measures across time, which is consistent with the nature of strategic factors, as they are unlikely to be transient in the near term. The temporal separation also reduces endogeneity concerns as brand managers

[13] We tested the stationarity of the dependent variable using different panel unit root tests. Across all of the tests, the null of presence of unit root was strongly rejected ($p<.001$).

Table 3: Variables Used in Step 2

Construct	Var. Name	Operationalization
Sales-Based Brand Equity	$SBBE_{ijq}$	Estimated portion of quarterly brand volume market share that is not explained by its marketing activities, product attributes, and other control variables in the first stage.
Expansion	EXP_q	Magnitude of expansion as the difference between cyclical GDP per capita and the prior trough.
Contraction	CON_q	Magnitude of contraction as the difference between cyclical GDP per capita and the prior peak.
Strategic Brand Factors	SBF_{ijq}^k ($k=1...6$)	• *Price Positioning* (value vs. premium; $SBF_{ijq}^1 = PRICE_{ijq}$): Whether brand *i*'s average paid price in the four quarters before current time period is above average of other brands in category *j* (=.5; premium) or not (=-.5; value). • *Ad Spending* (low vs high; $SBF_{ijq}^2 = AD_{ijq}$): Whether brand *i*'s average ad expenditure in the four quarters before current period is above average of other brands in category *j* (=.5) or not (=-.5). • *Line Length* (short vs. long; $SBF_{ijq}^3 = LL_{ijq}$): Whether brand *i*'s average line length in the four quarters before current time period is above average of other brands in category *j* (=.5) or not (=-.5). • *Distribution Breadth* (selective vs. extensive; $SBF_{ijq}^4 = DIST_{ijq}$): Whether brand *i*'s average distribution intensity in the four quarters before current time period is above average of other brands in category *j* (=.5; extensive) or not (=-.5; selective). • *Brand Architecture* (single-category vs. umbrella branding; $SBF_{ij}^5 = ARCH_{ij}$): Whether brand *i* is offered in multiple categories (=.5; umbrella brand) or in one category (=-.5; single-category brand). • *Market Position* (follower vs. leader; $SBF_{ijq}^6 = POS_{ijq}$): Whether the brand is among the top quartile of its category in terms of average market share in the four quarters before current time (=.5; leader) or not (=-.5; follower).
Marketing Activity of Other National Brands	$CONTROLS_{ijq}^l$ ($l=1...4$)	Other brands' quarterly paid price ($CONTROLS_{ijq}^1 = OTHERSPP_{ijq}$): (Log-transformed) average brand paid price in category *j,* excluding focal brand *i,* in quarter *q*. Other brands' quarterly advertising ($CONTROLS_{ijq}^2 = OTHERSAD_{ijq}$): (Log-transformed) average brand ad expenditures in category *j,* excluding focal brand *i,* in quarter *q*. Other brands' quarterly line length ($CONTROLS_{ijq}^3 = OTHERSLL_{ijq}$): (Log-transformed) average brand line length in category *j,* excluding focal brand *i,* in quarter *q*. Other brands' quarterly distribution intensity ($CONTROLS_{ijq}^4 = OTHERSDIST_{ijq}$): (Log-transformed) average brand distribution in category *j,* excluding focal brand *i,* in quarter *q*.
Private Label Market Share	$CONTROLS_{ijq}^5$	(=$PLMS_{jq}$) category's total private label volume market share in category *j*, averaged across months in quarter *q*.

are unlikely to be able to accurately forecast the state of the economy several quarters in advance and hence adjust their SBF-affecting actions in anticipation of the macroeconomic shock.

In Equation (6), α_2 - α_7 capture the main effect of SBF variables on SBBE; i.e., general differences in SBBE due to the SBFs, irrespective of economic conditions. It should be noted that main effect of *ARCH* is not identified since it is a time-invariant characteristic and hence the effect is subsumed within brand fixed effects. α_8 (and α_{15}) hold the main effect of macroeconomic expansions (contractions) on SBBE. α_9 - α_{14} (α_{16} - α_{21}) capture how equity of brands with different SBFs are affected differentially during expansions (contractions). Thus, our modeling approach distinguishes between general effect of SBFs, as well as how these effects change during expansions and contractions, which is in line with van Heerde et al. (2013).

Control Variables and Fixed Effects. We include several control variables in the model ($CONTROLS^{l}_{ijq}$, $l = 1 \ldots 5$). We account for marketing activities of other brands in the category by averaging paid price, advertising, line length, and distribution of all other brands in the category. We account for the presence and strength of private labels in a category by controlling for category's total private label market share ($PLMS_{jq}$).

We also include several sets of fixed effects in our model. First, we include 324 brand dummies ($\sum BRAND_b$) to account for unobserved time-invariant brand-specific factors that might influence SBBE (e.g., country of origin, heritage). To control for seasonal fluctuations in SBBE estimates in some categories (see Figure 2), we include three quarterly dummies ($\sum QUARTER_q$). To account for general year-specific shocks to SBBE, we include yearly dummies ($\sum YEAR_y$).

Multicollinearity. Having a large number of interaction terms might lead to multicollinearity. In our empirical setting, all the variance inflation factor (VIF) values are well below 10 (average VIF=2.80), thereby alleviating multicollinearity concerns. Further, as shown in Web Appendix I, all correlations between our focal independent variables (and their interactions) are below .7.

Estimation. Since the dependent variable in Equation (6) is an estimated variable, we use weighted least squares (WLS), with the inverse of SBBE's standard errors from Equation (3) as weights in our estimation (Bezawada and Pauwels 2013; Datta, Ailawadi, and van Heerde 2017). We estimate standard errors using two-way cluster-adjusted robust standard errors (at brand and quarter levels) that accounts for within-panel and within-time dependencies across observations (Seiler, Tuchman, and Yao 2021).

Results

We present model-free evidence in Web Appendix J. We build our final model by successively adding blocks of predictors to arrive at our full model (see Web Appendix K). Table 4 provides the parameter estimates for equation (6). We find that long line length (α_4=.0341, p<.01), extensively distributed (α_5=.0418, p<.01), and market leader brands (α_7=.0246, p<.05) on average have higher SBBE than selectively distributed, short line length, and market follower brands. We do not find significant difference in SBBE of value vs. premium (α_2=-.0012, p>.10) and low vs. high ad spender (α_3=.0083, p>.10) brands. The main effects of expansions (α_8=-.0949, p>.10) and contractions (α_{15}=-.1011, p>.10) on SBBE are non-significant, suggesting that SBBE of an 'average brand' does not change during expansions and contractions.[14]

Expansions and Strategic Brand Factors

Although the main effect of expansions on SBBE is not significant, we find that brands with different strategic characteristics are differentially affected by expansions. In line with H_{1EXP}, SBBE of premium brands is higher than SBBE of value brands during expansions (α_9=.6165, p<.05). This suggests that in good economic times when consumers have fewer budgetary

[14] An 'average brand' is a brand that hypothetically scores zero on all six SBF variables. In an additional analysis we removed all 12 interaction effects and both EXP_q and CON_q were again non-significant.

Table 4: Main Results

	Predictors	Expected Effect	Symbol	Estimate	Std. Error
	Intercept		α_0	$.3095^{***}$	.0388
	Past Level of Brand Equity ($SBBE_{ijq-1}$)		α_1	$.8626^{***}$	.0120
Strategic Brand Factors (SBFs)	Value vs. premium price positioning ($PRICE_{ijq}$)		α_2	-.0012	.0063
	Low vs. high ad spenders (AD_{ijq})		α_3	.0083	.0069
	Short vs. long line length (LL_{ijq})		α_4	$.0341^{***}$	.0087
	Selective vs. extensive distribution ($DIST_{ijq}$)		α_5	$.0418^{***}$	.0103
	Single- vs. umbrella-category branding ($ARCH_{ij}$)		α_6	NA†	
	Follower vs. leader market position (POS_{ijq})		α_7	$.0246^{**}$	.0112
Differential Effect of Expansions for Different Brands	Magnitude of Expansion (EXP_q)		α_8	-.0949	.1807
	EXP_q * $PRICE_{ijq}$	H_{1EXP}: +	α_9	$.6165^{**}$	.3690
	EXP_q * AD_{ijq}	H_{2EXP}: +	α_{10}	.1655	.6269
	EXP_q * LL_{ijq}	H_{3EXP}: +	α_{11}	$.9600^{**}$	.4982
	EXP_q * $DIST_{ijq}$	H_{4EXP}: +	α_{12}	1.6825^{**}	.7785
	EXP_q * $ARCH_{ij}$	H_{5EXP}: -	α_{13}	.3898	.4422
	EXP_q * POS_{ijq}		α_{14}	$.5672^{*}$	.3279
Differential Effect of Contractions for Different Brands	Magnitude of Contraction (CON_q)		α_{15}	-.1011	.2304
	CON_q * $PRICE_{ijq}$		α_{16}	.2116	.1423
	CON_q * AD_{ijq}	H_{2CON}: +	α_{17}	$.3602^{*}$	.2399
	CON_q * LL_{ijq}	H_{3CON}: -	α_{18}	$-.5414^{***}$	.1752
	CON_q * $DIST_{ijq}$	H_{4CON}: +	α_{19}	$.6786^{**}$	.3697
	CON_q * $ARCH_{ij}$	H_{5CON}: +	α_{20}	$.4897^{***}$	.1931
	CON_q * POS_{ijq}	H_{6CON}: +	α_{21}	.2307	.4507
Control Variables	Other Brands' Paid Price ($OTHERSPP_{ijq}$)		α_{22}	.0197	.0559
	Other Brands' Ad Expenditures ($OTHERSAD_{ijq}$)		α_{23}	-.0001	.0009
	Other Brands' Line Length ($OTHERSLL_{ijq}$)		α_{24}	-.0053	.0068
	Other Brands' Distribution ($OTHERSDIST_{ijq}$)		α_{25}	$-.2866^{***}$	.0377
	Private Label Market Share ($PLMS_{jq}$)		α_{26}	-.0589	.0437
	Brand Fixed Effects (324 Dummies)			Included	
	Year Fixed Effects (15 Dummies)			Included	
	Quarter Fixed Effects (3 Dummies)			Included	

*** $p<.01$; ** $p<.05$; * $p<.10$ (one-sided p-values for hypothesized effects and two-sided for others).
Significance assessed using 2-way cluster-adjusted SEs (at brand and quarter levels).
N=20,800 (due to the nature of operationalization of most SBF variables that utilize past four quarters of data, we do not use first year of data [1994] in our second-stage analysis).
† Main effect of *ARCH* is not identified since it is a time-invariant characteristic and hence the effect is subsumed within brand fixed effects.

restrictions, premium brands are preferred by them. We do not find significant evidence for differences in SBBE of low vs. high ad spender brands during expansions (α_{10}=.1655, p>.10), hence H_{2EXP} is not supported. During expansions, brands with long line length outperform brands with short line length (α_{11}=.9600, p<.05). Thus, H_{3EXP} is supported.

In line with H_{4EXP}, in expansions, extensively distributed brands do better equity-wise compared to selectively distributed brands (α_{12}=1.6825, p<.05). We do not find any difference in brand equity of single-category vs. umbrella-category brands during expansions (α_{13}=.3898, p>.10), thus H_{5EXP} is not supported. SBBE of market leader brands outperform that of follower brands during expansionary periods (α_{14}=.5672, p<.10), which provides support for the bandwagon effect (i.e., the pleasure that consumers gain from using a product when more people are using it).[15]

Contractions and Strategic Brand Factors

While non-significance of CON_q suggests that contractions do not generally affect SBBE of brands, there is significant heterogeneity with respect to strategic brand factors. SBBE of value and premium brands do not significantly differ during contractions (α_{16}=.2116, p>.10). We conjecture that higher product quality associated with premium brands (and hence higher functional utility) provides a countervailing force to the higher price associated with them. In line with H_{2CON}, high ad spenders, compared to low ad spenders, have higher SBBE during contractions (α_{17}=.3602, p<.10).

Consistent with H_{3CON}, we find that brands with short line length do better in contractions compared to those with long line length (α_{18}=-.5414, p<.01). Brands with extensive distribution are estimated to have higher SBBE during contractions vis-à-vis brands with selective

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[15] To better understand the magnitude of the interaction effects, it should be noted that EXP_q ranges from 0 to .032 while CON_q ranges from 0 to .059.

distribution (α_{19}=.6786, p<.05). Hence, H_{4CON} is supported.[16] In line with H_{5CON}, we find that in contractions, umbrella-category brands have higher SBBE compared to single-category brands (α_{20}=.4897, p<.01). Finally, we do not find significant difference in SBBE of market leaders and followers in contractions (α_{21}=.2307, p>.10). Therefore, H_{6CON} is not supported. It is possible that during contractions when consumers lose trust in the economic system, they react more negatively towards leading brands since these brands "may be seen to benefit most from this unfair system" (Dekimpe and Deleersnyder 2018, p. 54). This alternative mechanism might have weighted out the higher functional utility associated with market leaders.[17]

Long-term Effects

Our main findings in Table 4 present the short-term differences in equity of different types of brands during the business cycle. Such differences carry over into subsequent quarters because of the inertia of brand equity, which is around .86 (Table 4), implying that 86% of brand equity carries over into the next quarter. This renders brand equity stickier than revenues, which have a quarterly carryover coefficient of .6 (Clarke 1976). The greater stickiness of brand equity makes it even more worthwhile to invest in brands because the long-term differences across different types of brands are substantially larger than their short-term differences. Figure 3 shows the long-term implication of our main findings, using $\alpha_{LT} = \alpha_{ST}/(1-\alpha_{SBBE(t-1)})$.

Figure 3 shows that entering expansions or contractions with different SBFs has considerable long-term SBBE implications. In assessing the magnitude of differences observed in Figure 3, it is worth noting that the average (median) brand-specific standard deviation in SBBE is .54 (.46).

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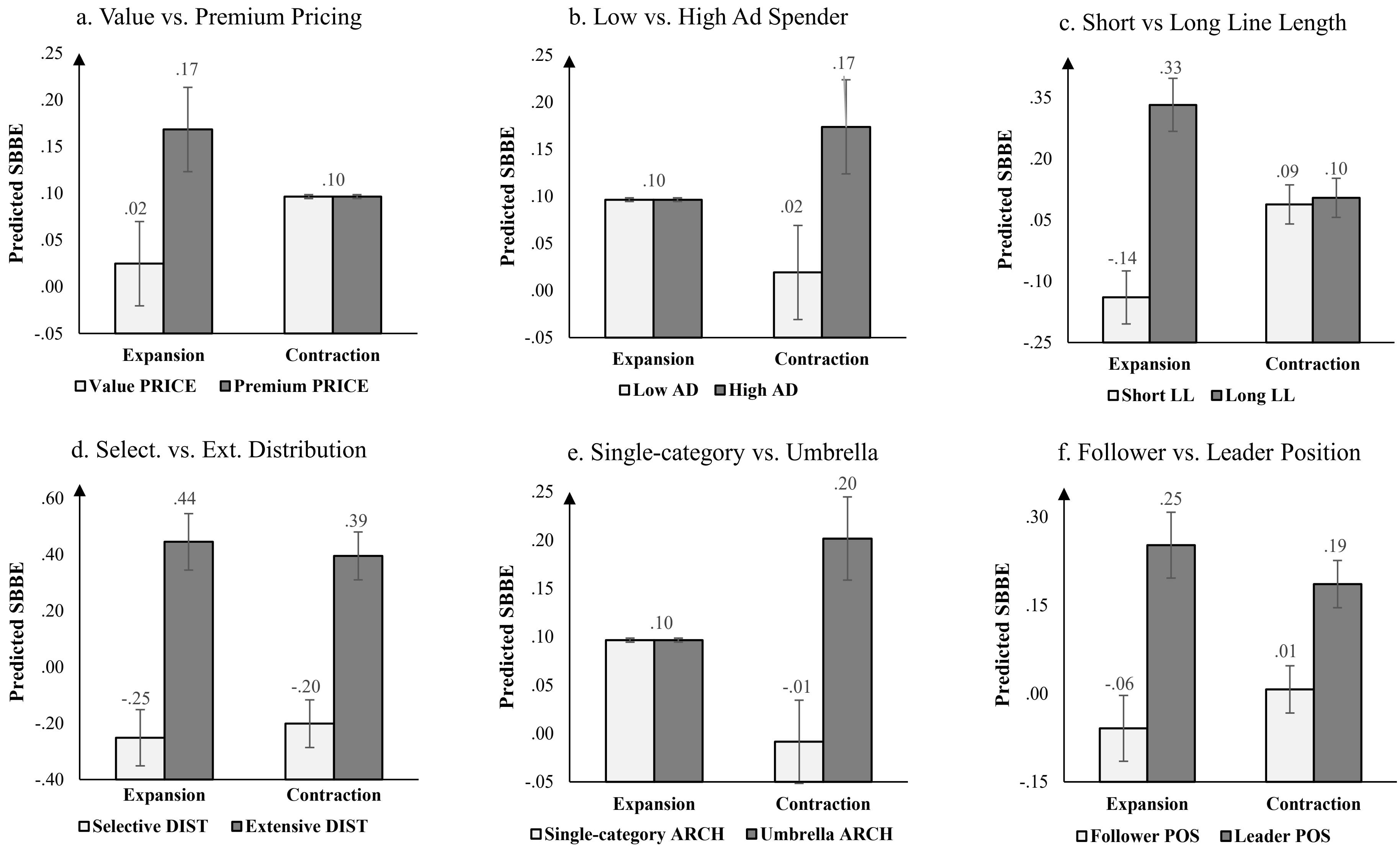
[16] Considering our finding regarding attributes of extensive distribution during expansions (α_{12}=1.6825, p<.05), it appears that the relation between distribution's effect on SBBE and state of economy follows a V-shape: in regular times, distribution's effect on SBBE is smaller (yet significant) but in recessions or expansions, extensive distribution is linked with higher SBBE.

[17] We thank the AE for suggesting this explanation.

Figure 3: Long-term Effects of the Business Cycle on Different Types of Brands



Note. We set *EXP* and *CON* to their maximum observed values (.032 and .059 respectively). The error bars of predicted value represent one SE range.

In expansions, the most important factors are strategic decisions made with regard to line length and distribution. Their effects can be categorized as large, according to Cohen (1988): Cohen's d of .87 and 1.29, respectively.[18] Next is market position (d = .58), while strategic decisions made with respect to price also play a role, although only modest in size (d = .27). The outcome of the strategic decisions regarding distribution is the single most important factor by far in determining how brand equity will hold up (or not) in contractions (d = 1.10). Other factors that matter are brand architecture (d = .39), market position (d = .33), and advertising (d = .29).

Validation Checks

Relation with Consumer-Based Brand Equity

Datta, Ailawadi, and van Heerde (2017) showed that SBBE and CBBE are moderately correlated with each other. If we have correctly followed the SBBE procedure in estimating brand equity, our estimates should show similar correlations with CBBE values. We obtained Young & Rubicam's Brand Asset Valuator (BAV) scores in the UK. For the period of our study, Young & Rubicam collected BAV data in 1997, 2000, 2002, 2005, 2006, and 2008. We calculated correlations between our SBBE estimates and BAV's aggregate score (see Table 5). The correlations range between .27 and .35 across years and are significant and comparable in magnitude to correlations

Table 5: Correlation between our SBBE Estimates and BAV's Brand Equity Scores

Year	**Overall**	**1997**	**2000**	**2002**	**2005**	**2006**	**2008**
r (SBBE, BAV)	.31†	.30	.35	.30	.27	.31	.34
r (within category SBBE rank, within category BAV rank)	.58	.60	.66	.60	.56	.57	.52
Number of Observations	847	125	129	135	149	153	156

All correlations are significant at $p < .001$. Following Datta, Ailawadi, and van Heerde (2017, p. 10), to allow for comparability, we standardize SBBE estimates and BAV scores across brands in each product category.
† To the best of our knowledge, Datta, Ailawadi, and van Heerde (2017) did not report the correlation between their SBBE estimates and BAV's Brand Asset score. Instead, they reported correlations between their SBBE estimates and the four dimensions of BAV's Brand Asset score. The four correlations were .39, .35, .53, and -.14, suggesting an average (unweighted) correlation of .28 which is comparable with our .31 correlation.

[18] Benchmarks are: small effect d = .2; medium effect d = .5; large effect d = .8.

reported by Datta, Ailawadi, and van Heerde (2017). Moreover, correlation of within category rankings of SBBE and BAV values range from .52 to .66. These observations provide evidence for the validity of our SBBE measures.

Relation with Revenue Premium

Ailawadi, Lehmann, and Neslin (2003) proposed revenue premium – operationalized as the differential revenue that a brand generates compared to that of a baseline private label product in its category – as measure of SBBE. We assess how well our intercept-based SBBE measure aligns with Ailawadi et al.'s revenue premium measure. To measure revenue premium, we considered quarterly sales of an average private label brand in the product category as our benchmark (i.e., total sales of all private labels in the category divided by the number of private labels in the category). The resulting correlation between our SBBE estimates and the revenue premium measure is .34. By-category correlation between SBBE estimates and the revenue premium measure has a median of .47, 10^{th} percentile of .16, and 90^{th} percentile of .63. Moreover, the rank correlation between SBBE and revenue premium is .70. These results provide evidence for convergent validity of our measure.

Stability of Brand Equity Estimates

Following Ailawadi, Lehmann, and Neslin (2003), we calculated the correlation between brand equity estimates and their first lag to assess the relative stability of our equity estimates overtime. The correlation is .96 in our sample, which is highly similar to the values reported by these authors: .96 (local sample) and .98 (national sample). In Web Appendix G, we report correlations between brand equity estimates and their first lag separately for each category. The correlations are above .88 across all 35 product categories. These findings suggest that our estimates do not exhibit erratic changes.

Other Robustness Checks

We also conduct a series of additional robustness checks and report the results in Web Appendix L. We briefly mention the nature of these analyses but refer for details to Web Appendix L. We include the following second-stage robustness checks:

- Operationalizing CON_q via a different time-series filtering approach.
- Specifying cluster-adjusted standard errors at different levels of aggregation.
- Accounting for category-specific and brand-specific seasonal patterns.
- Controlling for marketing mix activities in the current time period.
- Using category medians to operationalize the first four SBF variables.

We include these first-stage robustness checks:

- Controlling for lagged effects of marketing mix instruments.
- Allowing the effects of marketing variables to vary across the business cycle.
- Using value (instead of volume) market share as the dependent variable.
- Removing lagged market share as an independent variable.
- Removing Gaussian Copulas from the first-stage.

Our results are mostly robust across the 12 analyses that we report in Web Appendix L.

Discussion

Our paper straddles the brand equity and business cycle literatures. We proposed a framework for examining the impact of macroeconomic expansions and contractions on brand equity, analyzed through the lens of strategic brand factors. Using a utility-based framework, we developed specific hypotheses that underlie this framework. We tested these hypotheses using household panel data on 325 CPG national brands in 35 categories across almost two decades in the UK. We found evidence that the effect of economic conditions on brand equity is systematically moderated by six strategic brand equity factors.

Managerial Implications

For many firms, brands constitute one of their most valuable assets. Edeling and Fischer (2016) reported that a 1% change in brand equity translates into .33% change in market capitalization. Our study documents that macroeconomic conditions affect brand equity and that the effect depends on the strategic positioning of the brand. Kantar (2021, p. 6) maintained that "In good times and tough times, strong brands win." In their work, strong brands are brands that are high on differentiation (captured by our strategic brand factors premium priced and high advertising), high on meaningfulness (captured by long line length and high advertising), and high on salience (extensive distribution, umbrella brand architecture, and leading market position). Table 6 summarizes our long-term findings (Figure 3), taking into account both main effects and interaction effects, organized along Kantar's three components of strong brands.

Table 6: Aligning our Findings with Kantar's Three Components of Strong Brands

Kantar Component of Strong Brands	**Level of Strategic Brand Factor**	**Do Strong Brands Win?**	
		Expansion	Contraction
High Differentiation	Premium Priced	Yes	No effect
	High Advertising	No effect	Yes
High Meaningfulness	Long Line Length	<u>Yes</u>	No effect [a]
	High Advertising	No effect	Yes
High Salience	Extensive Distribution	<u>Yes</u>	<u>Yes</u>
	Umbrella Brand	No effect	Yes
	Market Leader	Yes	Yes

[a] The strong negative interaction effect and the strong positive main effect cancel each other out. Large effects (as determined by Cohen's d) are underlined.

Our findings provide broad support for Kantar's claim. Table 6 shows that in expansions as well as in contractions, strong brands do indeed win in terms of creating more brand equity than weak brands, at least if we take the aggregate of the strategic brand factors for each Kantar component.

Yet, the overall support for Kantar's sweeping claim disguises the fact that various strategic brand factors have a notably different effect on brand equity. Some strategic brand factors matter much more than others. In particular, the outcomes of strategic decisions with respect to distribution and line length emerge as the key factors to consider.

In contractions, the effect of distribution is the largest contributor to brand equity by far. It is important to keep this in mind given current economic turmoil. Further, distribution has a large effect in expansions as well. In short, in good times and bad times, extensively distributed brands win. Managers of brands that have a selective distribution need to consider whether this is a strategic choice or the unwanted result of bad implementation of strategies to expand distribution. If it is a strategic choice, our findings point to the consequences. If it is an unwanted outcome, they may need to either increase investments in channel incentives (Ailawadi and Farris 2020) or, if the firm already spends a lot on trade marketing, examine why channel incentives do not result in expanded distribution.

In expansions, a wide assortment is also a strong contributor to brand equity, while it does not destroy brand equity in contractions. Given this finding, expanding the assortment should be a priority for brand management, unless there are other overriding considerations (e.g., lack of resources). As mentioned before, strategic brand factors are sticky but not immutable. It is possible to change the brand's competitive positioning from a limited variety brand to a broad assortment brand, if brand management so decides. However, this will take time. A starting point is to invest more in R&D. With the elevated risks of a recession in 2023-2024 (Kiley 2022; Torry and DeBarros 2022), managers planning for the long term, might want to go against the general practice of cutting R&D expenditures during recessions (Barlevy 2007; Steenkamp and Fang 2011), and instead invest more on R&D. Given the time it takes to develop new products, they might be ready to launch just when the economy bounces back, reaping full benefits of assortment expansion.

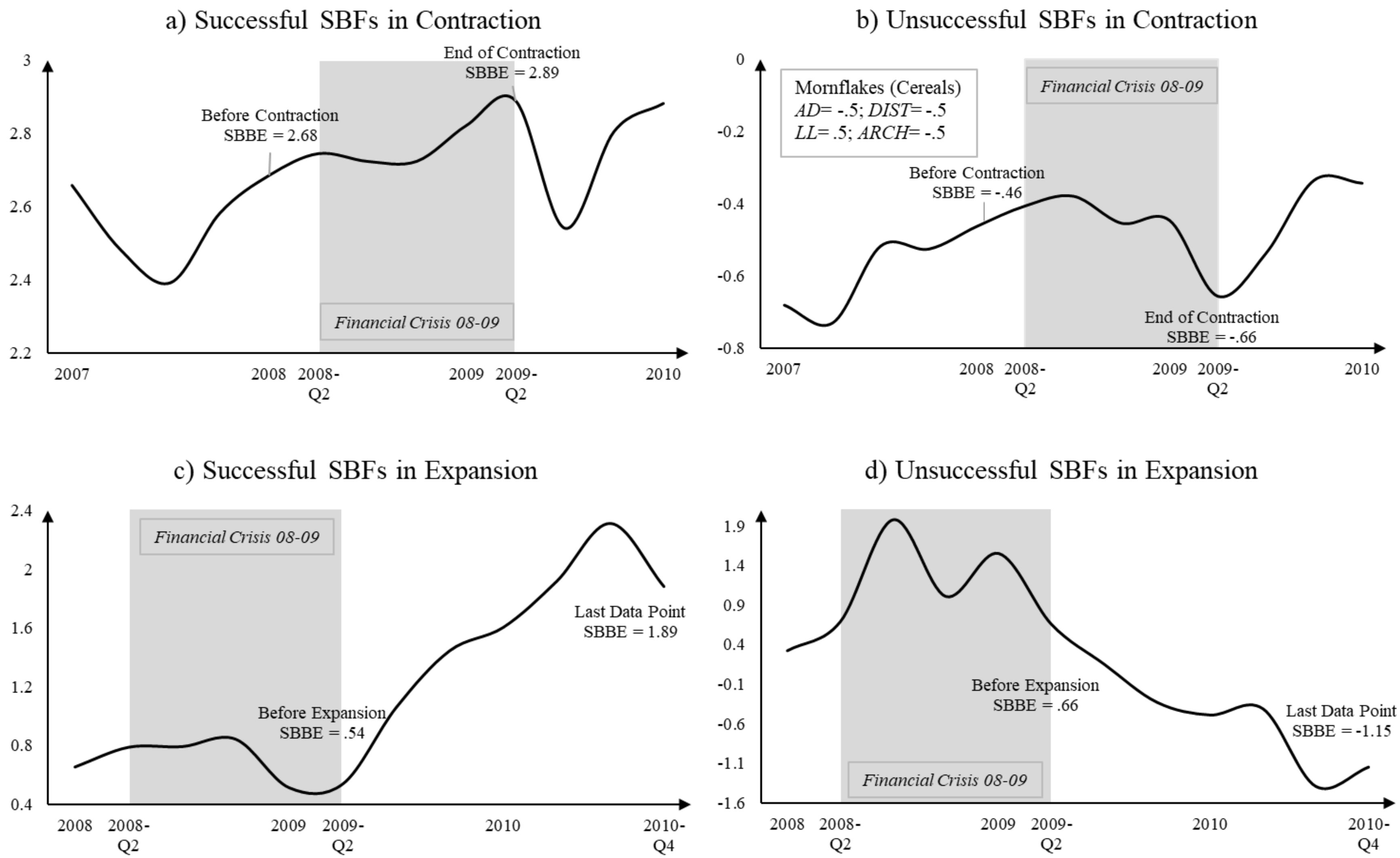
Further, a premium price position and market leadership build brand equity in expansions while advertising, using an umbrella brand architecture, and market leadership contribute to brand equity in contractions, but the effect of management decisions with respect to these factors has only a modest effect on brand equity. Thus, while these factors do matter, they are of secondary importance when it comes to growing brand equity. The key takeaway is that if the brand manager wants to grow brand equity for the long term, expanding distribution and line length are the two strategic brand factors to concentrate on.

To further illustrate the role of strategic brand factors in influencing SBBE during the business cycle, Figure 4 presents SBBE of four brands that had ‘successful or ‘unsuccessful strategic brand factors during the 2008 financial crisis and the expansionary period that followed. We define successful and unsuccessful strategic brand factors based on our results regarding the strategic brand factors that significantly help or hurt brands during contractions or expansions. As depicted in Figure 4, successful strategic brand factors led to growth in SBBE of Johnsons (Fairy; known as Dawn in the US) during the 2008 financial crisis (the expansionary period after the financial crisis). On the other hand, brands with unsuccessful strategic brand factors, Mornflakes and Heinz, lost SBBE during the global recession and the subsequent expansion, respectively.

Limitations

This study has several limitations that future research should address. Our study focused on the CPG industry in the UK. Future research should examine other industries in different countries to generalize or nuance our findings and uncover additional patterns regarding how different types of brands are affected by macroeconomic fluctuations. Further, we focused on examining the equity of national brands. It could be argued that in the current marketplace private labels do command considerable equity (Keller, Dekimpe, and Geyskens 2016). Since the distribution of private labels is typically restricted to the retailer’s own stores and product level advertising is limited, current brand equity methods are not ideal for the estimation of private label brand equity. We need new methods for the measurement of brand equity of private labels.

Figure 4: Example Brands with Different Strategic Brand Factors in Expansions and Contractions



Our research examined the overall patterns across brands in 35 CPG categories and did not examine category-specific patterns. Product categories vary along many dimensions such as consumer involvement (Zaichkowsky 1985), brand relevance (Fischer, Völckner, and Sattler 2010), perceived risk (Bettman 1973), and complexity (Agustin and Singh 2005). Future research should examine heterogeneity in our results across product categories in function of these (and other) important category-level characteristics.

In this research, we focused on sales-based brand equity. While sales-based brand equity captures observed value added by the brand in the marketplace, it does not say anything about consumers' attitudes and thought processes. To better understand why and how consumer attitudes towards different brands change during expansions and contractions, future research could also consider consumer-based brand equity measures. Finally, we conceptually linked the six strategic brand factors in our framework to Kantar's three components of brand strength. Future research should conduct in-depth conceptual and empirical examination of the relationships between different elements in the two frameworks.

Conclusion

Our research documents the role that management decisions with respect to strategic brand factors play in helping (or hurting) a brand during macroeconomic expansions and contractions. We show that a premium price position and market leadership build brand equity in expansions while advertising, using an umbrella brand architecture, and market leadership contribute to brand equity in contractions. However, two factors dominate: distribution and line length. A wide assortment plays a key role in growing brand equity in expansions, and extensively distributed brands win in expansions and contractions. If the brand manager wants to grow brand equity for the long term, expanding distribution and line length are the two strategic brand factors to concentrate on.

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WEB APPENDIX

Brand Equity in Good and Bad Times:
What Distinguishes Winners from Losers in CPG Industries?

Koushyar Rajavi (Koushyar.rajavi@scheller.gatech.edu)
Assistant Professor of Marketing, Scheller College of Business,
Georgia Institute of Technology

Tarun Kushwaha (tkushwah@gmu.edu)
Professor of Marketing, School of Business,
George Mason University

Jan-Benedict E.M. Steenkamp (jbs@unc.edu)
C. Knox Massey Distinguished Professor of Marketing, Kenan-Flagler Business School,
University of North Carolina

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WEB APPENDIX A – RESEARCH ON THE IMPACT OF MACROECONOMIC FLUCTUATIONS ON MARKETING-RELATED PHENOMENA

Paper	Outcome Variable	Moderating Effects	Level of Analysis	Key Findings
Deleersnyder et al. 2004	Sales of Durables	Product Type, Product Life Cycle, etc.	Industry	Durables are very sensitive to business-cycle fluctuations. Nature of the durable and the stage in a product's life cycle moderate the extent of sensitivity in durable sales patterns.
Lamey et al. 2007	Share of Private Labels	-	Product Category	Private label share behaves cyclically and business cycles have temporary and permanent impacts on private label share.
Deleersnyder et al. 2009	Advertising Spending	National Culture	Advertising Media-Country	Advertising is sensitive to business-cycles. Advertising behaves less cyclically in countries high in long-term orientation and power distance and low in uncertainty avoidance.
Kamakura and Du 2012	Customer Preferences for Categories	Type of Goods and Services	Household	For any given consumption budget, expenditure shares for positional goods/services will decrease during a recession, while shares for non-positional goods/services will increase.
Srinivasan, Lilien, and Sridhar (2011)	Effectiveness of Advertising and R&D	Market share, Financial leverage, and Product-market profile	Firm	The greater the firm's market share, the more an increase in R&D spending during recessions increases its profits. The greater the firm's financial leverage, the more an increase in advertising spending in recessions increases profits.
Steenkamp and Fang 2011	Effectiveness of advertising and R&D	Industry cyclicality	Firm	Increasing advertising and R&D in downturns have a stronger effect on profit and market share than increasing advertising or R&D in upturns. Advertising effectiveness, especially in downturns, in particular, is systematically moderated by the degree of cyclicality of the industry.
Lamey et al. 2012	Share of Private Labels	National Brands' Marketing	Product Category	Private-label share behaves countercyclically. Brands' procyclical behavior regarding new product introductions, advertising, and promotions is associated with more pronounced cyclical changes in PL share.
Gordon, Goldfarb, and Li 2013	Price Elasticity	Category's Price Sensitivity	Household	Price sensitivity is countercyclical and rises when the economy weakens. The relationship between price sensitivity and business cycles correlates strongly with the average level of price sensitivity in a category.
van Heerde et al. 2013	Advertising and Price Elasticity	Brand Segments, Product Type	Brand	Long-term price sensitivity decreases during expansions, whereas long-term advertising elasticities increase. These patterns vary across different product categories and brands.
This Study	Brand Equity	Strategic Brand Factors	Brand	In expansions, premium brands, brands with long line length, extensively distributed brands, and market followers perform better on brand equity, whereas in contractions, high ad spender, low line length, extensively distributed, and umbrella brands fare better than other brands.

WEB APPENDIX B – COMPARING UTILITY FUNCTIONS FOR DIFFERENT CONDITIONS

Elements of Utility Function		**Strategic Brand Factors**					
		Differentiation		**Meaningfulness**		**Salience**	
		Price Positioning (Value vs. Premium)	**Advertising Spending (Low vs. High)**	**Line Length (Short vs. Long)**	**Distribution Intensity (Selective vs. Extensive)**	**Brand Architecture (Single vs. Umbrella)**	**Market Position (Follower vs. Leader)**
Price		$P_{PRM} > P_{VAL}$ (a)			$P_{EXT} < P_{SEL}$		
Functional Attributes		$\boldsymbol{X}_{f,PRM} > \boldsymbol{X}_{f,VAL}$ (a)	$\boldsymbol{X}_{f,HI\text{-}AD} > \boldsymbol{X}_{f,LO\text{-}AD}$		$\boldsymbol{X}_{f,EXT} > \boldsymbol{X}_{f,SEL}$	$\boldsymbol{X}_{f,UMB} > \boldsymbol{X}_{f,SIN}$	$\boldsymbol{X}_{f,LEA} > \boldsymbol{X}_{f,FOL}$
Functional Risk		$\boldsymbol{\sigma}_{f,PRM} < \boldsymbol{\sigma}_{f,VAL}$		$\boldsymbol{\sigma}_{f,LNG} > \boldsymbol{\sigma}_{f,SHR}$		$\boldsymbol{\sigma}_{f,UMB} < \boldsymbol{\sigma}_{f,SIN}$	
Emotional Attributes		$\boldsymbol{X}_{e,PRM} > \boldsymbol{X}_{e,VAL}$	$\boldsymbol{X}_{e,HI\text{-}AD} > \boldsymbol{X}_{e,LO\text{-}AD}$	$\boldsymbol{X}_{e,LNG} > \boldsymbol{X}_{e,SHR}$	$\boldsymbol{X}_{e,EXT} > \boldsymbol{X}_{e,SEL}$		$\boldsymbol{X}_{e,LEA}$ <or> $\boldsymbol{X}_{e,FOL}$
Emotional Risk			$\boldsymbol{\sigma}_{e,HI\text{-}AD} < \boldsymbol{\sigma}_{e,LO\text{-}AD}$			$\boldsymbol{\sigma}_{e,UMB} > \boldsymbol{\sigma}_{e,SIN}$	
Net Effect of Relevant Components (all else equal)							
on Utility During Expansions	(b) $\alpha_{EXP} < \alpha_{CON}$ $\boldsymbol{\omega}_{e,EXP} > \boldsymbol{\omega}_{e,CON}$ $\boldsymbol{r}_{e,EXP} > \boldsymbol{r}_{e,CON}$	(c) $U_{PRM,EXP} = C_{PRM,EXP}$ $-\alpha_{EXP}*P_{PRM}$ $+\boldsymbol{\omega}_{e,EXP}*\boldsymbol{X}_{e,PRM}$ >> $U_{VAL,EXP} = C_{VAL,EXP}$ $-\alpha_{EXP}*P_{VAL}$ $+\boldsymbol{\omega}_{e,EXP}*\boldsymbol{X}_{e,VAL}$	$U_{HI\text{-}AD,EXP} = C_{HI\text{-}AD,EXP}$ $+\boldsymbol{\omega}_{e,EXP}*\boldsymbol{X}_{e,HI\text{-}AD}$ $-\boldsymbol{r}_{e,EXP}*\boldsymbol{\sigma}_{e,HI\text{-}AD}$ >> $U_{LO\text{-}AD,EXP} = C_{LO\text{-}AD,EXP}$ $+\boldsymbol{\omega}_{e,EXP}*\boldsymbol{X}_{e,LO\text{-}AD}$ $-\boldsymbol{r}_{e,EXP}*\boldsymbol{\sigma}_{e,LO\text{-}AD}$	$U_{LNG,EXP} = C_{LNG,EXP}$ $+\boldsymbol{\omega}_{e,EXP}*\boldsymbol{X}_{e,LNG}$ >> $U_{SHR,EXP} = C_{SHR,EXP}$ $+\boldsymbol{\omega}_{e,EXP}*\boldsymbol{X}_{e,SHR}$	$U_{EXT,EXP} = C_{EXT,EXP}$ $+\boldsymbol{\omega}_{e,EXP}*\boldsymbol{X}_{e,EXT}$ >> $U_{SEL,EXP} = C_{SEL,EXP}$ $+\boldsymbol{\omega}_{e,EXP}*\boldsymbol{X}_{e,SEL}$	$U_{UMB,EXP} = C_{UMB,EXP}$ $-\boldsymbol{r}_{e,EXP}*\boldsymbol{\sigma}_{e,UMB}$ << $U_{SIN,EXP} = C_{SIN,EXP}$ $-\boldsymbol{r}_{e,EXP}*\boldsymbol{\sigma}_{e,SIN}$	$U_{LEA,EXP} = C_{LEA,EXP}$ $+\boldsymbol{\omega}_{e,EXP}*\boldsymbol{X}_{e,LEA}$ < OR > $U_{FOL,EXP} = C_{FOL,EXP}$ $+\boldsymbol{\omega}_{e,EXP}*\boldsymbol{X}_{e,FOL}$
on Utility During Contractions	$\alpha_{EXP} < \alpha_{CON}$ $\boldsymbol{\omega}_{f,CON} > \boldsymbol{\omega}_{f,EXP}$ $\boldsymbol{r}_{f,CON} > \boldsymbol{r}_{f,EXP}$	$U_{PRM,CON} = C_{PRM,CON}$ $-\alpha_{CON}*P_{PRM}$ $+\boldsymbol{\omega}_{f,CON}*\boldsymbol{X}_{f,PRM}$ $-\boldsymbol{r}_{f,CON}*\boldsymbol{\sigma}_{f,PRM}$ < OR > $U_{VAL,CON} = C_{VAL,CON}$ $-\alpha_{CON}*P_{VAL}$ $+\boldsymbol{\omega}_{f,CON}*\boldsymbol{X}_{f,VAL}$ $-\boldsymbol{r}_{f,CON}*\boldsymbol{\sigma}_{f,VAL}$	$U_{HI\text{-}AD,CON} = C_{HI\text{-}AD,CON}$ $+\boldsymbol{\omega}_{f,CON}*\boldsymbol{X}_{f,HI\text{-}AD}$ >> $U_{LO\text{-}AD,CON} = C_{LO\text{-}AD,CON}$ $+\boldsymbol{\omega}_{f,CON}*\boldsymbol{X}_{f,LO\text{-}AD}$	$U_{LNG,CON} = C_{LNG,CON}$ $-\boldsymbol{r}_{f,CON}*\boldsymbol{\sigma}_{f,LNG}$ << $U_{SHR,CON} = C_{LNG,CON}$ $-\boldsymbol{r}_{f,CON}*\boldsymbol{\sigma}_{f,SHR}$	$U_{EXT,CON} = C_{EXT,CONT}$ $-\alpha_{CON}*P_{EXT}$ $+\boldsymbol{\omega}_{f,CON}*\boldsymbol{X}_{f,EXT}$ >> $U_{SEL,CON} = C_{SEL,CONT}$ $-\alpha_{CON}*P_{SEL}$ $+\boldsymbol{\omega}_{f,CON}*\boldsymbol{X}_{f,SEL}$	$U_{UMB,CON} = C_{UMB,CON}$ $+\boldsymbol{\omega}_{f,CON}*\boldsymbol{X}_{f,UMB}$ $-\boldsymbol{r}_{f,CON}*\boldsymbol{\sigma}_{f,UMB}$ >> $U_{SIN,CON} = C_{SIN,CON}$ $+\boldsymbol{\omega}_{f,CON}*\boldsymbol{X}_{f,SIN}$ $-\boldsymbol{r}_{f,CON}*\boldsymbol{\sigma}_{f,SIN}$	$U_{LEA,CON} = C_{LEA,CON}$ $+\boldsymbol{\omega}_{f,CON}*\boldsymbol{X}_{f,LEA}$ >> $U_{FOL,CON} = C_{FOL,CON}$ $+\boldsymbol{\omega}_{f,CON}*\boldsymbol{X}_{f,FOL}$

To be read as

(a) Premium brands have higher prices ($P_{PRM} > P_{VAL}$) and also provide higher functional attributes ($\boldsymbol{X}_{f,PRM} > \boldsymbol{X}_{f,VAL}$) than value brands.

(b) During expansions (vs. contractions) consumers are less price sensitive ($\alpha_{CON} > \alpha_{EXP}$) and assign greater importance to emotional attributes ($\boldsymbol{\omega}_{e,EXP} > \boldsymbol{\omega}_{e,CON}$).

(c) Thus, all else equal, during expansions, the utility that consumers derive from premium brands ($U_{PRM,EXP} = C_{PRM,EXP} - \alpha_{EXP}*P_{PRM} + \boldsymbol{\omega}_{e,EXP}*\boldsymbol{X}_{e,PRM}$) will be more than that they will derive from value brands ($U_{VAL,EXP} = C_{VAL,EXP} - \alpha_{EXP}*P_{VAL} + \boldsymbol{\omega}_{e,EXP}*\boldsymbol{X}_{e,VAL}$). Here, C is the weighted sum of utility components not affected, in this case $C_{PRM,EXP} = \boldsymbol{\omega}_{f,EXP}*\boldsymbol{X}_{f,PRM} - \boldsymbol{r}_{e,EXP}*\boldsymbol{\sigma}_{e,PRM} - \boldsymbol{r}_{f,EXP}*\boldsymbol{\sigma}_{f,PRM}$ and $C_{VAL,EXP} = \boldsymbol{\omega}_{f,EXP}*\boldsymbol{X}_{f,VAL} - \boldsymbol{r}_{e,EXP}*\boldsymbol{\sigma}_{e,VAL} - \boldsymbol{r}_{f,EXP}*\boldsymbol{\sigma}_{f,VAL}$

WEB APPENDIX C – MARKET SHARE STATISTICS ACROSS CATEGORIES

Category	**# Brands**	**Brands with Lowest Avg MS**	**Brands with Highest Avg MS**	**Avg HHI[ψ]**
Artificial Sweeteners	5	Fuisana, Sucron	Hermesetas, Sweetex	.136
Bath Additives	8	E45, Badedas	Radox, Johnsons	.029
Bathroom Tissue	4	Izal, Nouvelle	Velvet, Andrex	.070
Breakfast Cereals	9	Scotts, Ready Brek	Weetabix, Kelloggs	.116
Butter	7	President, Kerrygold	Lurpak, Anchor	.161
Canned Fruit	9	Trout Hall, Bridge House	Del Monte, Princes	.020
Canned Soup	4	Weight Watchers, Covent Garden	Baxters, Heinz	.230
Cat Food	11	Purina, Friskies	Whiskas, Felix	.111
Cereal Bars	3	Tracker	Jordans	.044
Cleansers (Facial)	13	Mudd, Ponds	Clean & Clear, Clearasil	.031
Conditioners	11	Vitapointe, Nicky Clarke	Alberto, Pantene	.031
Cooking Sauces	18	Heinz, Encona	Dolmio, Homepride	.037
Deodorants	13	Old Spice, Amplex	Lynx, Sure	.069
Dog Food	16	Frolic, Masterchoice	Winalot, Pedigree	.053
Dry Pasta	3	Marshalls	Buitoni	.003
Frozen Fish	8	Kershaws, Lyons Seafoods	Birds Eye, Youngs	.150
Fruit/Yoghurt Juice	18	Yoplait, Roses	Tropicana, Robinsons	.076
Ground/Bean Coffee	4	Rombouts, Lavazza	Douwe Egbert, Lyons	.021
Household Cleaners	8	Ecover, Stardrops	Cif, Flash	.028
Instant Coffee	4	Red Mountain, Mellow Birds	Maxwell House, Nescafe	.283
Laundry Detergents	8	Ecover, Dreft	Ariel, Persil	.082
Margarine	8	Summer County, Willow	Stork, Flora	.060
Mineral Water	10	San Pellegrino, Malvern	Highland Spring, Evian	.010
Potato chips	7	KP Brannigans, Highlander	Walkers, Kettle Foods	.223
Razor Blades	5	Personna, Laser	Bic, Gillette	.213
Sanitary Protection Products	9	Interlude, Helen Harper	Tampax, Always	.062
Shampoo	13	Gliss Corimist, Simple	Pantene, Head & Shoulders	.023
Shower Prod.	11	Badedas, Simple	Radox, Imperial Leather	.045
Soft Drinks	29	Ben Shaw, Appletiser	Coca Cola, Pepsi	.025
Stout	3	Mackeson	Guinness	.579
Table Sauces	5	Hammonds, C&B Branston	H.P. Sauces, Heinz	.157
Tea	12	Glengettie, Nambarrie	Tetley, P.G.Tips	.070
Toothpaste	13	Oral B, Euthymol	Colgate, Aquafresh	.145
Washing Up Products	6	Surcare, Ecover	Finish, Fairy	.095
Yoghurt	10	Longley Farm, Nestle	Ski, Muller	.106

[ψ] Based on average HHI in each category across 203 months. Monthly HHI is calculated based on square of market share of the top three national brands in the category in terms of monthly volume market share.

WEB APPENDIX D – SAMPLE STATISTICS ACROSS DIFFERENT CATEGORIES AND BRANDS

Table WA.D1 – Marketing Mix Instruments across Categories

Category	# Brands	Price Promo. Depth (%)	Advertising (000 pounds)	Distribution (%)	Line Length
Artificial Sweeteners	5	1.4 (2.7)	21.4 (84.9)	67.6 (29.6)	5.0 (3.4)
Bath Additives	8	4.6 (6.0)	28.5 (141.4)	68.9 (25.9)	8.9 (8.6)
Bathroom Tissue	4	3.1 (4.8)	198.0 (330.9)	81.8 (21.2)	19.3 (14.3)
Breakfast Cereals	9	2.5 (3.6)	676.0 (1,448.7)	93.3 (7.6)	23.1 (24.6)
Butter	7	1.7 (3.4)	97.9 (255.8)	73.2 (33.2)	4.2 (3.5)
Canned Fruit	9	3.8 (5.2)	5.3 (50.5)	52.4 (31.3)	12.7 (13.4)
Canned Soup	4	2.6 (3.8)	59.9 (203.1)	90.7 (8.8)	40.6 (26.0)
Cat Food	11	2.1 (3.3)	137.5 (324.2)	85.4 (23.2)	44.2 (58.2)
Cereal Bars	3	2.6 (4.6)	10.9 (54.6)	89.3 (6.5)	9.7 (5.8)
Cleansers (Facial)	13	3.8 (5.0)	51.7 (13.6)	69.8 (25.3)	6.5 (5.3)
Conditioners	11	4.6 (6.6)	21.9 (100.5)	56.3 (31.0)	9.3 (11.2)
Cooking Sauces	18	3.2 (4.5)	99.3 (258.7)	84.6 (18.0)	23.7 (20.4)
Deodorants	13	4.0 (4.8)	138.1 (383.5)	78.7 (22.9)	19.5 (15.5)
Dog Food	16	1.6 (3.2)	76.6 (235.7)	70.3 (33.8)	21.5 (30.5)
Dry Pasta	3	4.4 (6.5)	7.8 (35.6)	68.1 (29.4)	11.9 (8.3)
Frozen Fish	8	3.3 (4.2)	40.5 (173.5)	60.7 (34.5)	19.4 (24.8)
Fruit/Yoghurt Juice	18	3.0 (4.9)	87.7 (254.9)	67.4 (31.7)	11.5 (12.3)
Ground/Bean Coffee	4	3.6 (5.2)	40.1 (137.5)	83.2 (15.9)	9.4 (6.7)
Household Cleaners	8	3.0 (4.3)	137.2 (263.4)	71.5 (32.9)	11.5 (11.3)
Instant Coffee	4	4.0 (6.0)	351.5 (732.2)	85.2 (17.4)	16.9 (21.5)
Laundry Detergents	8	2.7 (3.6)	677.2 (728.1)	88.3 (19.3)	23.0 (19.3)
Margarine	8	2.6 (4.7)	157.1 (345.0)	85.9 (26.9)	5.2 (3.6)
Mineral Water	10	2.6 (5.2)	42.3 (153.1)	58.7 (33.2)	7.6 (5.9)
Potato chips	7	3.9 (6.5)	209.7 (487.6)	78.0 (26.6)	23.6 (22.4)
Razor Blades	5	2.7 (3.9)	209.5 (447.9)	65.9 (38.5)	19.0 (17.0)
Sanitary Protection Prod.	9	3.2 (3.9)	173.5 (325.5)	74.3 (36.0)	14.9 (7.4)
Shampoo	13	4.3 (6.2)	125.8 (296.6)	66.0 (34.1)	11.2 (12.2)
Shower Prod.	11	5.9 (7.5)	85.5 (232.5)	73.2 (26.8)	12.7 (10.2)
Soft Drinks	29	3.3 (4.9)	155.4 (480.6)	73.3 (30.7)	15.3 (10.8)
Stout	3	2.9 (4.9)	438.9 (759.3)	83.5 (13.5)	6.6 (6.2)
Table Sauces	5	2.4 (3.7)	89.2 (256.1)	85.6 (19.9)	10.3 (8.2)
Tea	12	3.3 (5.0)	123.8 (324.4)	81.8 (19.2)	10.5 (8.5)
Toothpaste	13	3.1 (4.3)	169.9 (351.1)	83.6 (15.7)	11.8 (13.4)
Washing Up Prod.	6	2.4 (3.6)	213.6 (369.2)	82.4 (22.2)	14.7 (16.8)
Yoghurt	10	2.4 (3.5)	175.0 (415.3)	79.4 (23.8)	16.6 (14.5)

Average (standard deviation) of marketing mix instruments across the whole time period of 203 months and across all the brands in a category reported. We do not report summary statistics for regular price (*PRICE*) as that variable depends on unit of measurement in each category (which we report in Web Appendix D) and hence difficult to interpret. The advertising columns describe raw advertising expenditures and not the advertising stock which we use in our first-stage estimation.

Table WA.D2 – Within-brand Variation in Marketing Mix Instruments

	Price Promo. Depth (%)	Advertising (000 pounds)	Distribution (%)	Line Length
Within-brand average (averaged across 325 brands)	3.2	143.9	74.7	15.4
Within-brand average (25th percentile)	2.1	2.0	61.2	4.6
Within-brand average (median)	3.1	30.4	85.8	9.2
Within-brand average (75th percentile)	4.0	140.8	93.7	20.8
Within-brand std. dev. (averaged across 325 brands)	4.4	173.2	11.3	.6
Within-brand std. dev. (25th percentile)	2.9	9.7	2.6	.1
Within-brand std. dev. (median)	4.0	111.2	8.6	.4
Within-brand std. dev. (75th percentile)	5.4	263.9	18.7	.7
Overall standard deviation (across all observations)	4.9	434.7	28.8	20.1

WEB APPENDIX E – PRODUCT ATTRIBUTES ACROSS DIFFERENT CATEGORIES

Category	Unit of Sales	Attributes
Artificial Sweeteners	Grams	Multi-Pack, Large, Tablets, Granules / Powders
Bath Additives	Milliliters	Multi-Pack, Large, Liquid, Salts, Baby, Aromatherapy
Bathroom Tissue	Count (Packs)	Multi-Pack, Large, White, Quilted, Peach, Pink, Green, Moist, Soft
Breakfast Cereals	Grams	Multi-Pack, Large, Crispy, Crunchy, Flakes, Crunchy, Oat, Fruit, Nut
Butter	Grams	Multi-Pack, Large, Spreadable, Light, Salted
Canned Fruit	Grams	Multi-Pack, Large, Slices, Halves, Chunk, Syrup, Juice, Segments, Pieces
Canned Soup	Milliliters/Grams	Multi-Pack, Large, Wet, Fresh, Vegetable, Broth, Organic
Cat Food	Grams	Multi-Pack, Large, Jelly, Adult, Chunks, Kitten, Canned, Dry, Chicken
Cereal Bars	Grams	Multi-Pack, Large, Chewy, Crunchy, Berry
Cleansers (Facial)	Milliliters/Grams	Multi-Pack, Large, Facial, Scrub, Wipes, Medicated, Mask, Lotion
Conditioners	Milliliters	Multi-Pack, Large, Normal, Dry, Damaged, Frizz, Perm
Cooking Sauces	Milliliters/Grams	Multi-Pack, Large, Additive, Pour-Over, Jelly, Pasta, Jar
Deodorants	Milliliters	Multi-Pack, Large, Bodyspray, Sensitive, 24h, Dry, Sport, Men, Women
Dog Food	Grams	Multi-Pack, Large, Dry, Beef, Vegetable, Puppy, Canned, Soft / Moist, Biscuit
Dry Pasta	Grams	Multi-Pack, Large, Wheat, Verdi, Shapes, Twirl
Dry Soup	Grams	Multi-Pack, Large, Dry, Instant, Quick, Veg, Noodle, Sachet, Packet
Frozen Fish	Grams	Multi-Pack, Large, Filet, Pie, Prawn, Breaded, Salmon, Scampi, Haddock
Fruit/Yoghurt Juice	Milliliters	Multi-Pack, Large, Pure, Juice Drinks, High Juice, Added Sugar, Yoghurt, Low Calorie
Ground/Bean Coffee	Grams	Multi-Pack, Large, Filter, Medium, Decaf, Single, Espresso, Pod
Household Cleaners	Milliliters/Grams	Multi-Pack, Large, Wipes, Kitchen, Spray, Bath, Bleach, Cream
Instant Coffee	Grams	Multi-Pack, Large, Blend, Decaf, Cappuccino, Powder, Unsweetened, Pure
Laundry Detergents	Milliliters/Grams	Liquid, Large, Tabs, Caps, Powder, Concentrate
Margarine	Grams	Multi-Pack, Large
Mineral Water	Milliliters	Multi-Pack, Large, Glass Bottle, Plastic Bottle, Fruit, Spring, Carbonated, Flavored
Peanut Butter	Grams	Multi-Pack, Large, Crunchy, Organic, Smooth
Potato chips	Grams	Multi-Pack, Large, Assorted, Salted, Roasted, Vinegar, Cheese
Razor Blades	Count	Multi-Pack, Large, Sensitive, Fixed, Women, Cartridge
Sanitary Protection Products	Count	Multi-Pack, Large, Digital, Wing, Applicator, Night, Ultra, Normal, Super
Shampoo	Milliliters	Multi-Pack, Large, Frequent, Herbal, Dry, Damaged, Fine, Perm, Volume
Shower Prod.	Milliliters	Multi-Pack, Large, Gel, Fresh, Cream, Women, Active, Sport
Soft Drinks	Milliliters	Multi-Pack, Large, Cola, Lemon, Diet, Cherry, Canned, PET Bottle, Glass Bottle
Stout	Milliliters	Multi-Pack, Large, Can, Bottle, Draught
Table Sauces	Grams	Multi-Pack, Large, Glass Bottle, Plastic Bottle, Chili, Sweet, BBQ, Tomato, Brown
Tea	Grams	Multi-Pack, Large, Specialty, Round, Pyramid, One Cup, PMP
Toothpaste	Milliliters	Multi-Pack, Large, Pump, Whitening, Mint, Gel, Cool, Sensitive, Paste
Washing Up Products	Milliliters/Grams	Multi-Pack, Large, Lemon, Liquid, Tablet, Concentrated, Powder, Dishwash
Yoghurt	Grams	Multi-Pack, Large, Strawberry, Raspberry, Greek, Natural, Diet, Cherry, Vanilla

Notes on our approach in identifying product attributes:

Some of the product attributes such as product size were easily derived from the "barcode description" file that was available to us. Regarding size, in each category, we calculated average SKU size and defined SKUs that were above average size to be "large" and the rest to be "not large" SKUs. The same goes for the "Multi-pack" attribute that we have in most categories; the data specifies whether a SKU has one unit of product or multiple units.

As for the remaining attributes, we applied text mining techniques to the SKU "description" column that we had in our "barcode description" file (on a total of 26,914 SKUs that were marketed from 1994 to 2010 in 37 product categories). For example, a breakfast cereal SKU by Alpen is described in the following way "ALPEN NUTTY CRUNCH 500GM". Our algorithm allowed us to define "nutty" and "crunchy" attributes based on this description. We did the text mining to hundreds or thousands of SKUs in each category and based on each SKU description, we detected different attributes. Once we discovered all possible attributes across all SKUs in a category, we counted the frequency of each attribute amongst the SKUs in the category. To keep things manageable, we only focused on the most important attributes in each category; i.e., attributes with most frequency across all the SKUs in each category. Thereby, we limited number of attributes to a maximum of nine in each product category.

WEB APPENDIX F – BY-CATEGORY SUMMARY OF FIRST-STAGE RESULTS

Category	Advertising (*AdStock*)						Price Promotion Depth (*Promo*)					Distribution Intensity (*Dist*)					Product Line Length (*LL*)					Regular Price (*Price*)				
	B	Mean†	Med.	#Sig >0	#Sig <0	λ	B	Mean	Med.	#Sig >0	#Sig <0	B	Mean	Med.	#Sig >0	#Sig <0	B	Mean	Med.	#Sig >0	#Sig <0	B	Mean	Med.	#Sig >0	#Sig <0
Artificial Sweeteners	5	.01	.02	0	0	.50	5	.17	.19	3	0	5	.57	.58	5	0	5	.45	.63	1	0	5	-.70	-.92	0	2
Bath Additives	8	.00	-.01	1	0	.90	8	.33	.28	6	0	8	.40	.37	6	0	8	.80	.92	3	0	8	-.38	-.48	0	1
Bathroom Tissue	4	.04	.06	2	0	.70	4	.08	.07	1	0	4	.66	.66	4	0	4	.35	.44	1	0	4	.22	.18	1	0
Breakfast Cereals	9	.01	.01	4	1	.00	9	.24	.19	9	0	9	.90	.89	5	1	9	.46	.49	3	0	9	-.15	-.12	1	3
Butter	7	.02	.01	2	0	.50	7	.26	.26	6	0	7	.37	.34	4	0	7	.13	-.04	1	0	7	-3.23	-3.20	0	6
Canned Fruit	9	-.03	-.01	0	1	.80	9	.15	.12	4	0	9	.20	.18	2	0	9	1.92	2.30	7	0	9	-1.25	-1.13	0	6
Canned Soup	4	.02	.03	1	0	.90	4	.26	.32	4	0	4	.35	.61	1	0	4	.24	.29	1	0	4	-.01	-.15	1	0
Cat Food	11	.03	.02	3	1	.90	11	.19	.23	8	0	11	.45	.34	6	0	11	.30	.27	4	1	11	-.54	-.51	0	4
Cereal Bars	3	.02	.02	0	0	.90	3	.17	.17	3	0	3	.48	.51	0	0	3	.37	.34	1	0	3	-.25	-.22	0	0
Cleansers (Facial)	13	-.01	-.02	1	5	.40	13	.22	.14	6	0	13	.63	.61	10	0	13	.96	.97	7	0	13	-.60	-.50	0	9
Conditioners	11	.14	.07	3	0	.90	11	.15	.10	4	0	11	.54	.57	9	0	11	1.05	.78	6	0	11	-1.02	-1.02	0	8
Cooking Sauces	18	.01	.01	3	2	.40	18	.25	.21	11	0	18	.18	.08	5	2	18	.81	.75	12	1	18	-.98	-.90	1	10
Deodorants	13	.03	.03	1	0	.70	13	.15	.18	7	0	13	.12	.17	5	2	13	.68	.69	7	0	13	-.43	-.58	0	4
Dog Food	16	.01	.00	1	2	.90	16	.20	.19	13	0	16	.23	.28	8	1	16	.16	.15	3	1	16	-.68	-.27	0	6
Dry Pasta	3	-.01	-.03	0	0	.90	3	.26	.25	3	0	3	.12	.10	0	0	3	1.61	1.63	3	0	3	-3.77	-3.63	0	3
Frozen Fish	8	.06	-.01	2	1	.90	8	.21	.23	6	0	8	.49	.51	8	0	8	1.60	1.70	7	0	8	-.13	-.10	2	2
Fruit/Yoghurt Juice	18	.00	.01	3	3	.80	18	.20	.16	11	0	18	.12	.06	4	0	18	.62	.53	8	1	18	-.79	-1.02	2	7
Ground/Bean Coffee	4	.04	.04	1	0	.90	4	.29	.28	4	0	4	.44	.45	3	0	4	.95	1.04	4	0	4	-.69	-.63	0	3
Household Cleaners	8	.00	.00	1	1	.10	8	.32	.43	6	0	8	.29	.29	5	0	8	1.25	1.19	5	0	8	-.47	-.40	1	4
Instant Coffee	4	.00	.00	0	1	.00	4	.08	.07	1	0	4	.51	.52	4	0	4	.97	1.05	3	0	4	.26	-.04	1	0
Laundry Detergents	8	.01	.02	0	0	.30	8	.41	.41	7	0	8	.57	.54	8	0	8	.34	.39	4	0	8	-.56	-.52	0	1
Margarine	8	.00	-.02	2	2	.90	8	.20	.20	7	0	8	.54	.48	5	0	8	.82	.94	4	0	8	-.89	-.78	0	3
Mineral Water	10	-.03	-.04	0	1	.80	10	.39	.33	9	0	10	.37	.34	5	0	10	.86	.85	3	0	10	-1.60	-1.51	0	6
Potato chips	7	.01	.00	2	2	.40	7	.25	.24	5	0	7	.92	1.10	5	0	7	.95	1.13	5	0	7	-.46	-.60	0	7
Razor Blades	5	.03	.02	1	1	.80	5	.11	.08	1	0	5	.40	.40	4	0	5	.16	.24	2	0	5	-.34	-.36	0	4
Sanitary Prot. Prod.	9	.02	.03	1	1	.70	9	.10	.09	2	0	9	.14	.20	4	1	9	.50	.70	6	0	9	-.35	-.27	1	4
Shampoo	13	.01	.01	4	1	.30	13	.15	.12	7	1	13	.53	.69	10	0	13	.71	.69	7	0	13	.23	.15	4	2
Shower Prod.	11	.02	.00	3	1	.90	11	.24	.24	6	0	11	.59	.57	8	0	11	1.05	1.28	6	0	11	.24	.40	1	0
Soft Drinks	29	.01	.01	5	4	.40	29	.19	.19	18	1	29	.22	.21	10	2	29	.47	.50	13	1	29	-.88	-1.35	6	13
Stout	3	.02	.03	1	0	.90	3	.08	.11	3	0	3	.24	.33	3	0	3	.41	.55	2	0	3	.08	.15	0	0
Table Sauces	5	.10	.11	3	0	.90	5	.22	.31	4	0	5	.15	.18	0	0	5	.36	.25	1	0	5	-.78	-.68	0	1
Tea	12	.03	.04	6	0	.40	12	.26	.25	9	0	12	.56	.67	9	0	12	1.02	1.35	8	1	12	-.89	-.92	1	7
Toothpaste	13	.00	.01	3	1	.00	13	.12	.10	7	0	13	.42	.39	9	0	13	.66	.29	6	0	13	-.49	-.43	1	9
Washing Up Prod.	6	.05	.05	1	0	.90	6	.26	.23	6	0	6	.68	.68	5	0	6	.15	.06	1	0	6	-.16	-.23	1	1
Yoghurt	10	.06	.07	7	0	.70	10	.17	.18	7	0	10	.31	.34	4	0	10	.33	.52	5	0	10	-.11	-.04	0	0

† Meta-analytic weighted means reported

WEB APPENDIX G – SBBE ESTIMATES BY CATEGORY

Category	# Brands	Brands with Lowest Avg SBBE †	Brands with Highest Avg SBBE †	Corr(*SBBE*, *l1.SBBE*)
Artificial Sweeteners	5	Sucron, Canderel	Hermesetas, Sweetex	.917
Bath Additives	8	E45, Matey	Dove, Radox	.891
Bathroom Tissue	4	Izal, Velvet	Nouvelle, Andrex	.958
Breakfast Cereals	9	Mornflakes, Kelloggs	Scotts, Jordans	.912
Butter	7	St. Ivel, Wheelbarrow Butter	Lurpak, Anchor	.989
Canned Fruit	9	Trout Hall, Valfruta	Princes, Fruitini	.934
Canned Soup	4	Weight Watchers, Heinz	Baxters, Covent Garden	.948
Cat Food	11	Arthurs, Katkins	Go-Cat, Felix	.975
Cereal Bars	3	Tracker	Jordans	.883
Cleansers (Facial)	13	Anne French, Oxy	Clean & Clear, Johnsons	.926
Conditioners	11	Revlon, Nicky Clarke	Alberto, Pantene	.935
Cooking Sauces	18	Crosse & Blackweel, Napolina	Sacla, Amoy	.927
Deodorants	13	Mum, Arrid	Sure, Adidas	.970
Dog Food	16	Tex, Chappie	Hi-Life, Bakers Dog Food	.980
Dry Pasta	3	Napolina	Marshalls	.943
Frozen Fish	8	Macrae, Lyons Seafoods	Kershaws, Youngs	.962
Fruit/Yoghurt Juice	18	Southern Delight, Sunpride	Tropicana, Ocean Spray	.956
Ground/Bean Coffee	4	Rombouts, Lyons	Douwe Egbert, Lavazza	.925
Household Cleaners	8	Ajax, Domestos	Dettol, Mr Muscle	.960
Instant Coffee	4	Red Mountain, Mellow Birds	Maxwell House, Nescafe	.928
Laundry Detergents	8	Daz, Ariel	Fairy, Bold	.966
Margarine	8	Summer County, Vitalite	I C B I N B, St Ivel	.987
Mineral Water	10	Abbey Well, Malvern	San Pellegrino, Evian	.967
Potato chips	7	KP Brannigans, Golden Wonder	KP, Kettle Foods	.979
Razor Blades	5	Personna, Bic	Gillette, Wilkinson Sword	.945
Sanitary Protection Products	9	Interlude, Tampax	Carefree, Always	.973
Shampoo	13	Timotei, Wash & Go	Head & Shoulders, T/Gel	.941
Shower Prod.	11	Badedas, Nivea	Imperial Leather, Johnsons	.888
Soft Drinks	29	Ben Shaw, Carters	Dr. Pepper, Coca Cola	.962
Stout	3	Mackeson	Guinness	.919
Table Sauces	5	Daddies Sauce, C&B Branston	H.P. Sauces, Heinz	.915
Tea	12	Lift, Tetley	Yorkshire Tea, R. Twining	.941
Toothpaste	13	Mentadent, Thera-Med	Colgate, Sensodyne	.973
Washing Up Products	6	Persil, Morning Fresh	Finish, Fairy	.953
Yoghurt	10	Longley Farm, Nestle	Yoplait, Rachels	.963

† Brands with lowest and highest average SBBEs in a product category are determined based on average of a brand's SBBE estimates during all time periods, weighted by inverse of the standard error for each estimate.

WEB APPENDIX H – OPERATIONALIZING BUSINESS CYCLES USING TIME-SERIES FILTERING

Hodrick and Prescott (1997) filter (hereinafter, HP filter) has been widely used in marketing research on business cycles (e.g., Lamey et al 2007; 2012; Deleersnyder et al 2009; Steenkamp and Fang 2011). The HP filter breaks down a time-series into (1) a gradually evolving trend component that represents long-term changes in a series and (2) cyclical fluctuations around the trend component that represent short-term changes in a series. In HP filters, the trend component (X^{tr}) is extracted by minimizing the following formula:

$$(1)\ \sum_{q=1}^{Q}\left(\hat{X}_{ijq}-\hat{X}_{ijq}^{tr}\right)^2+\lambda\sum_{q=2}^{Q-1}\left[\left(\hat{X}_{ijq+1}^{tr}-\hat{X}_{ijq}^{tr}\right)-\left(\hat{X}_{ijq}-\hat{X}_{ijq-1}^{tr}\right)\right]^2$$

with λ being the smoothing parameter. Following past research, for quarterly data, we use λ = 1600 (Hodrick and Prescott 1997; Ravn and Uhlig 2002; Kesavan and Kushwaha 2014). Consistent with past research (Lamey et al. 2007), we use inflation-adjusted GDPPC as the proxy for economic activity. Since SBBE estimates are at a quarterly level, we use quarterly GDPPC ($GDPPC_q$). For log-transformed $GDPPC_q$ (i.e., $lnGDPPC_q$), we extract its cyclical component ($lnGDPPC_q^{cyc}$), which is a measure of business cycles:[1]

$$(2)\ lnGDPPC_q^{cyc}=lnGDPPC_q-lnGDPPC_q^{tr}$$

Next, we use $lnGDPPC_q^{cyc}$ to operationalize the extent of expansions (EXP_q) and contractions (CON_q) at any point in time. We follow van Heerde et al. (2013) and define the magnitude of expansion (contraction) as the difference between the actual level of the cyclical component of the macroeconomic fluctuations at quarter q and the prior trough (peak):

$$(3)\ EXP_q=\begin{cases}lnGDPPC_q^{cyc}-\left(prior\ trough\ in\ lnGDPPC_q^{cyc}\right) & ;if\ \Delta lnGDPPC_q^{cyc}>0\\ 0 & ;if\ \Delta lnGDPPC_q^{cyc}\le 0\end{cases}$$

$$(4)\ CON_q=\begin{cases}0 & ;if\ \Delta lnGDPPC_q^{cyc}>0\\ \left(prior\ peak\ in\ lnGDPPC_q^{cyc}\right)-lnGDPPC_q^{cyc} & ;if\ \Delta lnGDPPC_q^{cyc}\le 0\end{cases}$$

EXP_q (CON_q) takes positive values during economic upturns (downturns) and 0 during downturns (upturns). This operationalization allows us to capture the magnitude of expansions or slowdowns, with the value of EXP_q (CON_q) capturing the *percentage* improvement (decline) in the economy

[1] For a detailed discussion on the rationale behind business cycle filtering and methodological details, see Deleersnyder et al. (2004) and Lamey et al. (2007, 2012).

during expansions (contractions).

We note that van Heerde et al. (2013) use Christiano-Fitzgerald (CF) filtering approach when applying filters to their GDP variable. We followed the CF filtering procedure which led to a revised $lnGDPPC_q^{cyc}$ (and subsequently a revised CON_q) which were strongly correlated with the $lnGDPPC_q^{cyc}$ (and CON_q) that were based on HP filtering approach (r>.9). Moreover, as we show in the robustness section, majority of our findings remain substantively unchanged when we follow the CF filtering approach (see Web Appendix L).

WEB APPENDIX I – CORRELATION TABLE FOR FOCAL SECOND-STAGE PREDICTOR VARIABLES

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
1) *PRICE*	1.00																		
2) *AD*	.13	1.00																	
3) *LL*	-.01	.49	1.00																
4) *DIST*	.04	.39	.48	1.00															
5) *ARCH*	-.01	.05	.02	.00	1.00														
6) *POS*	.08	.59	.64	.45	.01	1.00													
7) *EXP*	.00	-.01	-.01	.01	.00	.00	1.00												
8) *CON*	.00	.00	.00	.01	.00	.00	-.31	1.00											
9) *EXP*PRICE*	.57	.09	.01	.03	.00	.06	.00	.00	1.00										
10) *EXP*AD*	.08	.54	.29	.20	.01	.33	-.35	.11	.16	1.00									
11) *EXP*LL*	.01	.30	.56	.26	.01	.36	-.21	.06	.02	.58	1.00								
12) *EXP*DIST*	.03	.21	.26	.55	.00	.25	.26	-.08	.06	.25	.39	1.00							
13) *EXP*ARCH*	.00	.02	.01	.00	.49	.00	-.52	.16	.01	.19	.12	-.13	1.00						
14) *EXP*POS*	.05	.32	.35	.23	.00	.53	-.37	.12	.10	.66	.67	.30	.20	1.00					
15) *CON*PRICE*	.41	.06	.00	.02	.00	.03	.00	-.02	.00	.00	.00	.00	.00	.00	1.00				
16) *CON*AD*	.06	.38	.20	.14	.02	.22	.12	-.38	.00	-.04	-.02	.03	-.06	-.04	.16	1.00			
18) *CON*LL*	.00	.21	.40	.19	.02	.26	.07	-.23	.00	-.02	-.01	.02	-.04	-.03	.04	.60	1.00		
17) *CON*DIST*	.02	.15	.19	.39	.01	.17	-.09	.31	.00	.03	.02	-.02	.05	.03	.08	.21	.38	1.00	
19) *CON*ARCH*	.01	.02	.01	.00	.34	.01	.18	-.56	.00	-.06	-.04	.05	-.09	-.07	.03	.26	-.15	.17	1.00
20) *CON*POS*	.03	.22	.24	.16	.01	.38	.13	-.41	.00	-.04	-.03	.03	-.07	-.05	.09	.67	.25	.67	.27

WEB APPENDIX J – MODEL-FREE EVIDENCE FOR DIFFERENCES IN SBBE OF BRANDS IN EXPANSIONS AND CONTRACTIONS DEPENDING ON THEIR STRATEGIC BRAND FACTORS

We compare average SBBE of observations representing different strategic brand characeristics. We do this separately for “regular times”, expansions, and contractions. We define regular times as quarters in which magnitude of expansions or contractions were smaller than .5% ($0<EXP_q\leq.005$ or $0<CON_q\leq.005$) which accounts for roughly one-third of the quarters in the time period of our data. The differences due to SBFs during regular times provides the baseline effect and corresponds to the main effects in our model (α_2 through α_7). In this analysis, expansions are the time periods with EXP_q>.005 and contractions are time periods with CON_q>.005. Majority of the observed patterns are in line with our main findings:

Regular Times (Baseline)		**Expansions**		**Contractions**	
Value	Premium	Value	Premium	Value	Premium
-.0660	.1357	-.1113	.2042	-.0815	.1527
Δ = .2017		Δ = .3155		Δ = .2342	
Low *AD*	High *AD*	Low *AD*	High *AD*	Low *AD*	High *AD*
-.1105	.3637	-.1635	.5290	-.1920	.6068
Δ = .4742		Δ = .6925		Δ = .7988	
Short *LL*	Long *LL*	Short *LL*	Long *LL*	Short *LL*	Long *LL*
-.1559	.3418	-.1955	.4425	-.1295	.2929
Δ = .4977		Δ = .6380		Δ = .4224	
Selective Dist.	Extensive Dist.	Selective Dist.	Extensive Dist.	Selective Dist.	Extensive Dist.
-.3754	.2592	-.5266	.3813	-.5741	.3617
Δ = .6346		Δ = .9079		Δ = .9358	
Single-category	Umbrella	Single-category	Umbrella	Single-category	Umbrella
-.0084	.1952	-.0121	.2359	-.0163	.2485
Δ = .2036		Δ = .248		Δ = .2648	
Follower	Leader	Follower	Leader	Follower	Leader
-.1086	.4006	-.1612	.5858	-.1362	.4717
Δ = .5092		Δ = .7470		Δ = .6079	

WEB APPENDIX K – ADDING BLOCKS OF PREDICTORS TO BUILD THE FINAL MODEL

	Predictors	Expected Effect	M0: Only Controls	M1: M0+ SBFs	M2: M1+ EXP & Its Interact.	M3: M2+ CON & Its Interact.
	Intercept		.3207***	.3071***	.3083***	.3095***
	$SBBE_{ijq-1}$		.8802***	.8657***	.8634***	.8626***
Strategic Brand Factors	$PRICE_{ijq}$			.0042	.0007	-.0012
	AD_{ijq}			.0110*	.0107	.0083
	LL_{ijq}			.0372***	.0307***	.0341***
	$DIST_{ijq}$			.0529***	.0466***	.0418***
	$ARCH_{ij}$			NA†	NA†	NA†
	POS_{ijq}			.0280**	.0265**	.0246**
Differential Effect of Expansions for Different Brands	EXP_q				-.0602	-.0949
	$EXP_q * PRICE_{ijq}$	H_{1EXP}: +			.5173*	.6165**
	$EXP_q * AD_{ijq}$	H_{2EXP}: +			.0164	.1655
	$EXP_q * LL_{ijq}$	H_{3EXP}: +			1.1843***	.9600**
	$EXP_q * DIST_{ijq}$	H_{4EXP}: +			1.3898*	1.6825**
	$EXP_q * ARCH_{ij}$	H_{5EXP}: -			.1718	.3898
	$EXP_q * POS_{ijq}$				.4584*	.5672*
Differential Effect of Contractions for Different Brands	CON_q					-.1011
	$CON_q * PRICE_{ijq}$					.2116
	$CON_q * AD_{ijq}$	H_{2CON}: +				.3602*
	$CON_q * LL_{ijq}$	H_{3CON}: -				-.5414***
	$CON_q * DIST_{ijq}$	H_{4CON}: +				.6786**
	$CON_q * ARCH_{ij}$	H_{5CON}: +				.4897***
	$CON_q * POS_{ijq}$	H_{6CON}: +				.2307
Control Variables	$OTHERSPP_{ijq}$		.0288	.0183	.0186	.0197
	$OTHERSAD_{ijq}$		.0001	-.0001	-.0001	-.0001
	$OTHERSLL_{ijq}$		-.0058	-.0055	-.0050	-.0053
	$OTHERSDIST_{ijq}$		-.2962***	-.2861***	-.2874***	-.2866***
	$PLMS_{jq}$		-.0679	-.0592	-.0609	-.0589
	Brand FEs		Included	Included	Included	Included
	Year FEs		Included	Included	Included	Included
	Quarter FEs		Included	Included	Included	Included

*** p<.01; ** p<.05; * p<.10 (one-sided p-values for hypothesized effects and two-sided for others). Significance assessed using 2-way cluster-adjusted SEs (at brand and quarter levels). N=20,800 (due to the nature of operationalization of most SBF variables that utilize past four quarters of data, we do not use first year of data [1994] in our second-stage analysis).

† Main effect of *ARCH* is not identified since it is a time-invariant characteristic and hence the effect is subsumed within brand fixed effects.

WEB APPENDIX L – ADDITIONAL ROBUSTNESS CHECKS

We conduct a series of robustness checks to assess the sensitivity of our findings with respect to different choices in our first- and second-stage models. Below we describe these checks:

<u>Second-stage robustness checks</u>:

1- Operationalizing EXP_q and CON_q via another time-series filtering approach: we follow van Heerde et al. (2013) and construct EXP_q and CON_q using the Christiano-Fitzgerald (CF) filtering approach. Results are reported in Table WA.K1. All our results are substantively unchanged, with the exception being $CON_q * DIST_{ijq}$ which is no longer significant. Moreover, $EXP_q * ARCH_{jq}$ that was not significant in our main analysis was found to be positive and significant in this analysis (in line with H5e).

2- Specifying cluster-adjusted standard errors at different levels of aggregation: our main analysis utilized a rigorous two-way clustering approach for the standard errors (at brand and quarter levels) that accounts for within-time (cross-brand) and within-brand correlations across observations. Following Seiler, Tuchman, and Yao (2021), we show robustness of our results to alternative standard error specifications at different levels of aggregation. These results are reported in Tables WA.K2a (clustered SEs at brand and year levels), and WA.K2b (clustered SEs at brand and quarter*category levels).

3- Accounting for category-specific and brand-specific seasonal patterns: in our main analysis, we include quarter fixed effects to account for seasonal patterns in SBBE. But perhaps the seasonal patterns in SBBE are category-specific or brand-specific. We address such concerns by including quarter*category and quarter*brand fixed effects in analyses which we report in WA.K3a and WA.K3b, respectively.

4- Controlling for marketing mix activities in the current time period: we add five marketing mix variables that represent quarterly advertising, regular price, price promotion, line length, and distribution intensity of the focal brands to equation 6. We create these variables by averaging monthly values of these variables that we use in our first-stage model. Upon adding these variables, we realized that inclusion of distribution intensity led to serious multicollinearity issues and maximum VIF value rose to 34.52. We therefore removed distribution intensity from our model. Results are reported in Table WA.K4.

5- Using category medians to operationalize the first four SBF variables: in our main analysis, we used category means in the past four quarters to operationalize four SBF variables (i.e., value vs. premium pricing, low vs high ad spenders, short vs. long line length, and selective vs. extensive distribution). In WA.K5 we present results after using category medians to operationalize these variables. All of our findings remain unchanged.

First-stage robustness checks:

6- Controlling for lagged effects of marketing mix instruments: we add first lag of the marketing mix instruments to the market share attraction model that we utilize to obtain SBBE estimates. Since advertising stock already incorporates previous advertising expenditures, we only include lagged values of the other marketing mix instruments. The new results are reported in Table WA.K6.

7- Allowing the effects of marketing variables to vary across the business cycle: in our first-stage analysis, we add interactions of the five marketing mix instruments with the variables representing expansions (EXP_q) and contractions (CON_q). These interactions would account for the possibility that the effects of marketing mix instruments on market share might be different in expansions and contractions. We report the results in Table WA.K7. Most of our findings are replicated. It is also worth noting that unlike our main analysis and in line with H_{6c}, we find support for $CON_q * POS_{ijq}$.

8- Using value (instead of volume) market share as the dependent variable: in our first-stage analysis, we used volume market share as our dependent variable. We redo our analyses by using value market share in the first-stage analysis (see Table WA.K8).

9- Removing lagged market share: in the first-stage model, to account for dynamics and state dependence in market share, we included lagged market share as an independent variable. We follow Datta, Ailawadi, and van Heerde (2017) by specifying a first-stage model without lagged market share. In Table WA.K9 we report the results of our analysis if lagged market share is not added in the first-stage model. All our findings are replicated.

10- Removing Gaussian Copulas from the first-stage: it could be argued that with the inclusion of lagged dependent variable, multiple marketing mix instruments, and product attributes there is little endogeneity concerns in our first-stage model. In WA.K10 we report the results of analysis without Gaussian Copulas in our first-stage model.

Overall, our results remain generally robust across the 12 analyses presented in Web Appendix L. In the table below we summarize how many times we find support for the focal interactions that were significant in our main analysis:

Effect	EXP_q* $PRICE_{ijq}$	EXP_q* LL_{ijq}	EXP_q* $DIST_{ijq}$	EXP_q * POS_{ijq}	CON_q * AD_{ijq}	CON_q* LL_{ijq}	CON_q* $DIST_{ijq}$	CON_q* $ARCH_{ij}$
Supported in # Analyses	10/12	12/12	10/12	8/12	11/12	11/12	9/12	11/12

Table WA.L1 – Using Christiano-Fitzgerald (CF) Filtering to Operationalize *EXP* and *CON*

	Predictors	Expected Effect	Main Finding	Estimate
	Intercept			.3094***
	$SBBE_{ijq-1}$			.8649***
Strategic Brand Factors	$PRICE_{ijq}$			-.0024
	AD_{ijq}			.0103*
	LL_{ijq}			.0348***
	$DIST_{ijq}$			.0391***
	$ARCH_{ij}$			NA†
	POS_{ijq}			.0245**
Differential Effect of Expansions for Different Brands	EXP_q			-.3551
	$EXP_q * PRICE_{ijq}$	H_{1EXP}: +	+	.7475**
	$EXP_q * AD_{ijq}$	H_{2EXP}: +	NS	-.1947
	$EXP_q * LL_{ijq}$	H_{3EXP}: +	+	.8093**
	$EXP_q * DIST_{ijq}$	H_{4EXP}: +	+	2.1197***
	$EXP_q * ARCH_{ij}$	H_{5EXP}: -	+	1.1570***
	$EXP_q * POS_{ijq}$		+	.6620*
Differential Effect of Contractions for Different Brands	CON_q			-.0328
	$CON_q * PRICE_{ijq}$		NS	.2479
	$CON_q * AD_{ijq}$	H_{2CON}: +	+	.4324*
	$CON_q * LL_{ijq}$	H_{3CON}: -	-	-.3604**
	$CON_q * DIST_{ijq}$	H_{4CON}: +	+	.4621
	$CON_q * ARCH_{ij}$	H_{5CON}: +	+	.8381***
	$CON_q * POS_{ijq}$	H_{6CON}: +	NS	-.0571
Control Variables	$OTHERSPP_{ijq}$			.0142
	$OTHERSAD_{ijq}$			.0001
	$OTHERSLL_{ijq}$			-.0046
	$OTHERSDIST_{ijq}$			-.2836***
	$PLMS_{jq}$			-.0537
	Brand Fixed Effects			Included
	Year Fixed Effects			Included
	Quarter Fixed Effects			Included

*** p<.01; ** p<.05; * p<.10 (one-sided p-values for hypothesized effects and two-sided for others). Significance assessed using 2-way cluster-adjusted SEs (at brand and quarter levels). N=20,800 (due to the nature of operationalization of most SBF variables that utilize past four quarters of data, we do not use first year of data [1994] in our second-stage analysis).

† Main effect of *ARCH* is not identified since it is a time-invariant characteristic and hence the effect is subsumed within brand fixed effects.

Table WA.L2 – Clustering Standard Errors at Different Levels of Aggregation

	Predictors	Expected Effect	Main Finding	a. Clustered SEs at Brand & Year	b. Clustered SEs at Brand & Qtr*Cat
	Intercept			.3095***	.3095***
	$SBBE_{ijq-1}$			.8626***	.8623***
Strategic Brand Factors	$PRICE_{ijq}$			-.0012	-.0001
	AD_{ijq}			.0083	.0090
	LL_{ijq}			.0341***	.0336***
	$DIST_{ijq}$			.0418***	.0425***
	$ARCH_{ij}$			NA†	NA†
	POS_{ijq}			.0246**	.0261**
Differential Effect of Expansions for Different Brands	EXP_q			-.0949	-.2220
	$EXP_q * PRICE_{ijq}$	H_{1EXP}: +	+	.6165*	.5489*
	$EXP_q * AD_{ijq}$	H_{2EXP}: +	NS	.1655	.7763
	$EXP_q * LL_{ijq}$	H_{3EXP}: +	+	.9600**	.8138*
	$EXP_q * DIST_{ijq}$	H_{4EXP}: +	+	1.6825	1.4986**
	$EXP_q * ARCH_{ij}$	H_{5EXP}: -	NS	.3898	.2757
	$EXP_q * POS_{ijq}$		+	.5672*	.4677
Differential Effect of Contractions for Different Brands	CON_q			-.1011	-.2215
	$CON_q * PRICE_{ijq}$		NS	.2116	.0781
	$CON_q * AD_{ijq}$	H_{2CON}: +	+	.3602	.8860**
	$CON_q * LL_{ijq}$	H_{3CON}: -	-	-.5414**	-.6282**
	$CON_q * DIST_{ijq}$	H_{4CON}: +	+	.6786**	.4491
	$CON_q * ARCH_{ij}$	H_{5CON}: +	+	.4897*	.3943*
	$CON_q * POS_{ijq}$	H_{6CON}: +	NS	.2307	.1698
Control Variables	$OTHERSPP_{ijq}$			.0197	.0209
	$OTHERSAD_{ijq}$			-.0001	-.0001
	$OTHERSLL_{ijq}$			-.0053	-.0046
	$OTHERSDIST_{ijq}$			-.2866***	-.2867***
	$PLMS_{jq}$			-.0589	-.0654
	Brand Fixed Effects			Included	Included
	Year Fixed Effects			Included	Included
	Quarter Fixed Effects			Included	Included

*** p<.01; ** p<.05; * p<.10 (one-sided p-values for hypothesized effects and two-sided for others). Significance assessed using 2-way cluster-adjusted SEs (at brand and year levels on the "a" column, and brand and quarter*category levels on the "b" column). N=20,800 (due to the nature of operationalization of most SBF variables that utilize past four quarters of data, we do not use first year of data [1994] in our second-stage analysis).
† Main effect of *ARCH* is not identified since it is a time-invariant characteristic and hence the effect is subsumed within brand fixed effects.

Table WA.L3 – Accounting for Category-specific and Brand-Specific Seasonal Patterns

	Predictors	Expected Effect	Main Finding	a. Adding Cat.*Qtr Fixed Effects	b. Adding Brand*Qtr Fixed Effects
	Intercept			$.3094^{***}$	$.2605^{***}$
	$SBBE_{ijq-1}$			$.8632^{***}$	$.8850^{***}$
Strategic Brand Factors	$PRICE_{ijq}$			-.0014	-.0001
	AD_{ijq}			.0083	.0079
	LL_{ijq}			$.0339^{***}$	$.0260^{***}$
	$DIST_{ijq}$			$.0418^{***}$	$.0334^{***}$
	$ARCH_{ij}$			NA†	NA†
	POS_{ijq}			$.0242^{**}$	$.0178^{**}$
Differential Effect of Expansions for Different Brands	EXP_q			-.0865	-.1653
	$EXP_q * PRICE_{ijq}$	H_{1EXP}: +	+	$.6237^{**}$	$.5934^{*}$
	$EXP_q * AD_{ijq}$	H_{2EXP}: +	NS	.1634	.7930
	$EXP_q * LL_{ijq}$	H_{3EXP}: +	+	$.9415^{**}$	$.7093^{*}$
	$EXP_q * DIST_{ijq}$	H_{4EXP}: +	+	1.6520^{**}	1.1053
	$EXP_q * ARCH_{ij}$	H_{5EXP}: -	NS	.4064	.2353
	$EXP_q * POS_{ijq}$		+	$.5859^{*}$	.4110
Differential Effect of Contractions for Different Brands	CON_q			-.0906	-.2104
	$CON_q * PRICE_{ijq}$		NS	.2192	.2041
	$CON_q * AD_{ijq}$	H_{2CON}: +	+	$.3400^{*}$	$.6553^{*}$
	$CON_q * LL_{ijq}$	H_{3CON}: -	-	$-.5251^{***}$	$-.5540^{***}$
	$CON_q * DIST_{ijq}$	H_{4CON}: +	+	$.6556^{**}$	$.4248^{*}$
	$CON_q * ARCH_{ij}$	H_{5CON}: +	+	$.5153^{***}$	$.3868^{***}$
	$CON_q * POS_{ijq}$	H_{6CON}: +	NS	.2369	.1418
Control Variables	$OTHERSPP_{ijq}$			.0197	.0191
	$OTHERSAD_{ijq}$			-.0001	.0001
	$OTHERSLL_{ijq}$			-.0053	-.0031
	$OTHERSDIST_{ijq}$			$-.2866^{***}$	$-.2457^{***}$
	$PLMS_{jq}$			-.0589	-.0518
	Brand Fixed Effects			Included	Included
	Year Fixed Effects			Included	Included
	Quarter Fixed Effects			Included	Included
	Category*Quarter FEs			Included	
	Brand*Quarter FEs				Included

*** $p<.01$; ** $p<.05$; * $p<.10$ (one-sided p-values for hypothesized effects and two-sided for others). Significance assessed using 2-way cluster-adjusted SEs (at brand and quarter levels). N=20,800 (due to the nature of operationalization of most SBF variables that utilize past four quarters of data, we do not use first year of data [1994] in our second-stage analysis).

† Main effect of *ARCH* is not identified since it is a time-invariant characteristic and hence the effect is subsumed within brand fixed effects.

Table WA.L4 – Controlling for Marketing Mix Activities in the Current Period

	Predictors	Expected Effect	Main Finding	Estimate
	Intercept			.2849***
	$SBBE_{ijq-1}$			.8620***
Strategic Brand Factors	$PRICE_{ijq}$			-.0026
	AD_{ijq}			.0066
	LL_{ijq}			.0248***
	$DIST_{ijq}$			.0399***
	$ARCH_{ij}$			NA†
	POS_{ijq}			.0248**
Differential Effect of Expansions for Different Brands	EXP_q			-.1386
	$EXP_q * PRICE_{ijq}$	H_{1EXP}: +	+	.6065*
	$EXP_q * AD_{ijq}$	H_{2EXP}: +	NS	.2344
	$EXP_q * LL_{ijq}$	H_{3EXP}: +	+	.6684*
	$EXP_q * DIST_{ijq}$	H_{4EXP}: +	+	1.6846**
	$EXP_q * ARCH_{ij}$	H_{5EXP}: -	NS	.3423
	$EXP_q * POS_{ijq}$		NS	.2805
Differential Effect of Contractions for Different Brands	CON_q			-.1425
	$CON_q * PRICE_{ijq}$		NS	.1971
	$CON_q * AD_{ijq}$	H_{2CON}: +	+	.3307*
	$CON_q * LL_{ijq}$	H_{3CON}: -	-	-.7225***
	$CON_q * DIST_{ijq}$	H_{4CON}: +	+	.6757**
	$CON_q * ARCH_{ij}$	H_{5CON}: +	+	.4881**
	$CON_q * POS_{ijq}$	H_{6CON}: +	NS	.0423
Control Variables	$OTHERSPP_{ijq}$			.0207
	$OTHERSAD_{ijq}$			-.0001
	$OTHERSLL_{ijq}$			-.0150**
	$OTHERSDIST_{ijq}$			-.2823***
	$PLMS_{jq}$			-.0596
	Brand Fixed Effects			Included
	Year Fixed Effects			Included
	Quarter Fixed Effects			Included
	Ad Expenditures			.0001**
	Regular Price			-.0193
	Price Promotion			.2060**
	Line Length			.0012***

*** $p<.01$; ** $p<.05$; * $p<.10$ (one-sided p-values for hypothesized effects and two-sided for others). Significance assessed using 2-way cluster-adjusted SEs (at brand and quarter levels). N=20,800 (due to the nature of operationalization of most SBF variables that utilize past four quarters of data, we do not use first year of data [1994] in our second-stage analysis). † Main effect of *ARCH* is not identified since it is a time-invariant characteristic and hence the effect is subsumed within brand fixed effects.

Table WA.L5 – Using Category Medians to Operationalize the First Four SBF Variables

	Predictors	Expected Effect	Main Finding	Estimate
	Intercept			$.3107^{***}$
	$SBBE_{ijq-1}$			$.8632^{***}$
Strategic Brand Factors	$PRICE_{ijq}$			-.0083
	AD_{ijq}			$.0126^{*}$
	LL_{ijq}			$.0360^{***}$
	$DIST_{ijq}$			$.0398^{***}$
	$ARCH_{ij}$			NA†
	POS_{ijq}			$.0228^{**}$
Differential Effect of Expansions for Different Brands	EXP_q			.0146
	$EXP_q * PRICE_{ijq}$	H_{1EXP}: +	+	$.4230^{*}$
	$EXP_q * AD_{ijq}$	H_{2EXP}: +	NS	.4105
	$EXP_q * LL_{ijq}$	H_{3EXP}: +	+	$.5526^{*}$
	$EXP_q * DIST_{ijq}$	H_{4EXP}: +	+	1.5445^{*}
	$EXP_q * ARCH_{ij}$	H_{5EXP}: -	NS	.3724
	$EXP_q * POS_{ijq}$		+	$.7968^{***}$
Differential Effect of Contractions for Different Brands	CON_q			-.0481
	$CON_q * PRICE_{ijq}$		NS	.2364
	$CON_q * AD_{ijq}$	H_{2CON}: +	+	$.5797^{**}$
	$CON_q * LL_{ijq}$	H_{3CON}: -	-	$-.9597^{***}$
	$CON_q * DIST_{ijq}$	H_{4CON}: +	+	$.7332^{**}$
	$CON_q * ARCH_{ij}$	H_{5CON}: +	+	$.5276^{***}$
	$CON_q * POS_{ijq}$	H_{6CON}: +	NS	.3679
Control Variables	$OTHERSPP_{ijq}$			.0200
	$OTHERSAD_{ijq}$			-.0001
	$OTHERSLL_{ijq}$			-.0056
	$OTHERSDIST_{ijq}$			$-.2862^{***}$
	$PLMS_{jq}$			-.0595
	Brand Fixed Effects			Included
	Year Fixed Effects			Included
	Quarter Fixed Effects			Included

*** $p<.01$; ** $p<.05$; * $p<.10$ (one-sided p-values for hypothesized effects and two-sided for others). Significance assessed using 2-way cluster-adjusted SEs (at brand and quarter levels). N=20,800 (due to the nature of operationalization of most SBF variables that utilize past four quarters of data, we do not use first year of data [1994] in our second-stage analysis).

† Main effect of *ARCH* is not identified since it is a time-invariant characteristic and hence the effect is subsumed within brand fixed effects.

Table WA.L6 – Controlling for Lagged Effects of Marketing Mix Instruments

	Predictors	Expected Effect	Main Finding	Estimate
	Intercept			.0108***
	$SBBE_{ijq-1}$			.8594***
Strategic Brand Factors	$PRICE_{ijq}$			.0022
	AD_{ijq}			.0080
	LL_{ijq}			.0345***
	$DIST_{ijq}$			.0369***
	$ARCH_{ij}$			NA†
	POS_{ijq}			.0245**
Differential Effect of Expansions for Different Brands	EXP_q			.0313
	$EXP_q * PRICE_{ijq}$	H_{1EXP}: +	+	.6047**
	$EXP_q * AD_{ijq}$	H_{2EXP}: +	NS	.3305
	$EXP_q * LL_{ijq}$	H_{3EXP}: +	+	.5965*
	$EXP_q * DIST_{ijq}$	H_{4EXP}: +	+	1.5647**
	$EXP_q * ARCH_{ij}$	H_{5EXP}: -	NS	.2661
	$EXP_q * POS_{ijq}$		+	.7191**
Differential Effect of Contractions for Different Brands	CON_q			-.0722
	$CON_q * PRICE_{ijq}$		NS	.2107
	$CON_q * AD_{ijq}$	H_{2CON}: +	+	.3848*
	$CON_q * LL_{ijq}$	H_{3CON}: -	-	-.6697***
	$CON_q * DIST_{ijq}$	H_{4CON}: +	+	.7245**
	$CON_q * ARCH_{ij}$	H_{5CON}: +	+	.5360**
	$CON_q * POS_{ijq}$	H_{6CON}: +	NS	.4357
Control Variables	$OTHERSPP_{ijq}$			.0015
	$OTHERSAD_{ijq}$			-.0001
	$OTHERSLL_{ijq}$			.0061
	$OTHERSDIST_{ijq}$			-.2251***
	$PLMS_{jq}$			-.0453
	Brand Fixed Effects			Included
	Year Fixed Effects			Included
	Quarter Fixed Effects			Included

*** $p<.01$; ** $p<.05$; * $p<.10$ (one-sided p-values for hypothesized effects and two-sided for others). Significance assessed using 2-way cluster-adjusted SEs (at brand and quarter levels). N=20,800 (due to the nature of operationalization of most SBF variables that utilize past four quarters of data, we do not use first year of data [1994] in our second-stage analysis).

† Main effect of *ARCH* is not identified since it is a time-invariant characteristic and hence the effect is subsumed within brand fixed effects.

Table WA.L7 – Allowing the Effects of Marketing Variables to vary across the Business Cycle in the First-stage Model

	Predictors	Expected Effect	Main Finding	Estimate
	Intercept			-.2343
	$SBBE_{ijq-1}$			.3622**
Strategic Brand Factors	$PRICE_{ijq}$			-.0481
	AD_{ijq}			-.0037
	LL_{ijq}			.1724***
	$DIST_{ijq}$			.1916**
	$ARCH_{ij}$			NA†
	POS_{ijq}			.2185***
Differential Effect of Expansions for Different Brands	EXP_q			-.2826
	$EXP_q * PRICE_{ijq}$	H_{1EXP}: +	+	4.1135**
	$EXP_q * AD_{ijq}$	H_{2EXP}: +	NS	.6347
	$EXP_q * LL_{ijq}$	H_{3EXP}: +	+	2.3533*
	$EXP_q * DIST_{ijq}$	H_{4EXP}: +	+	7.3954*
	$EXP_q * ARCH_{ij}$	H_{5EXP}: -	NS	2.5506
	$EXP_q * POS_{ijq}$		+	2.5921*
Differential Effect of Contractions for Different Brands	CON_q			-.2880
	$CON_q * PRICE_{ijq}$		NS	5.0389
	$CON_q * AD_{ijq}$	H_{2CON}: +	+	4.5851*
	$CON_q * LL_{ijq}$	H_{3CON}: -	NS	1.2563
	$CON_q * DIST_{ijq}$	H_{4CON}: +	+	8.5827**
	$CON_q * ARCH_{ij}$	H_{5CON}: +	NS	-4.7153
	$CON_q * POS_{ijq}$	H_{6CON}: +	+	7.0962**
Control Variables	$OTHERSPP_{ijq}$			-.0493
	$OTHERSAD_{ijq}$			.0023
	$OTHERSLL_{ijq}$			.0239
	$OTHERSDIST_{ijq}$			-1.0064***
	$PLMS_{jq}$			-.2353
	Brand Fixed Effects			Included
	Year Fixed Effects			Included
	Quarter Fixed Effects			Included

*** $p<.01$; ** $p<.05$; * $p<.10$ (one-sided p-values for hypothesized effects and two-sided for others). Significance assessed using 2-way cluster-adjusted SEs (at brand and quarter levels). N=20,800 (due to the nature of operationalization of most SBF variables that utilize past four quarters of data, we do not use first year of data [1994] in our second-stage analysis).

† Main effect of *ARCH* is not identified since it is a time-invariant characteristic and hence the effect is subsumed within brand fixed effects.

Table WA.L8 – Using Value Market Share in the First-stage Model

	Predictors	Expected Effect	Main Finding	Estimate
	Intercept			.0144***
	$SBBE_{ijq-1}$			.8644***
Strategic Brand Factors	$PRICE_{ijq}$			.0026
	AD_{ijq}			.0074
	LL_{ijq}			.0294***
	$DIST_{ijq}$			.0498***
	$ARCH_{ij}$			NA†
	POS_{ijq}			.0337***
Differential Effect of Expansions for Different Brands	EXP_q			-.0322
	$EXP_q * PRICE_{ijq}$	H_{1EXP}: +	NS	.2723
	$EXP_q * AD_{ijq}$	H_{2EXP}: +	NS	.2035
	$EXP_q * LL_{ijq}$	H_{3EXP}: +	+	.8385**
	$EXP_q * DIST_{ijq}$	H_{4EXP}: +	+	1.5654**
	$EXP_q * ARCH_{ij}$	H_{5EXP}: -	NS	.4064
	$EXP_q * POS_{ijq}$		NS	.5753
Differential Effect of Contractions for Different Brands	CON_q			-.0204
	$CON_q * PRICE_{ijq}$		NS	.0872
	$CON_q * AD_{ijq}$	H_{2CON}: +	+	.5522***
	$CON_q * LL_{ijq}$	H_{3CON}: -	-	-.4003**
	$CON_q * DIST_{ijq}$	H_{4CON}: +	NS	.4307
	$CON_q * ARCH_{ij}$	H_{5CON}: +	+	.5255***
	$CON_q * POS_{ijq}$	H_{6CON}: +	NS	.0626
Control Variables	$OTHERSPP_{ijq}$			-.0432
	$OTHERSAD_{ijq}$			.0008
	$OTHERSLL_{ijq}$			.0003
	$OTHERSDIST_{ijq}$			-.2663***
	$PLMS_{jq}$			-.0553
	Brand Fixed Effects			Included
	Year Fixed Effects			Included
	Quarter Fixed Effects			Included

*** p<.01; ** p<.05; * p<.10 (one-sided p-values for hypothesized effects and two-sided for others). Significance assessed using 2-way cluster-adjusted SEs (at brand and quarter levels). N=20,800 (due to the nature of operationalization of most SBF variables that utilize past four quarters of data, we do not use first year of data [1994] in our second-stage analysis).

† Main effect of *ARCH* is not identified since it is a time-invariant characteristic and hence the effect is subsumed within brand fixed effects.

Table WA.L9 – Removing Lagged Market Share in the First-stage Model

	Predictors	Expected Effect	Main Finding	Estimate
	Intercept			.3095***
	$SBBE_{ijq-1}$			.8626***
Strategic Brand Factors	$PRICE_{ijq}$			-.0012
	AD_{ijq}			.0083
	LL_{ijq}			.0341***
	$DIST_{ijq}$			.0418***
	$ARCH_{ij}$			NA†
	POS_{ijq}			.0246**
Differential Effect of Expansions for Different Brands	EXP_q			-.0949
	$EXP_q * PRICE_{ijq}$	H_{1EXP}: +	+	.6165**
	$EXP_q * AD_{ijq}$	H_{2EXP}: +	NS	.1655
	$EXP_q * LL_{ijq}$	H_{3EXP}: +	+	.9600*
	$EXP_q * DIST_{ijq}$	H_{4EXP}: +	+	1.6825**
	$EXP_q * ARCH_{ij}$	H_{5EXP}: -	NS	.3898
	$EXP_q * POS_{ijq}$		+	.5672*
Differential Effect of Contractions for Different Brands	CON_q			-.1011
	$CON_q * PRICE_{ijq}$		NS	.2116
	$CON_q * AD_{ijq}$	H_{2CON}: +	+	.3602*
	$CON_q * LL_{ijq}$	H_{3CON}: -	-	-.5414***
	$CON_q * DIST_{ijq}$	H_{4CON}: +	+	.6786**
	$CON_q * ARCH_{ij}$	H_{5CON}: +	+	.4897***
	$CON_q * POS_{ijq}$	H_{6CON}: +	NS	.2307
Control Variables	$OTHERSPP_{ijq}$			.0197
	$OTHERSAD_{ijq}$			-.0001
	$OTHERSLL_{ijq}$			-.0053
	$OTHERSDIST_{ijq}$			-.2866***
	$PLMS_{jq}$			-.0589
	Brand Fixed Effects			Included
	Year Fixed Effects			Included
	Quarter Fixed Effects			Included

*** $p<.01$; ** $p<.05$; * $p<.10$ (one-sided p-values for hypothesized effects and two-sided for others). Significance assessed using 2-way cluster-adjusted SEs (at brand and quarter levels). N=20,800 (due to the nature of operationalization of most SBF variables that utilize past four quarters of data, we do not use first year of data [1994] in our second-stage analysis).
† Main effect of *ARCH* is not identified since it is a time-invariant characteristic and hence the effect is subsumed within brand fixed effects.

Table WA.L10 – Removing Gaussian Copulas from the First-stage Model

	Predictors	Expected Effect	Main Finding	Estimate
	Intercept			.0106***
	$SBBE_{ijq-1}$			.8592***
Strategic Brand Factors	$PRICE_{ijq}$			-.0001
	AD_{ijq}			.0047
	LL_{ijq}			.0387***
	$DIST_{ijq}$			.0487***
	$ARCH_{ij}$			NA†
	POS_{ijq}			.0279**
Differential Effect of Expansions for Different Brands	EXP_q			.0606
	$EXP_q * PRICE_{ijq}$	H_{1EXP}: +	NS	.4827
	$EXP_q * AD_{ijq}$	H_{2EXP}: +	NS	.5693
	$EXP_q * LL_{ijq}$	H_{3EXP}: +	+	1.1081**
	$EXP_q * DIST_{ijq}$	H_{4EXP}: +	+	1.4247*
	$EXP_q * ARCH_{ij}$	H_{5EXP}: -	NS	.4539
	$EXP_q * POS_{ijq}$		+	.5533*
Differential Effect of Contractions for Different Brands	CON_q			-.0898
	$CON_q * PRICE_{ijq}$		NS	.0653
	$CON_q * AD_{ijq}$	H_{2CON}: +	+	.4380**
	$CON_q * LL_{ijq}$	H_{3CON}: -	-	-.5650***
	$CON_q * DIST_{ijq}$	H_{4CON}: +	+	.4799*
	$CON_q * ARCH_{ij}$	H_{5CON}: +	+	.3507*
	$CON_q * POS_{ijq}$	H_{6CON}: +	NS	.3077
Control Variables	$OTHERSPP_{ijq}$			.0196
	$OTHERSAD_{ijq}$			.0001
	$OTHERSLL_{ijq}$			.0099
	$OTHERSDIST_{ijq}$			-.2725***
	$PLMS_{jq}$			-.0670
	Brand Fixed Effects			Included
	Year Fixed Effects			Included
	Quarter Fixed Effects			Included

*** $p<.01$; ** $p<.05$; * $p<.10$ (one-sided p-values for hypothesized effects and two-sided for others). Significance assessed using 2-way cluster-adjusted SEs (at brand and quarter levels). N=20,800 (due to the nature of operationalization of most SBF variables that utilize past four quarters of data, we do not use first year of data [1994] in our second-stage analysis).

† Main effect of *ARCH* is not identified since it is a time-invariant characteristic and hence the effect is subsumed within brand fixed effects.

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