COMPETING IN THE PURCHASE FUNNEL:
IMPACT ON SALES RESPONSIVENESS AND CONVERSION

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The authors thank participants of the 2015 Marketing Science Conference and the 2016 Theory Meets Practice Conference. The first two authors are for funding support from the Marketing Science Institute Support for this project.

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ABSTRACT

Our objective is to assess how competition influences the responsiveness to marketing mix and sales conversion of mindset metrics: *communication awareness, brand consideration* and *brand liking.* Our empirical analysis consists of 82 packaged goods brands from 5 grocery categories between January 2001 and December 2010 in Spain. We estimate the dynamic interactions between sales, marketing mix, and own and competitive mindset metrics using Bayesian vector-autoregressive models. Competition in the category is operationalized as the number of existing brands, and price and advertising competition intensity. We find positive moderation effects of the number of brands on the sales conversion and marketing responsiveness of mindset metrics indicative of positive spillovers across brands. While price competition intensity has a negative influence on conversion and responsiveness of awareness and liking, it has a positive effect on the marketing mix responsiveness of brand consideration. Advertising competition intensity has a positive impact on the conversion of all mindset metrics, but it generally exerts a negative impact on their responsiveness. Thus, the impact of competition varies by metric and by competition type.

Keywords: Mindset Metrics, Brand Sales, Market Competition, Bayesian Estimation, Vector Auto Regressive Modeling

INTRODUCTION

In an effort to enhance marketing's accountability in the organization, recent research has focused on the linkages between unobservable consumer mindset metrics and various financial and market outcomes (Fornell, Rust and Dekimpe 2010; Srinivasan and Hanssens 2009; Srinivasan, Vanhuele and Pauwels 2010). Access to such information may allow firms to monitor their brand performance over time, gain early signals of market performance, and identify specific remedial marketing actions (Keller and Lehman 2006; Pauwels and Joshi 2011; Hanssens et al. 2014). Yet, there is still limited research into how marketing mix efforts generate sales through changing consumers' minds and hearts (unobservable consumer mindset metrics) about a brand, and more importantly, on the role of competition in the purchase funnel (c.f., Bruce, Peters and Naik 2012; Pauwels, Erguncu and Yildirim 2013).

Consumer mindset metrics may serve as competitive tools by helping firms position their brands against competitors' offerings and benchmark their performance (Gupta and Zeithaml 2006). Recently, the *Marketing Science Institute* (2016) proposes amongst its 2016-2018 research priorities the need for significant research that enable marketers to gain new insight into the drivers of sales in today's highly competitive environment. In sum, it is no small task for brand managers to gain an understanding of the unobservable black box process of consumer mindset formation and sales conversion in the context of competition. Yet such an understanding is important to managers charged to allocate scarce marketing resources that provide long-lasting improvements in their brands' business performance relative to competition.

Our objective is to study an important unanswered question, in response to Srinivasan, Vanhuele and Pauwels (2010)'s and Hanssens et al. (2014) call for future research on the role of market competition on the sales conversion of consumer mindset metrics and their responsiveness to firms' marketing mix efforts.[1] We study three important consumer mindset metrics; i.e., communication awareness, brand consideration and brand liking. While communication awareness and brand consideration reflect the consumers' minds (i.e. the cognitive state), brand liking represents the consumers' hearts (i.e. affective state).

Our conceptual framework integrates marketing mix modeling, competitive strategy, and consumer behavior research. Similar to Nijs, Dekimpe, Steenkamp and Hanssens (2001), we operationalize market competition using measures that reflect the competitive market structure and the competitive strategic conduct in the market. These include (1) the number of brands existing in category, (2) advertising competition intensity, and (3) price competition intensity. Our measures of competition allow us to observe if there are any significant differences in the sales conversion of consumer mindset and their responsiveness to firms' marketing mix efforts moderated by the existence of competitive brands and the marketing strength of rival firms.

Referring to information processing and consumer attitude research (Abelson and Levi 1985; Chakravarti and Janiszweski 2003; Negungadi 1990; Posavac, Sanbonmatsu, and Ho 2002; Shiv and Fedorikhin 1999), we propose that competitive intensity plays two important roles in this process. First, we predict that a higher number of competing brands in a category exerts positive effects on the sales conversion and responsiveness of consumer mindset metrics. This may be because the brands that consumers evaluate are more likely to benefit from retrieval of other brands. On the contrary, we posit that price competition intensity should negatively influence the responsiveness and conversion of consumer mindset. Price advantage held by a few strong rival brands in the market may induce brand switching; and persuade consumer away

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1 Similar to Hanssens et al. (2014) we refer to the effects marketing mix efforts exert on consumer mindset metrics as the *marketing responsiveness* and the effects of mindset metrics on sales as their *sales conversion*.

from the focal brand. We argue that advertising competition intensity negatively influences the marketing mix responsiveness of the mindset metrics, but positively influences their sales conversion. When competing brands advertise at higher levels, they may persuade consumers away from the focal brand reducing the consumer responsiveness to its marketing mix spending, but also contribute to its sales conversion by increasing the salience of the entire category. Our results support our hypotheses in general (with an exception of a few relationships) and we infer that category competition has both adverse and favorable effects. Specifically, we find positive moderation effects by the number of brands on the sales conversion and responsiveness of mindset metrics indicative of positive spillovers across brands. Price competition intensity in general has a negative influence on conversion and responsiveness of mindset metrics. The only exception to these results are the ones on brand consideration: the marketing mix responsiveness of brand consideration is negatively influenced by the number of alternatives in the category, and is positively affected by price competition intensity. Advertising competition intensity positively influences the sales conversion of mindset metrics, it generally exerts a negative impact on the responsiveness of mindset metrics. The only exceptions are the price responsiveness of awareness and liking; the effects of advertising competition are significant and positive. Thus, the impact of competition on the conversion and responsiveness of consumer mindset varies by the metrics and by competition type. Brand consideration responds differently compared to communication awareness and brand liking, due to the confined space in the consumers' consideration set and cognitive demands required for consumers to include more brands in their (limited) consideration sets. Each type of competition differentially diminishes the ability of marketing to move the needle on mindset metrics.

Based on a rich dataset of 82 packaged goods brands from five grocery categories for the period between January 2001 and December 2010, we first examine the process wherein marketing mix efforts influence consumer mindset, which further generate brand sales. We estimate the dynamic interactions between sales, marketing mix (advertising, price, promotion, and distribution) and mindset metrics using Bayesian vector-autoregressive (BVAR) models. We first obtain the immediate and cumulative sales elasticities from the generalized impulse response functions, following which we investigate the moderating role of competition.

Our study provides several contributions to the aforementioned literature. Table 1 shows a comparative summary of the paper's contributions as compared to both Srinivasan et al. (2010) and Hanssens et al. (2014). While previous research has investigated the inclusion of consumer mindset metrics into a marketing mix-sales model (e.g., Srinivasan et al. 2010; Hanssens et al. 2014), we incorporate the role of market competition for the first time into models of mindset metrics and sales. As such, our study is the first to provide quantitative evidence on the effects of competition on sales conversion of marketing mix through consumer mindset metrics. We contribute to new substantive findings on the effects of competition, in which the predominant assumption is that competition is not desirable, by demonstrating that competition may in fact have both desirable and adverse effects on the marketing mix-sales relationship. We provide managerial guidelines on the conditions under which competition serves as a benefit versus hindrance to the consumer mindset process. Finally, ours is the first study to apply Bayesian vector autoregressive (BVAR) modeling to the context of customer mindset metrics. In a standard VAR model, a large number of parameters may result in a good model fit, but could result in multicollinearity and in loss of degrees of freedom, leading to inefficient estimates in the impulse-response functions. Bayesian models alleviate such issues due to shrinkage, which imposes restrictions on the parameters of the VAR model (Pauwels, Demirci, Yildirim and Srinivasan 2016; Horvath and Fok 2013; Sims and Zha 1998).

--- Insert Table 1 about here ---

The rest of the paper is organized as follows. In the next section, we define the consumer mind set metrics, followed by a review of relevant literature to help put in perspective our conceptual framework and contribution. Next, we provide the definitions of the three indicators of competitive intensity (i.e., the number of brands existing in category, price competition intensity and advertising competition intensity) and develop our conceptual framework hypotheses on the moderating impact. We then describe our empirical approach, which includes Bayesian vector-auto regressive models. Following, we start our empirical analysis by presenting our data of 82 packaged goods brands from five grocery categories for the period between January 2001 and December 2010. We continue with an exposition of the results of our empirical analysis in the discussion section. Finally, we conclude with a summary of our results and their implications for managers and academics.

LITERATURE REVIEW

Market Competition

Marketing strategy research distinguishes between the structure of the competition and the conduct of the rivals in a market (Caves 1972; Nijs et al. 2001). To study the effects of market competition, we consider three key dimensions of competition. First, the extent of competition manifests in the competitive marketing clutter, frequently operationalized with the number of brands competing in the category (Nijs et al. 2001). We argue that the higher the number of brands in a category, the greater the complexity of consumers' decision-making process. The larger the number of brands in the category, the greater is the competitive set of offerings for consumers to consider, like, and choose.

Second, price competition intensity due to price reductions and promotions (Blattberg and Wisniewski 1989) could also influence both the sales responsiveness and conversion of the mindset metrics. Intense price competition may elevate the importance of the brands' price benefits in the consumers' decision process. High price competition intensity indicates that the focal brand has a strong few rival brands, which often deal at substantial price discounts and/or hold a stronger price advantage than the other brands in the category. In categories where there is low price competition intensity, brands do not employ price as a significant source for differentiation advantage.

Finally, advertising competition intensity could influence the sales responsiveness and conversion of the mindset metrics (Danaher, Bonfrer and Dhar 2008). Advertising competition intensity reflects the concentration of the advertising efforts by the rival brands in a category. The higher (vs. lower) the advertising competition intensity, the greater marketing communications and messaging by fewer (vs. more) alternative brands. Hence, higher advertising competition intensity indicates that the focal brand faces strong competition from a strong few rival brands, which have significantly higher advertising spending than the rest in the category.

Research suggests that when faced with greater marketing due to a higher number of brand alternatives, consumers tend to reduce the number of products they evaluate by using simple rather than complex decision rules (Abelson and Levi 1985; Chakravarti and Janiszweski 2003; Holbrook 1981; Keller and Staelin 1987; Lehmann and Pan 1994). On the other hand, greater information content (due to price competition intensity and/or advertising competition intensity) may lead to a decline in the decision quality, as individuals tend to simplify their decision making task by disproportionately weighting unfavorable information (Erdem and Swait 2004; Garbarino and Edell 1997; Posavac, Sanbonmatsu, and Ho 2002). Particularly, diverse information content may increase consumers' mental burden, and motivate them to decrease their cognitive processing and rely more on an affective evaluation process (Shiv and Fedorikhin 1999).

Next, we review the literature on mindset metrics, and formulate hypotheses on the moderation effects of the three competition factors on the market responsiveness and sales conversion of consumer mindset metrics.

Consumer Mindset Metrics

Communication awareness, brand consideration and brand liking are three important metrics in the 'brand purchase funnel', which has been extensively studied since Colley (1961). Communication awareness surprisingly does not even appear in consumer decision-making frameworks,[2] while "it is a truism of marketing that brand awareness is a necessary precondition for choice" (Nedungadi 1990). Communication awareness has also been shown to have nearly ten times the sales impact of any other type of mindset metric across industries (e.g., drugs, food

[2] We believe the answer lies in the distinction between "brand awareness or availability" and "brand accessibility or salience" (Tulving and Pearlstone 1966). In the experimental research on memory-based choice, subjects are typically provided all relevant choice alternatives but are required to retrieve some or all of the informational inputs for brand evaluation from their memory (Lynch and Srull 1982; Biehal and Chakravarthi 1986). We believe this setting most closely represents that of fast moving consumer goods, where the consumer observes all alternative brands offered by the retailer, but retrieves memory cues to respond to the retail environment stimuli. When brand choice is (partly) memory-based, the brand accessibility or salience matters more (Nedungadi 1990). We believe the common survey question 'have you seen communication for the brand in the last 6 months' is a proxy for brand salience, given that many consumers report having perceived any communication for brands, which did not even engage in marketing communication activities during the specified time.

and non-food fast moving consumer goods) and countries (e.g., Brazil, France, the U.K. and the U.S; Lautman and Pauwels 2009; Pauwels et al. 2013). Brand consideration reflects consumers' cognitive evaluation process. Extant studies on consideration are, however, mostly in the context of information processing and cost of thinking (Hauser and Wernerfelt 1990; Roberts and Lattin 1991; Shugan 1980). Brand liking, in contrast, is a key metric manifesting consumers' affective evaluation process of a brand (Bagozzi, Gopinath and Nyer 1999; Vakratsas and Ambler 1999). Overall, awareness and consideration have mostly been associated with consumers' minds, and liking with their hearts.

Studies have shown that consumer mindset metrics (1) help to explain sales beyond marketing actions (Srinivasan et al. 2010), (2) differ in terms of their responsiveness to marketing actions (Hanssens et al. 2014) and (3) differ in terms of their effectiveness in encouraging consumer purchase decisions (Pauwels et al. 2013). The importance of these mindset metrics lies in their ability to provide advanced signals of firms' brand performance by allowing the firms to direct their customers in the right direction across the different stages of the brand funnel (Keller and Lehman 2006; Pauwels and Joshi 2011. The pertinence of any mindset metric for managers depends on: (1) the sales conversion of the metric and (2) the responsiveness of the metric to marketing actions (Hanssens et al. 2014; Pauwels et al. 2013). Focusing solely on either the sales conversion or the responsiveness of a metric may not lead to the maximum sales performance driven by that metric. For instance, metrics with high conversion but low responsiveness signal a need to alter the marketing actions to influence the key performance indicators. In contrast, metrics with high responsiveness but low conversion may represent a mere focus on what managers are able to change, instead of what drives performance. Consistent with Hanssens et al. (2010) and Pauwels et al. (2013), we assess sales conversion by assessing the movement of sales due to changes in the mindset metrics, and examine marketing responsiveness by assessing the ability of marketing mix efforts to move the needle on the mindset metrics, incorporating the role of competition.

There is substantial research on the direct impact of advertising on sales and profitability (Dekimpe and Hanssens 1995, 1999; Hanssens, Parsons, and Schultz 1990; Leone 1995; Lodish et al. 1995). Others have focused on sales conversion of price promotions (Pauwels, Hanssens and Siddarth 2000; Srinivasan, Popkowski and Bass 2000), while Naik et al. (2005) also show joint effects of advertising and promotion on brand market shares. Referred to as *sales conversion/response models*, this stream of research quantify the short and long term sales impact of marketing mix efforts, taking into account carryover and feedback effects (Srinivasan et al. 2010). Although relatively less prevalent, there are studies on the sales conversion and/or market share effects of consumer attitude metrics (Anderson et al. 2004; Fornell et al. 2010; Gupta and Zeithaml 2006; Luo, Homburg and Wieseke 2010; Mitra and Lynch 1995; Siddarth, Bucklin and Morrison 1995; Vakratsas and Ambler 1999). Chen et al. (2009)'s recent theoretical work shows the mediating role of consumer mindset metrics on the relationship between marketing actions and profits. Importantly, recent research that includes consumer mindset metrics into a marketing mix-sales model offers improved sales predictions (Bruce et al. 2012; Hanssens et al. 2014; Pauwels et al. 2013; Srinivasan et al. 2010).

Next, we discuss the moderation effects of these three factors on the market responsiveness and sales conversion of consumer mindset metrics.

CONCEPTUAL FRAMEWORK

We draw upon the consumer information processing and attitude research (Abelson and Levi 1985; Holbrook 1981) to develop our conceptual framework. Competition is a key element in memory-based models of consumer decision-making (Bronnenberg, Mahajan and Vanhonacker 2000; Burke and Srull 1982; Keller 1991). We build on this research to show *both* the desirable and adverse effects of market competition on the firms' marketing strategy implementation and performance. Figure 1 depicts our conceptual framework. We hypothesize and empirically examine the role of the number of brands in a category (H1), price competition intensity (H2) and advertising competition intensity (H3) on the responsiveness of consumer mindset metrics to marketing mix and on their sales conversion. Hence, we analyze how the effects vary by: (a) mindset metric (b) dimension of competition, and (c) time horizon.

--- Insert Figure 1 about here ---

Number of Brands

Prior research on consumer mindset metrics of marketing mix efforts, referred to as *marketing responsiveness,* suggests that marketing communications move consumers along the purchase funnel (Franses and Vriens 2004; Naik et al. 1998; Terui, Ban and Allenby 2011; Vaughn 1980). Marketing mix activities increase the salience of brands in the minds of the consumers (Alba et al 1991; Alba and Chattopadhyay 1986; Banerjee and Bandyopadhyay 2003). Research also documents the positive effects of marketing communications on the mind and heart share of brands through strengthening their favorable associations and/or diminishing the favorableness of the competitor brands' associations (Mitra and Lynch 1995; Lynch and Srull 1982).

More brands in the market not only entail more competition for market share, but also for the consumer's mind share and heart share. Including a brand to the consideration set comes at a cost to the consumer (Nedungadi 1990; Roberts and Lattin 1991, Siddarth et al. 1995). The higher the alternative brands in the market, the larger the motivation for consumers to simplify their information processing (Abelson and Levi 1985; Kalyanaram, Chandrashekaren and Dornoff, 1993; Lehmann and Pan 1994; Nedungadi 1990). On the other hand, the higher the number of brands in category, the higher the salience and familiarity of the category. Hence, given the information load due to clutter, marketing investments in a category with many brands may allow the investing firm's brands to thrive in such saturated categories, as they stand out from the in-the-trenches rivalry at the lower end of the market (Pauwels and Srinivasan 2004). And, given the overall salience of the category, each marketing investment by a brand may be more effective in gaining access to the consumers' mindset (c.f., Lamey et al. 2007; Terui et al. 2011).

In the presence of many alternative brands in the category, the brand already considered and liked by the consumers may gain from the retrieval of other competing brands. Research shows that cognitive demands for information processing and evaluation are lower for products that consumers are aware of and/or familiar with at a level to include them in their consideration sets (Alba and Hutchinson 1987). This is because "for a brand to be selected in memory-based choice, the consumer must recall that brand and fail to recall other brands that might otherwise be preferred" (Nedungadi 1990, p. 263). Indeed, several studies have reported positive spillover and/or free-riding effects of advertising (Alba and Chattopadhyay 1986; Bass et al. 2005; Nedungadi, Chattopadhyay and Muthukrishnan 2000; Steenkamp, Nijs, Hanssens and Dekimpe

2005; Naylor, Raghunathan and Ramanathan 2006). Hence, once a brand makes its way into the consumers' mindset, their exposure to any alternative in the category may boost its sales.

Furthermore, customer mindset metrics may serve as safeguards against competition. Specifically, brand liking may provide a shield against competitive brands trying to make large inroads into the consumers' hearts, since higher number of brands in a category increases the cognitive load for the consumers. In a market with many alternatives, the inclusion of a brand in the consumers' evoked, consideration and liked list may create 'asymmetric competition' shielding the brand from the competitors' marketing mix actions (Carpenter et al. 1988; p. 393). Thus, we hypothesize that:

H1a *The higher the number of brands in a category, the higher the marketing responsiveness of all three consumer mindset metrics of awareness, consideration and liking.*

H1b *The higher the number of brands in a category, the higher the sales conversion of all three consumer mindset metrics of awareness, consideration and liking.*

Price Competition Intensity

Research on attitude formation documents significant effects of marketing mix on consumers' brand awareness and preference (Mitra and Lynch 1995; Franses and Vriens 2004; Mehta et al. 2008; Naik et al. 1998). Specifically, marketing mix efforts increase the promoted brand's salience to the detriment of both competing brands and the strength of consumers' engagement with the brand (Alba et al 1991; Alba and Chattopadhyay 1986; Banerjee and Bandyopadhyay 2003). Substantial marketing mix spending reduces consumers' search costs and enhances their learning and utility (Batra, Myers and Aaker 1996; Chen et al. 2009). There is quite an agreement in the literature on the power of advertising in shifting consumer preferences towards the advertising firms (Batra et al. 1996; Chen et al. 2009; Soberman and Parker 2004). However, price competition may detract the consumers from such engagement. The Stigler-Telser-Nelson school (Stigler 1961; Telser 1964; Nelson 1975) suggests that as consumers learn, they become aware of the relevant dimensions of brand quality and become more receptive to price levels in a category (Gatignon 1984; Kanetkar et al. 1992). Intense price competition (i.e., a few brands hold stronger price advantage) may deter from perceiving the differentiated attributes and the unique benefits of the brands in the category (Degeratu et al. 2000). Mela et al. (1997) show that increased differentiation based on price raises consumers' price and promotion sensitivity, particularly in the long term.

Accordingly, price competition intensity in the category may further lead to a decline in the decision quality, as consumers may decrease their cognitive processing and evaluate the brands offering lower economy value unfavorably. Hence, we expect that consumers' mindset responsiveness to the focal brand's marketing efforts may decline, when other alternative brands in a category have stronger price advantages.

Furthermore, the higher the intensity of price competition in the market, the less the sales conversion of consumer mindset metrics because access to more affordable alternatives may induce their variety-seeking behavior and brand switching (Bell, Chiang and Padmanabhan 1999; Chiang 1991). Miniard et al.'s (2013) study suggests that when presented with comparatively priced products, consumers use price information to evaluate brands. They argue that information on varying brand prices may change the standard that consumers use in evaluating the focal brand. Earlier research shows that firms' price differentiation may shift consumers' reservation prices, leading them to consider and switch to other brands (Blattberg and Wisniewski 1989; Carpenter and Lehmann 1985). Research on price promotions also supports this notion and shows that promotion-induced brand switching most often occurs between adjacent brand tiers (Blattberg and Wisniewski 1989; Sivakumar and Raj 1997). Once consumers try other brands similar to the ones they like and become satisfied, they may move to a polygamous relationship, developing liking for other brands (Carroll and Ahuvia 2006). Thus, we propose that:

H2a *The higher price competition intensity in a category, the lower the marketing mix responsiveness of consumer mindset metrics.*

H2b *The higher price competition intensity in a category, the lower the sales conversion of consumer mindset metrics.*

Advertising Competition Intensity

To keep their brand name salient, even well-known brands need to invest heavily in advertising to cope with the competition in their markets (Alba et al. 1991; Belch and Belch 2004). When exposed to advertising messages by a concentrated number of (generally strong) rival brands, consumers may become less sensitive to the marketing mix efforts by the focal brand (c.f., Alba, Hutchinson, and Lynch 1991).

First, consumers' evoked and consideration sets are limited as each included brand involves learning and evaluation costs (Roberts and Lattin 1991). Research suggest that given the limitations of individuals' cognitive capacity, it is optimal for a brand *not* included in consumers' minds and hearts to spend heavily on marketing mix while their competitors cut back on their spending. This may allow marketing mix efforts of the brand to be more observable (Lamey, Deleersnyder, Dekimpe and Steenkamp 2007; Terui et al. 2011). A number of studies show that consumers are more responsive to the marketing mix actions (particularly, price changes) of higher-quality brands which spend heavily on advertising (Allenby and Rossi 1991; Blattberg and Wisniewski 1989; Sivakumar and Raj 1997).

Second, periods with low competitive intensity in advertising appear ideal for brands to make large inroads in consumers' hearts and even replace the formerly most beloved brands, as "85% of market leaders get dislodged during a recession" (Gulati et al 2010). Although consumers tend to exhibit inertial repeat purchase for the brands in their minds and hearts (which they are locked into as suggested by Banerjee and Bandyopadhyay 2003), they may be persuaded away when competing brands advertise at higher levels (Kanetkar, Weinberg, Weiss 1992; Mitra and Lynch 1995). Consumers may eventually consider purchasing and/ or develop liking towards other brands, when exposed to information on the benefits of other few alternative brands in the market (Posavac et al. 2002). Hence, the advertising competition intensity created by these competing brands may reduce the consumers' responsiveness to the focal brand's marketing mix efforts.

However, advertising competition intensity may have a positive impact on advertising-sales effectiveness. Mitra and Lynch (1995) showed how advertising increases the strength of a brand preference relative to the other brands in the consideration set. Firms advertise to boost sales by ensuring that consumers are aware of their brands and by persuading consumers of their superiority. However, if a brand is already known, considered and liked, it may benefit from the intense competition due to the heavy advertising investments by a few strong rivals. First, this may be due to the spillover effects of advertising as put forth by a number of researchers (c.f., Alba and Chattopadhyay 1986; Nedungadi et al. 2000; Steenkamp et al. 2005; Naylor et al. 2006). When the intensity of advertising competition increases in a category, it may lead to higher awareness, consideration and liking for *all* the brands in the category (Lamey et al. 2007;

Terui et al. 2011). Second, consumers' awareness, consideration and liking may serve as a safeguard against all other brands to make inroads into their minds, as the information content increases due to intense advertising competition. Research shows that greater ad exposure by several strong brands may even result in selective processing or even create consumer reactance (Kardes, Sanbonmatsu, Cronley and Houghton 2002; Sanbonmatsu, Posavac, Kardes, and Mantel 1998). Research also suggests that brand love and/ or liking is associated with resistance to negative information (Batra, Ahuvia, and Bagozzi 2012). Furthermore, lower-order affective processes drive consumers' purchasing behavior when processing resources are constrained due to information overload (Shiv and Fedorikhin 2002). Putting it differently, the cognitive load may lead the consumers to put disproportionately more weight on unfavorable information in the rival brand ads, and instead favor the brands they are already aware of, consider and like. Hence, we propose that:

H3a. *The higher the advertising competition intensity in a category, the lower the marketing responsiveness of consumer mindset metrics.*

H3b. *The higher the advertising competition intensity in a category, the higher the sales conversion of consumer mindset metrics.*

RESEARCH METHODOLOGY

Data and Variable Operationalization

Our data is provided by Prométhée, a brand performance tracker developed by Kantar Worldpanel. It is a comprehensive data set that combines different marketing mix efforts (advertising, promotion, price, and distribution), consumer mindset metrics (communication awareness, brand awareness, consideration, liking and purchase intention), and brand performance (sales volume). Our data covers the period between January 2001 and December 2010. It includes a complete set of observations from five categories on 82 brands operating in the Spanish market: bath gels (14), bottled water (14), dairy (22), laundry detergents (16), and soft drinks (16 brands). The data frequency is four weeks, resulting in 130 observations per brand, and the categories range from new to established, food to non-food, and perishable to non-perishable.

As the focal brand performance measure, we employed *sales volume* aggregated across all product forms of each brand (in milliliters for bath gels, water, milk and soft drinks, and grams for dairy products and laundry detergents). Specifically, the volume sales measure for each brand is operationalized as the sales volume increase in liters or grams *compared* to that of the same period in the last year. With regard to the *marketing mix* variables, we use the gross rating points of the brand's advertising for *advertising*. Promotions include special display for *promotion*, special offers, special packs and/or price discounts). *Price* is operationalized as the average price paid by the consumer per unit of the brand while *distribution* is measured as the value-weighted coverage (Hanssens et al. 2014).

We draw upon Srinivasan et al. (2010) to operationalize the mindset metrics: we measured *communication awareness* as the percentage of respondents who indicate they have seen an advertisement of the brand in the last two months, and *brand consideration* as the percentage of respondents that consider the brand for purchase among all other brands on the market. For *brand liking*, respondents are asked to rate all brands in the category based on a ten point scale ranging between '*like enormously*' and '*not at all*'. We employ the average brand ratings for the brand liking measure. Our selection of the mindset metrics reflects the three main stages of the hierarchy of effects: cognition, affect, and conation (c.f., Srinivasan et al. 2010; Hanssens et al. 2014). Brand awareness and purchase intention either show too little variation due to ceiling effects or are highly correlated with our choice of mindset metrics. Table 2 reports the descriptive statistics of our measures for each product category. Table 3 show their correlations for all 82 brands. Given that advertising awareness and brand awareness are highly correlated (0.64), they cannot be included in the same sales conversion model. Similarly, we also found purchase intention to be highly correlated with brand consideration and with sales (0.71 and 0.90 respectively) (c.f., Hanssens et al. 2014). Therefore, we chose to proceed with communication awareness, brand consideration and brand liking measures to examine the effects of consumer mindset metrics on the sales conversion of marketing mix efforts.

--- Insert Table 2 and Table 3 about here ---

Following Nijs, et al. (2001), we employed three measures to reflect the three key dimensions of competition to operationalize *market competition* (Bell et al. 1999; Gatignon 1984; Morgan and Rego 2009; Nijs et al. 2001): 1) Competitive structure is operationalized through the number of brands in the category. Competition intensity is measured using the Herfindahl index of the marketing mix efforts (sum of squares of the ratio of marketing mix efforts of the all other brands excluding the focal brand to the total efforts of the category) for 2) price promotion and 3) advertising.[3]

[3]To calculate advertising competition intensity in a three-brand market, we employed the following procedure. Assume a three-brand market, in which brand A has gross rating points of 50, brand B 30 and brand C 20. The advertising-shares of the three brands would be 0.5 for brand A, 0.3 for brand B 0.3 and 0.2 for brand C. Hence, based on our formula, advertising competition intensity for:
Brand A: $(0.3)^2 + (0.2)^2 = 0.13$
Brand B: $(0.5)^2 + (0.2)^2 = 0.29$
Brand C: $(0.5)^2 + (0.3)^2 = 0.36$
Therefore, irrespective of the number of competitors, brand C has more active and strong competitors compared to brand A and brand B, in terms of advertising.

Bayesian Vector Autoregressive Model Specification

Vector autoregressive (VAR) models measure dynamic relationships among different variables (Dekimpe and Hanssens 1999; Pauwels, Hanssens, and Siddarth 2002). VAR models have a number of advantages over alternative model specifications (Dekimpe and Hanssens 1995). They can estimate a system of equations simultaneously. In our context, it allows us to simultaneously incorporate marketing mix, mindset metrics and brand sales, and link the marketing variables to brand sales both directly and indirectly through each other. In addition, the effects of trend and seasonality can be controlled for. VAR models not only estimate immediate and lagged direct effects, but also capture more complex feedback effects among variables. Such requirements have led many previous researchers to specify a VAR model to investigate the dynamic relationships among marketing variables and brand performance (e.g. Wiesel et al. 2011). However, standard VAR modeling may suffer from overfitting problems: unrestricted VAR estimation may risk over-parametrization because the parameter space multiplies with the number of endogenous variables. A large number of parameters may produce a good model fit, but still suffer from multicollinearity and loss of degrees of freedom. This may diminish the efficiency in the parameter estimates and the performance in the impulse-response functions.

Bayesian models alleviate such overfitting problems through shrinkage, which imposes restrictions on the parameters of the VAR model (Horvath and Fok 2013; Pauwels et al. 2016; Ramos 2003). In our empirical application, the total number of parameters estimated is 377. Hence, we use Bayesian VAR modeling, which imposes stochastic constraints on the parameters of the VAR model. In conducting our analysis, we follow the 5-step procedure as outlined by Pauwels et al. (2016). In the first step, we consider the unrestricted VAR model and do not impose restrictions on the coefficients. We decide on taking natural logarithm (adding 0.0001 to avoid the log of 0) to smooth the distributions of the variables and to efficiently model diminishing returns. Unit roots do not affect the likelihood function in a BVAR model; and thus, unit root testing is not applicable to the Bayesian estimation (Sims, Stock and Watson 1990). Referring to Hanssens et al. (2014), our VAR model includes 11 endogenous variables: focal brand sales, focal brand marketing mix (i.e., advertising, promotions, price and distribution), and focal brand mindset metrics (i.e., communication awareness, brand consideration, and brand liking), and competitive mindset metrics. A typical unrestricted VAR with n endogenous variables and p lags can be written in matrix form as:

$$\Upsilon_t = \sum_{n=1}^{p} A_n \Upsilon_{t-n} + e_t, \qquad (1)$$

where $t = \{T_0, T_1, T_2, \dots, T\}$ is the time period index, Υ_t is the 11×1 vector of the endogenous variables, A_n are the coefficients matrices of the lags of endogenous variables, and e_t is the 10 x 1 vector of residuals. We determined the appropriate lags (n) by minimizing the Akaike (AIC) and Schwartz's Bayesian Information Criterion (SBIC) (c.f., Pauwels et al. 2002).

The second step involves imposing the restrictions on the coefficients of the VAR model. In the econometrics literature, Minnesota prior and Normal–Wishart prior are among the several priors used to estimate the Bayesian VAR models. However, the Minnesota prior which assumes a multivariate normal distribution, has been shown to improve forecasting performance compared to the Normal–Wishart prior (Banbura, Giannone, and Reichlin 2010). Prior restrictions for the equation model (1) can be written as:

$$\begin{bmatrix} z_{111} \\ z_{112} \\ \vdots \\ z_{nnk} \end{bmatrix} = \begin{bmatrix} \sigma/\sigma_{111} & 0 & \cdots & 0 \\ 0 & \sigma/\sigma_{112} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sigma/\sigma_{nnk} \end{bmatrix} \begin{bmatrix} a_{111} \\ a_{112} \\ \vdots \\ a_{nnk} \end{bmatrix} + \begin{bmatrix} v_{111} \\ v_{112} \\ \vdots \\ v_{nnk} \end{bmatrix} \qquad (2)$$

where z_{ijk} is the prior mean and σ_{ijk} is the standard deviation of the Minnesota prior imposed on variable j in equation i at lag k. The standard deviation defined by the Minnesota prior is as follows:

$$\sigma_{ijk} = \begin{cases} \dfrac{\theta}{k^{-\phi}}\ ,\ if\ i = j \\ \dfrac{\theta.w}{k^{-\phi}} * \left(\dfrac{\sigma_j^u}{\sigma_i^u}\right),\ if\ i \neq j \end{cases} \tag{3}$$

Here θ represents tightness; i.e., the standard deviation of the prior on the first lag of the dependent variable. A higher θ is indicative of lower effect of the lagged dependent variable in each equation. The parameter φ stands for the decay parameter taking the value between 0 and 1; and reflects the decrease in the standard deviation of the prior as the lag length of the model increases. This implies that further lags have less importance in the model. The parameter w specifies the relative effect in each equation for variables other than the dependent variables. The parameter ${\sigma^u}_j$ is the standard error of the residuals obtained from the estimation of unrestricted VAR on variable j. The ratio of the standard errors in Equation (3) is referred to as a scaling factor and accounts for the differences in the magnitudes of the variables across equations i and j. In order to find the best parameters, we consider three values for the weight parameter, w: 0.25, 0.50 and 0.75. For the tightness parameter θ, we assume four different values: 0.50, 0.30, 0.10 and 0.05. The first number (0.50) is a relatively loose value while the last number (0.05) is a tight value. We specify the lag decay parameter ϕ to be 1 as suggested by Doan et al. (1984). As a result, we determine the set of the hyperparameter values, i.e. w, θ, ϕ.

Third, with the selected parameters from the second step, we estimate BVAR(k) model using Theil and Goldberger's (1961) mixed estimation technique and supplement data with prior information on the distributions of the coefficients (Ramos 2003). Fourth, we calculate the generalized impulse response functions (GIRF) (simultaneous shocking approach) using the formula by Pesaran and Shin (1998). We used the generalized impulse response function (GIRF) to capture the over-time effects (direct and indirect) of each endogenous variable on the other variables. The GIRF simulates how a shock in one endogenous variable affects another endogenous variable after being played out through all the variables in the system. We employ the residual-based bootstrap technique to derive the standard errors of GIRF coefficients. Specifically, we (a) bootstrap the residuals of the BVAR(k) model, (b) obtain bootstrapped data using the estimated parameters and the bootstrapped residuals and (c) obtain new BVAR coefficient estimates and GIRF coefficient estimates using the bootstrapped data. We repeat (a), (b) and (c) 500 times to calculate the standard errors of the GIRF coefficients. Finally, we assess whether each impulse-response value is significantly different from zero as suggested (c.f., Pauwels et al. 2002), and accumulate all significant GIRF values to obtain the cumulative effect of each marketing variable on brand performance (Bronnenberg et al. 2000).

Moderation Analysis

Next, we test the extent to which competition in a category moderates the marketing mix responsiveness and sales conversions of consumer mindset metrics. We estimate a separate BVAR model for each of our 82 brands, with sales and marketing actions and mindset metrics as endogenous variables. From the Bayesian VAR model, we obtain immediate and cumulative marketing elasticities (since we have a log-log model specification) through generalized impulse response functions (Pauwels et al. 2002). Following standard practice in the literature, we defined the immediate impact as the effect derived from estimates of the VAR model for the first time period and the cumulative effect as the accumulated impact of the IRF until it becomes non-significant (Nijs et al. 2001; Srinivasan et al. 2004).

We use the estimated marketing elasticities using WLS regressions (using the inverse of their standard errors as weights) to investigate the moderation effects of marketing competition (Nijs et al. 2001; Hanssens et al. 2014) on both marketing responsiveness and sales conversion. We specify the immediate and cumulative elasticities of responsiveness and conversion as dependent variables in our model estimations, as indicated below:

$$IMM_t = \beta_0 + \beta_1 NUM\_BRANDS + \beta_2 PRICE\_INT + \beta_3 ADV\_INT + \beta_4 PERISH + \beta_5 PURCYC + \beta_6 INVOL + \eta_i \quad (4)$$

$$CUM_t = \beta_0 + \beta_1 NUM\_BRANDS + \beta_2 PRICE\_INT + \beta_3 ADV\_INT + \beta_4 PERISH + \beta_5 PURCYC + \beta_6 INVOL + \eta_i \quad (5)$$

where *IMM* indicate immediate elasticities, *CUM* indicate cumulative elasticities. The competitive variables of interest are the number of brands in the category (*NUM_BRANDS*), the intensity of price competition (*PRICE_INT*) and the intensity of advertising competition (*ADV_INT*). As control variables, following previous research (e.g., Nijs et al. 2001), we include the perishability of the product category (*PERISH*), the purchasing cycle (*PURCYC*), and the consumer involvement to the category (*INVOL*). The impact of mindset metrics may vary for more frequently purchased, perishable, and harder-to-store products (Ailawadi and Neslin 1998; Chintagunta and Haldar 1998). Higher levels of consumer involvement may correspond to a greater role for the consumer's state of mind, as reflected in advertising awareness, consideration, and liking for the brands in the category. When product category involvement is high and/or the product entails a frequent purchase, a brand needs to change consumers' hearts and minds in order to overcome consumers' reluctance to buy (Hanssens et al. 2014; Peter and Tarpy 1975). Hence, the importance of mindset metrics for brand sales is higher in such categories. In contrast, when product category involvement is low and/or the product is perishable, consumers may choose a brand without fundamentally changing their opinion about it. In such cases, the sales conversion of mindset metrics may be lower. To test our hypotheses, we estimate Equation (4) and (5) for the marketing mix responsiveness and the sales conversion of the three mindset metrics.

RESULTS

For each analyzed brands, both the AIC and SIC information criteria indicate the inclusion of one lag in the log-log model. The adjusted R-squared for the estimated models range from 0.17 to 0.99. As to out-of-sample forecasting, we set aside the last 20% of each brand's time series to calculate the Mean Average Percentage Error (MAPE) for the 1-step ahead and the h-step ahead forecasts (with h the maximum number of hold-out 26 weeks).

--- Insert Table 5 and Table 6 about here ---

While forecast errors are, as expected, larger for forecasts further in the future, the highest MAPE remains below XX%, which indicates that the high explanatory power of our models is not due to overfitting. In addition, the models indicate that there is no violation of the autocorrelation, heteroscedasticity, and normality assumptions for the residuals (Franses 2005), nor the present of omitted variable bias (Stock and Watson 2003)[4].We next discuss the immediate and cumulative elasticity estimates for sales conversion and marketing responsiveness, followed by a test of our proposed hypotheses using moderation analysis.

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[4] Ramsey RESET test tests the null hypothesis that the model has no omitted variable bias. The test results, available upon request, fail to reject that null hypothesis.

Magnitude of Immediate and Cumulative Effects

We estimated sales elasticities and mindset responsiveness using the models described in Equation (1). Table 4 reports the median of the significant and non-significant immediate and cumulative elasticities derived from IRFs of all 82 brands (taking $p < .05$ as a criterion). Consumer mindset metrics - awareness, consideration and liking - significantly increase brand sales in, on average, 99% of the 82 brands. In 24% of the cases, mindset metrics respond significantly to marketing mix actions.

Starting with the conversion of mindset metrics, the estimated short term sales elasticities for awareness, consideration and liking are 0.250, 0.220 and 0.200, respectively, while their cumulative sales elasticities are 0.260, 0.230 and 0.210 (all with $p < 0.05$). The sales conversion of advertising, price, promotion and distribution, respectively, are 0.040, 0.260, 0.170, and 0.250 in the short term; and 0.010, 0.160, 0.230 and 0.260 in the long term. With regard to mindset responsiveness, we find that communication awareness responds to advertising, price promotion and distribution: the immediate elasticities are 0.070, 0.320, 0.270 and 0.290 and the cumulative elasticities are 0.080, 0.180, 0.250 and 0.275, respectively. The immediate effects of advertising, price, promotion and distribution on brand consideration are -0.140, 0.090, -.170 and 0.190, while their cumulative effects are -0.125, -0.205, 0.010 and 0.130, respectively. Finally, for brand liking, the immediate effects of advertising, price, promotion and distribution are -0.100, 0.120, -0.110 and 0.180, and the cumulative effects are -0.100, -0.165, 0.020 and 0.110. The negative long term responsiveness of consideration and liking to advertising reflects the general premises of the literature on advertising repetition effects (Cacioppo and Petty 1979; Kirmani, 1997).

Moderators by Market Competition

Tables 5 and 6 report on results of the second-stage regression analyses of the short- and long term elasticities influenced by competition in the sales conversion and marketing mix responsiveness models. The tolerance values and variance inflation factors were within acceptable levels. Next, we report the long term results only, since the short term results are consistent with the long term findings. Table 7 summarizes the findings of our analysis and support of our hypotheses.

--- Insert Table 7 about here ---

Starting with the number of brands, it significantly and positively influences the marketing mix responsiveness of communication awareness (β = 0.378 and β = 0.426, both $p <$ 0.01) and brand liking (β = 0.221, β = 0.162; both $p < 0.01$), supporting our expectations. However, it negatively affects the marketing mix responsiveness of brand consideration (β = -0.545, β = -0.559; both $p < 0.01$). Hence, we find partial support for H1a. Consistent with H2b, the number of brands exerts a positive influence on the sales conversion of all three consumer mindset metrics of awareness, consideration and liking (β = 0.823 for awareness, β = 0.700 for consideration, β = 0.584 for liking; all $p < 0.01$).

Price competition, on the other hand, negatively influences the advertising responsiveness of awareness (β = -0.169, $p < 0.01$), and the advertising and pricing responsiveness of liking (β = -0.204, β = -0.080; both $p < 0.01$). Price competition effect on the marketing mix responsiveness of brand consideration is different compared to its effects on communication awareness and brand liking: it positively influences both the advertising and pricing responsiveness of consideration (β = 0.043, $p < 0.01$and β = 0.022, $p < 0.05$). Hence, we find partial support for H2a. The long term sales conversion elasticities of communication awareness, brand consideration and brand liking are higher in categories with lower price competition intensity (β = -0.079, β = -0.108, β = -0.102; all $p < 0.01$). Thus, we find support for H2b.

Advertising competition intensity, on the other hand, negatively influences the advertising responsiveness of all mindset metrics (β = -0.130 for awareness, β =-0.268 for consideration, β = -0.092 for liking; all $p < 0.01$) and the pricing responsiveness of consideration (β = -0.043; $p < 0.01$). However, it exerts a positive influence on the pricing responsiveness of awareness (β = 0.009; $p < 0.05$), and liking (β = 0.057, $p<0.01$). Thus, we find partial support for H3a as well. The long term sales elasticities of all three mindset metrics are higher in categories with higher advertising competition intensity (β = 0.099 for awareness, β = 0.136 for consideration, β = 0.175 for liking; all $p < 0.01$). Therefore, H3b is supported.

DISCUSSION OF FINDINGS

We first summarize the major findings on the immediate and cumulative elasticities (Table 4):

1. Distribution has the highest long term sales conversion, followed by promotion, price and then advertising;
2. Awareness and consideration (consumers' mind) convert into sales and are more responsive to marketing mix more than liking (consumers' heart);
3. Mindset metrics are more responsive to the focal brand's pricing and distribution efforts compared to advertising and promotion.

Our findings on the moderating effects of market competition on sales conversion and marketing mix responsiveness models are (Table 5 and 6):

1. Competition's impact on the sales conversion of mindset metrics is predominantly in the long term;
2. As we expected, the number of brands in the category generally positively influences the sales conversion and marketing mix responsiveness of mindset metrics. The exception is the marketing mix responsiveness of consideration, which is negatively affected by the number of brands;
3. We also found support for our hypotheses for price competition intensity: Price competition negatively influences the marketing mix responsiveness of all mindset metrics. As before, the only exception to this finding is consideration: price competition intensity positively influences the marketing mix responsiveness of consideration;
4. Advertising competition intensity negatively influences the marketing mix responsiveness of the mindset metrics, but positively influences their sales conversion, supporting our hypotheses. The exceptions are the pricing responsiveness of awareness and liking which are positively influenced by advertising competition.

Our results raises the issue of why marketing clutter due to a higher number of brands in the category exerts a negative impact on the marketing mix responsiveness of brand consideration. The higher the alternative brands in the market, the larger the consumers' tendency to simplify their cognitive processing and limit purchase alternatives to the brands in a restricted consideration set (Abelson and Levi 1985; Kardes et al.1993; Lehman and Pan 1994). Hauser and Wernerfelt (1990) show that consideration sets vary from two (for cars in Norway) to six (for shampoos in the US), while the number of available brands varies from 6 to 47. Roberts and Lattin's (1991) study on consideration set composition suggests that, when the number of brands in a category doubles, the size of the consideration set typically does not double. They state that, “the analysis of consideration sets is important…if consumers' evoked set sizes are small in relation to the number of brands” (p. 429). Hence, brand consideration becomes less responsive to marketing mix efforts when there are many brands in the category.

A second issue raised is why does price competition intensity positively influence the marketing mix responsiveness of brand consideration? Advertising and promotions increase the promoted brand’s salience to the detriment of competing brands (Alba et al 1991; Alba and Chattopadhyay 1986). Even well-known brands invest heavily in marketing to keep their brand name salient (Aaker and Meyers 1982; Alba et al. 1991; Belch and Belch 2004). Our findings show that in markets with intense price competition, investments in marketing actions become even more important for creating or increasing brand consideration. Consumers may become less attracted to the price advantages of rivals brands, when exposed to the ad messages by the focal brand indicating its product benefits (Alba, Hutchinson, and Lynch 1991). Thus, when there are strong rivals with price advantages in the category, marketing mix strategies may allow the focal brand to influence which brands consumers think about and consider for purchase.

On the other hand, empirical research drawing from acquisition-transaction utility theory (Thaler 1985) has shown other perceptual consequences of price beyond the economic value of the money saved such as consumer enthusiasm (Schindler 1998; Ailawadi, Neslin, and Gedenk 2001; Chandon, Wansink, and Laurent 2000). Schindler (1992) refers to this as the “smart shopper self-perception,” which represents more ego-related benefits such as a sense of accomplishment, a boost in self-esteem, and pride in shopping savoir fare (Garretson, Fisher and Burton 2002; Schindler 1988). Chandon et al. (2000) also state that promotion deals may offer hedonistic benefits such as fun, entertainment, self-esteem and intrinsic stimulation. More interestingly, Garretson, Fisher and Burton (2002) argue that finding bargains on brands may be an ego-gratifying experience compared to merely picking up continuously low priced products. In a similar vein, in categories with strong rivals, which often deal at substantial price discounts, the price changes of the focal brand may increase its consideration by the consumers. This is because responding to strong competition through price deals may enhance consumers' self-perception of smart shoppers and allow them to express their personal value (Chandon et al. 2000).

A third issue is why does advertising competition intensity exert a positive impact on the pricing responsiveness of awareness and liking, while it negatively influences the responsiveness of brand consideration? First, compared to awareness and liking, consumer consideration sets are limited as each included brand involves evaluation costs (Roberts and Lattin 1991). Given the limitations of individual's cognitive capacity, when strong rival brands boost their advertising efforts and create marketing clutter, they increase their chances to enter the consumers' consideration sets and sway choice away from the focal brand initially considered. However, given the spillover effects of advertising, these rival brands also increase the salience of the overall category when they raise their advertising efforts (Lamey, Deleersnyder, Dekimpe and Steenkamp 2007; Terui, Ban and Allenby 2011). In markets with high advertising competition, consumers are not only exposed to information on the unique benefits of the advertising brands, but also become knowledgeable about the overall product category benefits. When the category salience is heightened, the marketing mix actions of each firm in the market may also become more observable. This may make consumers' communication awareness and brand liking more responsive, because they do not entail a confined space or a limited set as is the case with consideration. Hence, in intense advertising competition, consumers become aware more easily and develop even more liking towards the focal brand, when its price creates value to the consumers.

CONCLUSIONS, IMPLICATIONS AND FUTURE RESEARCH

Our research offers both substantive and modeling contributions to the marketing strategy and consumer behavior research. First, ours is the first study to provide quantitative evidence on the impact of market competition on the sales conversion of firms' marketing mix efforts through consumer attitudes. Based on estimating Bayesian vector-autoregressive models for a rich dataset of 82 brands in five categories for over 10 years, we build on extant research to examine how competition moderates the impact of marketing actions on consumer mindset metrics and sales. Overall, market competition significantly influences sales conversion and marketing responsiveness in both the short term and the long term. The moderating impact of competition varies by mindset metric and by dimension of competition. The number of rival brands, which create competitive marketing clutter, largely has a positive influence on the conversion and responsiveness of mindset metrics. On the other hand, the impact of competition intensity due to strong rivals in the category is predominantly negative.

Second, we contribute to research on the effects of competition, in which the underlying assumption that it is not desirable, by showing that competition may both desirable and adverse effects on the marketing mix-sales relationship. We attribute the positive impact of competitive clutter due to high number of rival brands in the category to positive spillover effects across the competitive brands. The presence of few strong rivals (i.e., intense advertising competition) also hampers mindset responsiveness, i.e. the ability to increase share of mind and heart. However, brands already known and considered benefit from strong competitors, which invest heavily on advertising. Finally, the presence of strong competitors with price advantages (i.e., intense price competition) in general lessens consumers' engagement the focal brand, but increase the marketing mix responsiveness of brand consideration likely through stimulating a smart shopper self-perception.

Our research also provides important managerial implications. Starting with sales conversion, our results show that the most favorable market environment for superior sales return from mindset metrics is one with many alternative brands with high levels of advertising but low price competition. In other words, it may be more beneficial for firms to be amongst the brands that are known, considered, and liked by the consumers in markets with many competitors and where the competition centers on advertising. Once a brand enters their mind and heart in such categories, the probability of its purchase increases.

Turning to the responsiveness of mindset metrics to marketing, each dollar spent on marketing mix is more effective in gaining access to the consumers' hearts in categories with many alternatives. On the other hand, marketing mix investments provide higher returns in categories with fewer alternative brands when the aim is to enter into consumers' consideration set. These findings suggest that it becomes significantly more important (due to negative moderation) for the same level of brand sales to communicate the important benefits of their products to their consumers in high clutter markets, but to develop ads that speak to the consumers' hearts in low clutter markets. Intense advertising and price competition in general hinders the ability to create and enhance consumer mindset through marketing mix spending. Interestingly, our results show that price competition intensity may not always be bad. Price competition actually helps brands enter into consumers' consideration sets if firms respond by investing more on advertising and offering attractive prices. Overall, for managers, we show that (1) consumer mindset may serve as a shield against competition; and (2) competition differentially diminishes the ability of marketing to move the needle on mindset metrics.

This study has several limitations that suggest directions for future research. First, we focus on three mindset metrics. The inclusion of other metrics to the equation may further increase the explanatory power of the model. Second, because both mindset metrics and advertising variables are available for four-weekly periods (c.f. Srinivasan et al. 2010), we use this time interval for all variables including prices, which vary more frequently. Future research may assess robustness of our findings to varying levels of temporal aggregation. Third, the data sample covers one country (Spain) and five fast-moving consumer goods categories, and future research could generalize to these contexts, e.g., mature versus emerging countries, durable product categories, etc..

In summary, we urge (1) quantitative modelers of mindset metrics and sales to include competition into their models, (2) brand managers to note that customer mindset metrics serve as a shield for the brand against competition, and (3) both parties to note that the moderating impact of competition varies by mindset metric and by dimension of competition. Overall, we hope that this work contributes to the ongoing efforts of academic researchers and managers to integrate consumer attitudinal data with sales by helping to demonstrate the impact of competition on their brands' sustained business performance.

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Table 1. Relative Contributions of This Study

Features	*Srinivasan et al. 2010*	*Hanssens et al. 2014*	*This Study*
Research Objective	Descriptive: attitude/ transactions decomposition	Descriptive: attitude/ transactions decomposition; Normative: resource allocation	Descriptive: attitude/ transactions decomposition
Research Setting	B2C context	B2B context	B2C context
Dependent Variables	Multivariate vector: sales, and mind-set metrics of awareness, consideration and liking	Multivariate vector: sales and mind-set metrics of awareness, consideration and liking	Multivariate vector: sales, own mind-set metrics and competitive mindset metrics
Marketing Mix Decisions	Advertising, promotion, price and distribution	Advertising, promotion, and price	Advertising, promotion, price and distribution
Time-series Data	96 four weekly observations	96 four weekly observations	130 four weekly observations
Examines Marketing Mix–Sales	Yes	No	Yes
Theoretical Framework with Hypotheses	No	No	Yes
Formal Mediation Analysis	No	Yes	Yes
Examines Responsiveness	Only for items	Yes	Yes
Examines Sales Conversion	Yes	Yes	Yes
Competition in the Model	Yes	No	Yes
Empirical Application	Bottled juice, bottled water, cereals, and shampoos	Bottled juice, bottled water, cereals, and shampoos	Bath gels, bottled water, dairy, detergents, and soft drinks
Modeling Approach	Aggregate Vector Autoregressive model	Hierarchical Linear Model /Cross-effects model	Bayesian Vector Autoregressive model
Estimation	Standard econometric methods	MLE that relies on the EM algorithm	Bayesian methods
Impact of Competition in the Category	No	No	Yes

Table 2. Descriptive Statistics

		Sales	Communication Awareness	Brand Consideration	Brand Liking	Advertising	Price	Promotion	Distribution
Bath Gel	Mean	2.57	20.72	16.14	4.87	41.37	2.97	28.12	76.25
	Std. Dev.	*1.91*	*12.88*	*9.38*	*2.45*	*180.53*	*1.38*	*11. 80*	*19.86*
Dairy	Mean	2.2	19.31	12.17	3.81	194.38	2.12	26.6	54.11
	Std. Dev.	*3.02*	16.16	*11.37*	*3.50*	*425.76*	*1.65*	*25.83*	*37.37*
Detergent	*Std. Dev.*	2.53	20.68	13.09	4.60	144.83	2.71	32.16	76.65
	Std. Dev.	*2.65*	*8.44*	*7.71*	*3.40*	*271.46*	*0.80*	*18.52*	*22.61*
Soft Drink	Mean	4.03	26.46	18.76	5.87	205.14	0.77	51.48	88.33
	Std. Dev.	*5.24*	*16.43*	*14.76*	*7.28*	*410.61*	*0.22*	*20.20*	*14.57*
Bottled Water	Mean	3.08	21.41	16.57	5.78	113.24	0.31	62.16	0.31
	Std. Dev.	*3.08*	*21.43*	*16.57*	*5.78*	*113.40*	*20.12*	*20.01*	*62.16*

Table 3. Correlation Matrix

		1	*2*	*3*	*4*	*5*	*6*	*7*
1	Sales	1.00						
2	Advertising	0.38	1.000					
3	Price	-0.12	0.10	1.00				
4	Promotion	0.54	0.34	0.01	1.00			
5	Distribution	0.44	0.31	0.20	0.68	1.00		
6	Communication Awareness	0.64	0.52	0.16	0.57	0.63	1.00	
7	Brand Consideration	0.83	0.39	-0.01	0.58	0.59	0.81	1.00
8	Brand Liking	0.78	0.32	0.00	0.42	0.43	0.72	0.87

Table 4.a. Results for Immediate Mindset and Sales Elasticities

	Focal Brand Sales	Communication Awareness	Brand Consideration	Brand Liking
Communication Awareness	0.250			
Brand Consideration	0.220			
Brand Liking	0.200			
Advertising	0.040	0.070	-0.140	-0.100
Price	0.260	0.320	0.090	0.120
Promotion	0.170	0.270	-0.170	-0.110
Distribution	0.250	0.290	0.190	0.180

Table 4.b. Results for Cumulative Mindset and Sales Elasticities

	Focal Brand Sales	Communication Awareness	Brand Consideration	Brand Liking
Communication Awareness	0.260			
Brand Consideration	0.230			
Brand Liking	0.210			
Advertising	0.010	0.080	-0.125	-0.100
Price	0.160	0.180	-0.205	-0.165
Promotion	0.230	0.250	0.010	0.020
Distribution	0.260	0.275	0.130	0.110

Note: We report the median of significant and non-sigificant elasticities derived from IRFs of all 82 brands.

Table 5. Results on the Moderation Effects by Market Competition on Sales Conversion

IMMEDIATE EFFECTS	***Communication Awareness***	***Brand Consideration***	***Brand Liking***
Intercept	0.136 (0.02)	0.062 (0.01)	0.065 (1.7)
Number of Brands	0.311 (0.06)***	0.544 (0.03)***	0.49 (0.03)***
Advertising Competition Intensity	0.039 (0.02)**	0.121 (0.02)***	0.101 (0.03)***
Price Competition Intensity	-0.024 (0.01)**	-0.066 (0.01)***	-0.05 (0.01)***
Purchase Cycle	0.534 (0.09)	0.771 (0.05)	0.722 (0.01)
Perishability	0.659 (0.11)	1.028 (0.06)	0.945 (0.12)
Involvement	0.275 (0.05)	0.453 (0.03)	0.423 (0.01)
Adjusted R-squared	0.413	0.864	0.820
CUMULATIVE EFFECTS	***Communication Awareness***	***Brand Consideration***	***Brand Liking***
Intercept	0.065 (0.01)	0.010 (0.02)	0.064 (0.03)
Number of Brands	0.49 (0.04)***	0.700 (0.04)***	0.584 (0.06)***
Advertising Competition Intensity	0.101 (0.02)***	0.136 (0.02)***	0.175 (0.01)***
Price Competition Intensity	-0.05 (0.01)***	-0.108 (0.01)***	-0.102 (0.00)***
Purchase Cycle	0.722 (0.06)	0.109 (0.07)	0.840 (0.11)
Perishability	0.945 (0.07)	0.413 (0.08)	1.139 (0.12)
Involvement	0.423 (0.03)	0.607 (0.04)	0.523 (0.05)
Adjusted R-squared	0.942	0.799	0.977

NOTE: The table presents the parameter estimates and the standard errors in parentheses.
*, ** and *** = significant at .10, .05 and .01 respectively; ns=nonsignificant.

Table 6. Results on the Moderation Effects by Market Competition on Marketing Mix Responsiveness of:

	Communication Awareness		*Brand Consideration*		*Brand Liking*	
IMMEDIATE EFFECTS	***Advertising***	***Price***	***Advertising***	***Price***	***Advertising***	***Price***
Intercept	0.046 (0.02)	0.104 (0.01)	-0.017 (0.01)	-0.010 (0.01)	-0.087 (0.01)	0.024 (0.02)
Number of Brands	0.122 (0.04)***	0.460 (0.02)***	-0.459 (0.03)***	-0.243 (0.03)***	0.02 (0.02)ns	0.266 (0.05)***
Advertising Competition Intensity	-0.058 (0.02)***	0.006 (0.01)ns	-0.23 (0.02)***	-0.008 (0.01)ns	-0.029 (0.01)**	0.025 (0.02)*
Price Competition Intensity	-0.042 (0.01)***	0.012 (0.02)ns	0.055 (0.02)***	0.002 (0.00)ns	-0.065 (0.02)***	-0.028 (0.02)ns
Purchase Cycle	0.210 (0.08)	0.893 (0.05)	-0.735 (0.05)	-0.572 (0.06)	0.031 (0.05)	0.498 (0.09)
Perishability	0.275 (0.10)	1.027 (0.05)	-0.927 (0.06)	-0.506 (0.06)	0.044 (0.05)	0.572 (0.11)
Involvement	0.125 (0.04)	0.396 (0.02)	-0.434 (0.03)	-0.434 (0.04)	0.035 (0.03)	0.252 (0.05)
Adjusted R-squared	0.262	0.859	0.768	0.660	0.171	0.222
CUMULATIVE EFFECTS	***Advertising***	***Price***	***Advertising***	***Price***	***Advertising***	***Price***
Intercept	-0.016 (0.01)	0.080 (0.01)	0.001 (0.01)	-0.003 (0.01)	-0.028 (0.02)	0.024 (0.01)
Number of Brands	0.378 (0.01)***	0.426 (0.01)***	-0.545 (0.01)***	-0.559 (0.02)***	0.221 (0.02)***	0.162 (0.03)***
Advertising Competition Intensity	-0.130 (0.00)***	0.009 (0.00)**	-0.268 (0.02)***	-0.043 (0.01)***	-0.092 (0.02)***	0.057 (0.02)***
Price Competition Intensity	-0.169 (0.01)***	-0.023 (0.03)ns	0.043 (0.01)***	0.022 (0.01)**	-0.204 (0.02)***	-0.08 (0.02)***
Purchase Cycle	0.671 (0.02)	0.821 (0.03)	-0.793 (0.02)	-1.205 (0.04)	0.327 (0.06)	0.292 (0.06)
Perishability	0.846 (0.02)	0.963 (0.04)	-1.009 (0.02)	-1.209 (0.04)	0.437 (0.07)	0.319 (0.07)
Involvement	0.434 (0.01)	0.390 (0.02)	-0.498 (0.01)	-0.759 (0.03)	0.345 (0.05)	0.217 (0.04)
Adjusted R-squared	0.977	0.920	0.997	0.928	0.836	0.248

NOTE: The table presents the parameter estimates and the standard errors in parentheses.
*, ** and *** = significant at .10, .05 and .01 respectively; ns=nonsignificant**.**

Table 7. Summary of the Results for the Research Hypothesis

H:	Statement of Research Hypothesis:	Supported?
Baseline Hypotheses		
H1a	The higher the number of brands in a category, the higher the marketing responsiveness of all three consumer mindset metrics of awareness, consideration and liking.	**Yes; except for brand consideration**
H1b	The higher the number of brands in a category, the higher the sales conversion of all three consumer mindset metrics of awareness, consideration and liking.	**Yes**
H2a	The higher price competition intensity in a category, the lower the marketing mix responsiveness of consumer mindset metrics.	**Yes; except for brand consideration**
H2b	The higher price competition intensity in a category, the lower the sales conversion of consumer mindset metrics.	**Yes**
H3a	The higher the advertising competition intensity in a category, the lower the marketing responsiveness of consumer mindset metrics.	**Yes**
H3b	The higher the advertising competition intensity in a category, the higher the sales conversion of consumer mindset metrics.	**Yes; except pricing responsiveness of awareness and liking**

Figure 1. Conceptual Framework