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Document Version
Final published version

Published in:
International Journal of Research in Marketing

DOI:
10.1016/j.ijresmar.2023.11.001

Publication date:
2024

Citation for published version (APA):
Özturan, P., Deleersnyder, B., & Özsomer, A. (2024). Brand Advertising Competition Across Economic Cycles. *International Journal of Research in Marketing*, *41*(2), 325-343. https://doi.org/10.1016/j.ijresmar.2023.11.001

International Journal of Research in Marketing 41 (2024) 325–343

Contents lists available at ScienceDirect

International Journal of Research in Marketing

journal homepage: www.elsevier.com/locate/ijresmar

Brand advertising competition across economic cycles

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ARTICLE INFO

Article history:
First received on 18 January 2021 and was under review for 3 months
Available online 28 November 2023

Area Editor: Michael Braun
Accepting Editor: Alina Sorescu

Keywords:
Competitive advertising
Competitive reaction
TV advertising
Business cycle

ABSTRACT

This study investigates how brands' responses to competitors' advertising actions change over the business cycle. In an empirical analysis of advertising activity by 105 brands in six consumer packaged goods categories over 10 years in a market that experienced severe economic swings, we show that managers become more aggressive in contractions. Brands respond not only more often to competitors' advertising but also more intensely. Different brands react in contractions. Brand leaders respond less often and intensely in bad times; by contrast, premium-tier brands seem to avoid competition in good times but aggressively defend their position in bad times, especially against cheaper competitors, which are more popular in contractions. We corroborate the validity of our findings through in-depth interviews with executives and introduce two useful metrics, *aggressivity* and *receptivity*, to map changes in brand competition in an industry when economic conditions change. Collectively, the findings show how managers can better anticipate competitive advertising reactions in good and bad economic times.

1. Introduction

In saturated markets in which sales gains come primarily from brand switching, competition is fierce, and firms closely monitor the marketing actions of their rivals. With advertising as one of the most visible instruments, ad campaigns rarely go unnoticed and can trigger a sequence of intense and sometimes even destructive reactions in the market (Kilduff, 2019). For decades, big rivals Pepsi and Coca-Cola have openly fought their battles across the full range of advertising media, while the advertising war between the leading US beer brands Miller and Budweiser to promote their light beer ended up in court in 2019 (Chatterjee, 2019). These competitive battles, involving millions of advertising dollars, are not specific to the consumer packaged goods (CPG) market; they occur in practically every industry, with titan fights between McDonald's and Burger King, Visa and Mastercard, Nike and Adidas, and PlayStation and Xbox and Nintendo, to name a few.

Research on competitive advertising battles is still scant, with the rivalry beyond leading brands or beyond stable markets rarely examined. Limited empirical evidence does support competitive interdependencies between brands, finding the dominant reaction to be passive in nature (Leeflang & Wittink, 1996; Steenkamp, Nijs, Hanssens, & Dekimpe, 2005). Against this background, a growing stream of literature shows that both brand competition and advertising activity change drastically when the economic tide turns (see Web Appendix A). Changing market conditions and business cycles can structurally alter

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https://doi.org/10.1016/j.ijresmar.2023.11.001
0167-8116/

the competitive dynamics in a market. In expansions, even in mature industries, advertising campaigns can temporarily stimulate demand (Tellis & Tellis, 2009). But when an economic contraction hits, grocery budgets are under pressure, and consumers become more hesitant to buy, leading to reduced spending, such that any sales gain comes from stealing share from competitors (Kamakura & Du, 2012). Moreover, in contractions, consumers often break away from habitual buying and try different brands and retail formats. This situation fuels competitive pressure and redirects competition to different brands, particularly lower-tier brands and private labels as consumers migrate to cheaper alternatives (Lamey, Deleersnyder, Steenkamp, & Dekimpe, 2012; Scholdra, Wichmann, Eisenbeiss, & Reinartz, 2022).

At the same time, deteriorating market conditions prompt many firms to cut advertising spending drastically and shift budgets to promotions (Deleersnyder, Dekimpe, Steenkamp, & Leeflang, 2009). As a result, less funds are available to react. With smaller budgets and less consumer spending, whether advertising is more or less effective in contractions is unclear. Steenkamp and Fang (2011) find that ad effectiveness increases in contractions in the US market, whereas van Heerde, Gijsenberg, Dekimpe, and Steenkamp (2013) based on UK data find that ad effectiveness is (slightly) lower in contractions. Against this limited and conflicting evidence, investigating competitive advertising spending in relation to the business cycle is important. Firms build and maintain brand equity for the long run and responding to competitor brand advertising is essential to weather contractions (Rajavi, Kushwaha, & Steenkamp, 2022). In contractions, managers are pressured to pay more attention to competitors and fear more harm (Ozturan, Ozsomer, & Pieters, 2014), but at the same time, growing scrutiny and limited budgets make competitive advertising reactions less obvious. Finally, with many heterogeneous brands in the market, including lower-tier brands, responding to every competitor's action can be difficult. Selectively responding to different brands (e.g., market leaders, premium-tier brands, close competitors or sister brands) is likely, but how this selectivity will pan out is not clear.

Our main objective is to examine how reactions to TV advertising campaigns launched by competing brands in the CPG market change across alternative business cycle phases. We evaluate changes in both the reaction probability or "incidence" of responding to competitors' advertising and given a reaction, its intensity. Furthermore, we determine *which* brands in the CPG industry are likely to react to a competitor's advertising action and identify the brand drivers underlying this behavior across alternative economic conditions. As failure to properly account for competitive reactions leads to overspending on advertising (Leeflang, 2017) and wasted resources due to competitive interference (Danaher, Bonfrer, & Dhar, 2008), our study insights will help managers better anticipate potential reactions and assist them in their advertising decisions across changing economic conditions.

We analyze a unique, comprehensive dataset provided by Kantar Worldpanel that covers marketing activity of 105 different brands in six CPG categories sold in the Spanish market. The data span a 10-year period from 2001 to 2010, with severe economic contractions and strong expansions alternating. Our results largely show that macro-economic conditions shape the incidence and intensity of advertising reactions to competitive advertising. Reactions after competitive advertising are more likely *and* more intense in contractions than expansions. Moreover, different brands react in contractions; for example, market leaders tend to be less aggressive, while premium brands are more so.

In the remainder of this paper, we first review the literature and propose a research framework to understand competitive reactions to advertising across alternative business-cycle phases. We then describe the data, outline our method, and report the results. We introduce a useful management tool to track competitive advertising reactions by individual brands over the business cycle. Finally, we present the main insights, discuss managerial implications, and identify limitations that offer opportunities for future research.

2. Background literature

Brands use advertising not only tactically but also to position themselves in relation to their competitors (Rajavi et al., 2022). Research has shown that competitor advertising can have a severe cross-brand impact. Thus, managers are often tempted to retaliate to offset the expected or incurred sales losses in an attempt to restore their market position (Gijsenberg & Nijs, 2019; Leeflang & Wittink, 1996). Failure to react to a competitor's successful ad campaign can result in costly mistakes that can take years to recover from (Montgomery, Moore, & Urbany, 2005). Indeed, underreacting to competitors' marketing activities has more severe consequences for managers than missing out on an advertising opportunity or overreacting (Clark & Montgomery, 1996).

Against this background, we position our study at the intersection of two research streams in marketing (for an overview, see Web Appendix A). The first is a series of studies on *competitive advertising reactions* (Panel A). Studies have made substantial progress in quantifying the impact of competitive reactions on brand (or firm) performance. Among these studies, only Steenkamp et al. (2005) and Gijsenberg and Nijs (2019) focus on competitive reactivity by modeling advertising response rather than the performance or sales implications for brands. Apart from our focus on reactivity, we share with both articles a desire to identify drivers of this advertising response. These studies examine reactions using data in stable markets and do not consider how economic cycles may condition competitive reactivity. Given the changing competitive dynamics and the drastic reductions in ad budgets in downturns (Deleersnyder et al., 2009), we allow both the reaction incidence and intensity to differ depending on the state of the economy. Furthermore, by examining all brands offered by large retailers in a category, instead of only close, high-share competitors such as the top three brands in Steenkamp et al. (2005), we provide a comprehensive comparison of competitive reaction patterns, in which smaller, more distant competitors hold the potential to "nibble the big brands to death" (Swan, 2020).

The second research stream on which our work builds, consists of studies on *advertising decisions over the business cycle* (see Panel B in Web Appendix A). These studies focus on the adjustment in advertising spending by firms over the business cycle (Deleersnyder et al., 2009; Lamey et al., 2012), or they assess the differential consumer response to advertising by linking it to market share, profitability, or sales (Steenkamp & Fang, 2011; van Heerde et al., 2013). Our study differs from this work. While Deleersnyder et al. (2009) provide conceptual arguments related to herding behavior and competitive interference to explain firm reductions in advertising in contractions, we empirically evaluate if and how reactions to competitive advertising change over the business cycle. Thus, brand advertising (rather than sales) is our focal response variable, explained by competing brand advertising across varying economic conditions, next to other strategic reasons to advertise. The results, derived from a broad set of brands across six grocery categories in the volatile Spanish market, offer a basis to derive generalizations on advertising reactivity in the CPG market.

3. Research framework

3.1. Concept and dimensions of competitive advertising reactions

Unlike price promotions, advertising campaigns are fully under manufacturers' control and can be implemented independent of the retailer (Besanko, Dubé, & Gupta, 2005). Gijsenberg and Nijs (2019) provide a comprehensive analysis of brands' advertising motivations, including several non-competitive reasons such as demand seasonality, previous brand performance, and coordination with other marketing actions (e.g., price changes). Still, brand advertising observed in periods *after* a competitor advertises and that cannot be explained by these alternative motives are associated with competitive reactions. To provide first insights into the advertising dynamics, Web Appendix B plots the monthly advertising data for three competitors in the bottled water category in our dataset. Here, brands do not advertise continuously; instead, the dominant pattern is to switch on and off between periods with large advertising peaks alternated with extensive periods of no spending. Apart from seasonal spikes in the summer months, the brands occasionally engage in highly visible spending bursts to which competitors respond in the next period. After other strategic reasons to advertise are accounted for, a systematic advertising pattern by one brand, referred to as the defender, following the actions of a competitor in the *previous* period represents a competitive reaction (Clark & Montgomery, 1996; Dickson & Urbany, 1994; Metwally, 1978).

Given our monthly TV advertising data, we focus on advertising reactions to competitors' actions in the previous month. Danaher et al. (2008) and van Heerde et al. (2013) also rely on monthly data to assess competitive TV advertising effects in the CPG markets. Danaher et al. (2008, p. 217) find that spot TV advertising on local stations has a typical response or "lead" time from two weeks to two months, making TV advertising a suitable instrument for competitive responses. Moreover, industry reports show that a one-month response time for TV advertising is reasonable, especially for advertising clients of large media companies that have ready budgets, can create an ad quickly, and make decisions swiftly (eMarketer, 2006; Moore, 2018). In this context, Bruce, Becker, and Reinartz (2020, p. 242) conducted interviews with global media and brand managers to address the response time issue and noted that "it would be nearly impossible to adjust media budgets on a weekly basis and that, for several reasons, the highest frequency with which companies could adjust their budget is monthly."[1].

Apart from its probability, an advertising reaction can vary in magnitude or "intensity". As Web Appendix B shows, some of the reactions are much stronger than competitors' initial moves, especially reactions by the market leader. Therefore, in addition to the reaction *incidence*, we consider the magnitude of a reaction as a second dimension, capturing the reaction *intensity*. Drawing from the interfirm rivalry literature (e.g., Chen, 1996; Chen, Michel, & Lin, 2021), we expect the defender's reaction incidence and intensity to depend on its attention to the threat posed by a competitor's campaign, its motivation to respond, and the capacity to withstand or counter the threat. When the defender expects more damage from the competitor's move (i.e., more is at stake), the threat will be more severe and, thus, more likely to trigger a competitive reaction. At the same time, a reaction that is unlikely to restore the brand's position (ineffective) or that is inadequate due to insufficient resources (inability) will inhibit a brand's response. Finally, Web Appendix B shows that brands' sequential advertising moves are not only more common but also more intense during contraction periods. In our theorizing, we discuss how the reaction motivations change in an economic contraction, thereby influencing both the reaction incidence and intensity of brands. Furthermore, the effectiveness and ability motivations to respond are likely to differ across brands. We identify characteristics of both competing brands involved and the macro-economic conditions (expansions or contractions) as drivers of their advertising response. Our research framework in Fig. 1 summarizes these relationships.

[1] Arguments in support of an instantaneous advertising response with TV advertising in the same month are scarce. Although joint TV advertising by competing brands in the same month does occur in the data, other reasons such as seasonal demand could underlie these observations. Interviews with industry experts further revealed that the "remnant" or last-minute TV advertising market is not open to all brands, and advertisers can outbid each other. Consequently, there is no guarantee their ads will be aired. Still, when we account for instantaneous competitor advertising (T = 0) or allow for longer response times (T = 2) in our models, the results hardly change (see "Robustness checks" section).

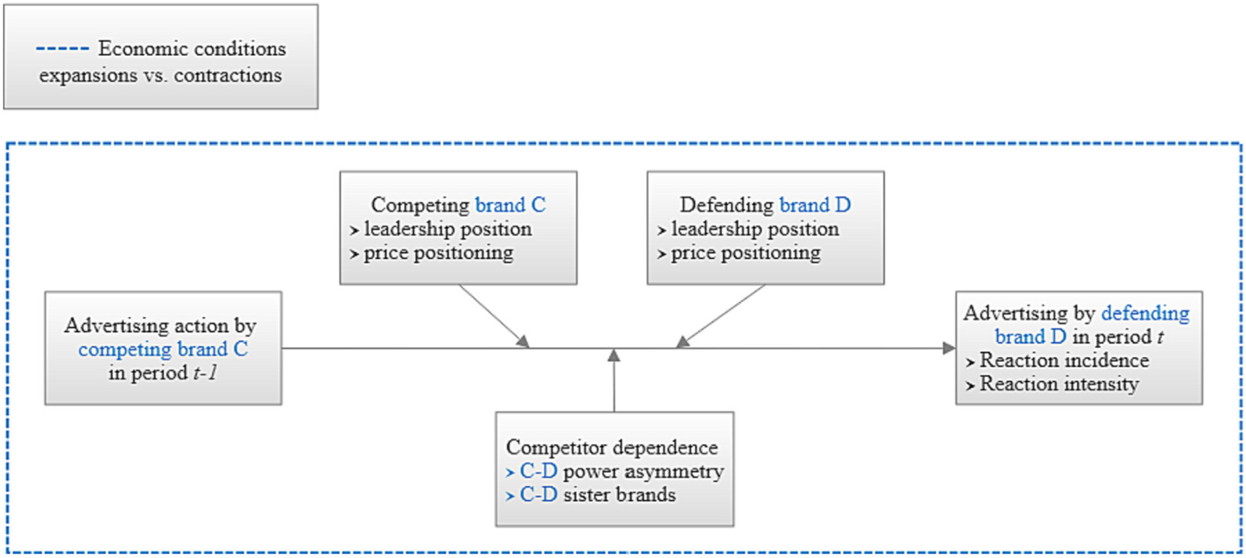

Fig. 1. Research framework.

3.2. Changing competitive advertising reactions over the business cycle

3.2.1. Reaction incidence

Research indicates that advertising decisions are driven primarily by sound internal reasoning and long-term brand-building efforts while competitive objectives are less prevalent (Gijsenberg & Nijs, 2019; Montgomery et al., 2005). The 2002–2005 UK data from which Gijsenberg and Nijs (2019) draw most of their results reflect prosperous economic times in which consumers are more affluent and CPG brands have ample advertising budgets. This situation changes in contractions. When consumers become more hesitant to buy and brand sales come primarily from stealing it from competitors, competitors' advertising actions become more threatening. In such environments, brands may never gain back the sales lost to competitors, even when the economy recovers (Lamey et al., 2012; Steenkamp & Fang, 2011). Thus, the likelihood to get hurt is higher when markets show minimal (no) growth, which shifts managers' focus to maintaining their position and preserving relative demand (Reibstein & Wittink, 2005). At the same time, managers have limited attention and time (Zaltman & Moorman, 1989). When fewer brands advertise, competitors' actions become more visible and easier to track. These unfavorable conditions, in which losses loom large and failure to respond has more severe consequences, evoke more aggressive responses and make firms more likely to defend their position by reacting to any threat (Clark & Montgomery, 1996; Ramaswamy, Gatignon, & Reibstein, 1994).

In contractions, the advertising market also has less friction, and therefore reactions are easier to execute than what is possible in expansions. More free space for TV advertisements in combination with contract cancellations makes it easier to react. According to Katz (2017, p. 201): "In boom years when economy is thriving, advertiser demand during the upfront period is high, but when a recession hits, advertisers are loathe to commit large funds in advance, so upfront deals tend to decrease while scatter buys rise." By contrast, during expansions, strategic advertising decisions are generally the outcome of a yearly planning process in which advertising budgets and their monthly allocation are predetermined in accordance with other marketing objectives. The institutional and operational costs in the company, coordination costs with the retailers' promotional calendars, and pre-commitments with advertising agencies to buy national media in good times make "constant tinkering with yearly plans prohibitively expensive" (Freimer & Horsky, 2012, p. 641).

In sum, the visibility and seriousness of the threat posed by an advertising action increase during contractions and brands also have more reaction opportunity with advertising, increasing the motivation and feasibility to defend their position compared with expansion times. Thus:

H1. The likelihood of a competitive advertising reaction is higher in contractions than expansions.

3.2.2. Reaction intensity

Economic conditions have a drastic impact on a brand's ability to counter a competitive advertising move. Firms have smaller budgets in contractions (Srinivasan, Lilien, & Rangaswamy, 2004), and with less funds, they become more cautious in spending and have less monetary resources reserved for advertising. Furthermore, in contractions, firms seek ways to renegotiate contracts with media companies. They try to "get better deals in light of rapidly declining ad markets and the wholesale retreat of entire sectors of advertisers, such as automakers and financial players, from media" (Parekh, 2009).

Changing advertisement budgets, media spending, and production costs are common, and asking agencies to reconsider their fees becomes accepted when the economic climate deteriorates. Budget constraints and greater scrutiny of advertising spending make excessive spending or overreaction less prevalent. Competitive advertising reactions in a contraction, if they occur, are expected to involve smaller budgets than in expansions, and the intensity of competitive reaction is likely to dampen. Thus:

H2. The intensity of a competitive advertising reaction is lower in contractions than expansions.

3.3. Brand factors underlying competitive reactions across economic conditions

We further evaluate which brands are more responsive to a competitor's advertising action. Apart from a brand's leading position and price tier in the market, we consider whether competitor dependence in terms of distant or close positioning and whether ownership by the same firm or not (sister brands) drive advertising response incidence and intensity across expansions and contractions. We provide a rationale for how each factor affects advertising reactions in expansions and formulate hypotheses about its differential influence on reaction incidence and intensity in contractions.

3.3.1. Response to the market leader

Follower brands risk greater damage when the leader advertises than when non-leading competitors advertise due to the well-known double-jeopardy phenomenon (Ehrenberg, Goodhardt, & Barwise, 1990). Their prominent positions in stores (share-of-shelf) and the media (share-of-voice) also make leaders' marketing actions more visible, while monitoring the many smaller players is prohibitively expensive (Clark & Montgomery, 1996; Rajavi et al., 2022). At the same time, a more loyal customer base makes it more difficult to gain (back) customers from leaders than from other competitors with similar capabilities (Gijsenberg & Nijs, 2019). Brands tend to match their advertising to that of other players (Allenby & Hanssens, 2005); thus, follower brands may have similar budgets to each other but lower budgets than the leader. Despite a more serious threat from the leader, the asymmetry in advertising budgets between leader and follower brands discourages a strong advertising reaction to the leader's actions. In line with this reasoning, Gijsenberg and Nijs (2019) find that followers' reactions to the market leader are higher in incidence but lower in intensity than their reactions to other followers. Thus, we expect a reaction in response to the market leader to differ from a reaction to other competitors.

In markets under pressure, any competitive action is not only more visible but also more threatening because of shrinking demand. Indeed, consumers engage less in habitual buying and are more likely to deliberately evaluate alternative offerings to economize on their spending (Scholdra et al., 2022). As a result, even non-leading brands can steal customers from other brands, threatening their long-term survival and thus providing a legitimate reason for other brands to react. Thus, in contractions *any* competing brand poses an imminent threat and therefore sets the ground for a competitive reaction. We expect the differential advertising reactions to leaders versus other follower brands observed in expansions to disappear in contractions, with reactions being more similar across all competitors. Thus:

H3a,b. The (a) differential reaction probability and (b) differential reaction intensity to the market leader versus other brands decreases in contractions compared with expansions.

3.3.2. Response to premium brands

Brands that are unique and distinctive can charge a premium (Keller, 2003). Premium brands are often higher-quality brands (Rajavi et al., 2022; Steenkamp, van Heerde, & Geyskens, 2010), and thus, during expansions, they pose a greater threat to other brands when they advertise because consumers are more likely to trade up to higher-quality brands following marketing communication. Indeed, Scholdra et al. (2022) find that households switch to more expensive brands during expansions to restore status. Lower-tier brands, by contrast, are less likely to steal consumers from other brands, and this asymmetry makes them less threatening (Bronnenberg & Wathieu, 1996). Thus, we expect the competitive reaction to premium brands to be more likely and more intense than that to less expensive offerings in expansions.

During contractions, however, the appeal of value brands increases considerably compared with higher-priced alternatives (Dekimpe & Deleersnyder, 2018). Consumers become more price sensitive and actively search for ways to economize on their expenses, not by consuming less but by shifting to cheaper brands (Lamey, Deleersnyder, Dekimpe, & Steenkamp, 2007; Lamey et al., 2012). Indeed, Scholdra et al. (2022) find shifts to lower-priced brands in shopping baskets even if households are not affected at a financial level. In trying times, frugal consumption seems to become more socially acceptable and even fashionable (Flatters & Willmott, 2009; Kamakura & Du, 2012). Value brands may benefit from lower price perceptions but suffer from higher functional risks (Rajavi et al., 2022). Therefore, we expect brands to respond less frequently and intensely to premium brand advertising and, instead, to closely follow the moves of lower-tier brands in contractions:

H4a,b. The (a) differential reaction probability and (b) differential reaction intensity to premium brands decreases in contractions compared with expansions.

3.3.3. Response by the market leader

Gijsenberg and Nijs (2019) find that market leaders react to competitor advertising more often (higher incidence) and with higher budgets (higher intensity) than other brands. This asymmetry is consistent with the leaders' superior monitoring and positional defense capabilities. The double-jeopardy phenomenon makes leaders more resilient and better able to counter a competitive action, as they can effectively gain back the (loyal) buyers lost after a competitor's move (Ehrenberg et al., 1990). Compared with smaller brands, leaders also have larger budgets and the necessary funds available to react (Allenby & Hanssens, 2005; Debruyne, Frambach, & Moenaert, 2010). Being a leader in a category signals legitimacy which in turn sets the stage for a stronger response. Thus, the legitimacy and credibility associated with a leader's position are important triggers to react more frequently and more intensely when competitors advertise.

In contractions, when most brands reduce marketing and only a minority with proactive attitudes and sufficient slack resources can go against the grain (Ozturan et al., 2014; Srinivasan, Rangaswamy, & Lilien, 2005), a leader may have both a greater motivation and ability to retaliate. Leaders have more to lose, while they are more capable of reacting because of their slack resources and larger budgets. Indeed, macro conditions' effect on shopping outcomes, such as shifting to lower-tier brands or private labels, linger longer than micro conditions, such as changes in household income since not all customers lost in contractions are gained back after income is restored (Lamey et al., 2007; Scholdra et al., 2022). This makes leaders more likely (from a greater threat of losing their leadership position) to engage in advertising reactions and more aggressive (from a greater reaction ability given larger budgets and likely returns) than they would be in expansions. By contrast, most non-leader brands are likely to be in survival mode, with cautious managers fearing making mistakes and adopting a "wait and see" attitude. These managers may be caught in analysis paralysis (Ozturan et al., 2014). Therefore, in contractions, market leaders are likely to react more often and more intensely with advertising than in expansions:

H5a,b. The (a) differential reaction probability, and (b) differential reaction intensity by the market leader increases in contractions compared with expansions.

3.3.4. Response by premium brands

Premium brands appeal to consumer segments that are typically less price sensitive and more focused on quality (Keller, 2003). They also benefit more from a loyal customer base than price fighters, whose consumers are primarily attracted to lower prices. Because premium brands are less affected by competitors' actions (Putsis & Dhar, 1998), their incentive to respond when other brands advertise will likely be lower in expansions. Furthermore, premium brands' advertising is more focused on communicating a higher quality and image, which provides consumers a reason to pay a premium. Advertising reactions to lower-priced competitors, by contrast, could make the premium brand's price disadvantage more salient, which may backfire (Steenkamp et al., 2010). Therefore, we expect higher-priced brands to be less responsive to competitors' actions and have a lower reaction probability and intensity than other brands.

Yet, in contractions, higher-priced brands are likely to turn into more aggressive competitors for two reasons. First, when consumers become more price sensitive, competitor advertisements may more effectively stimulate brand switching, resonating particularly with premium-tier customers who are looking for better value alternatives (Lamey et al., 2012; van Heerde et al., 2013). In contractions, premium brands need to advertise to hinder consumers from focusing too much on price (Lamey et al., 2012). Second, communicating superior quality through advertising is even more fundamental to provide consumers a reason to pay a premium, despite poor economic times. Advertising can highlight the quality and reliability of premium brands to reduce uncertainty (Scholdra et al., 2022) and to appeal to social-status maintenance needs of premium brand users. Indeed, at times when competitors advertise, intensely communicating other brand benefits to compensate for unfavorable price becomes more important in contractions to convince consumers to stay with premium brands. Thus:

H6a,b. The (a) reaction probability, and (b) reaction intensity by premium brands increases in contractions compared with expansions.

3.3.5. Response between distant competitors

The power difference or 'asymmetry' between brands can drive competitive reactions (Steenkamp et al., 2005). Close competitors that are more similar serve the same consumer segments, and their substitution patterns are stronger. Therefore, both are more likely to be in a competitive mindset and react to each other's marketing moves, which represent a more serious threat (Chen, 1996). The reaction is also likely to be more intense given the greater ability to defend their position against comparable competitors. Indeed, with close substitutes, any sales gain by one brand can be easily recouped by the competitor if it responds (Steenkamp et al., 2005). By contrast, if the positioning of a brand pair is more distant and one brand clearly dominates, they are less likely and less motivated to follow each other's moves.

When markets shrink, any competitor becomes more threatening as substitution patterns between them intensify, raising the likelihood and intensity of retaliatory behavior also between more distant competitors. Furthermore, when fewer brands advertise, even distant competitors' actions become salient and threatening. Thus, competitors' advertising is more likely to generate a response independent of their positioning (Steenkamp et al., 2005) and we expect the probability of a reaction based on competitors' positioning to vanish in contractions:

H7a,b. The (a) differential reaction probability, and (b) differential reaction intensity between distant competitors decreases in contractions compared with expansions.

3.3.6. Response between sister brands

Characteristics of reward or resource allocation systems within multi-brand firms may foster competition between sister brands. In many companies, brand managers are largely in control of their marketing budgets, which are set independently from other business units (Chandy & Tellis, 1998). Higher levels of internal autonomy and an active internal market can encourage rivalry between sister brands. Empirical evidence shows that advertising reactions do not differ for sister brands and that to prevent category-reminder benefits from spilling over to competitor firms, they often advertise in sync: "Brands with a same owner thus seem to compete with each other in almost the same way they would with brands from other firms" (Gijsenberg & Nijs, 2019, p. 244). Thus, we expect no difference in the reaction probability or intensity to sister brand advertising compared with other competitors.

During contractions, when firms are in a survival mode, limited budgets restrict managers' decision autonomy, and control often shifts from the brand level to the firm's top management (Srinivasan, Lilien, & Sridhar, 2011). Internal competition and reactions to sister brands may therefore diminish. Indeed, when budgets and investment options are managed more centrally, we expect both the incidence and magnitude of reactions between sister brands to decrease:

H8a,b. The (a) reaction probability and (b) reaction intensity among sister brands decreases in contractions compared with expansions.

4. Data

4.1. Data sources and setting

Marketing data came from Prometheus, a brand performance tracker developed by Kantar Worldpanel. They cover marketing actions of 153 brands (including 15 private labels) manufactured by 27 different suppliers in six categories (bath gel, bottled water, dairy, laundry detergent, milk, and soft drink) sold in the Spanish CPG market. The data are available for 130 four-week periods from 2001 to 2010. For brands introduced or removed during this period, the series are shorter. Table 1 provides an overview of the brands and their advertising activity by category.

In 2010, Spain was the 12th largest economy worldwide and the 5th largest in the European Union.[2] According to the Organisation for Economic Co-operation and Development (OECD) (composite leading indicators 2016), our data period is characterized by four business cycle phases. At the beginning of the 21st century, the country faced an economic contraction that lasted until November 2004 (phase 1), followed by a takeoff in terms of economic growth that reached a peak in March 2008 (phase 2). The peak was followed by a deep recession that ended in August 2009 (phase 3), after which the Spanish economy again recovered (phase 4). Against this background, the categories we include have mature but cyclical profiles, giving us a relevant context to analyze brand competition over the business cycle.

Brand *advertising* covers broadcast TV commercials and is expressed in gross rating points (GRPs), a product of the percentage of the target market reached with an advertisement multiplied by the audience exposure frequency (i.e., if an advertisement reaches 30% of the target market and has four exposures, GRP is 120). GRPs correlate positively with actual expenditures (Hu, Lodish, & Krieger, 2007). Thus, they capture the magnitude of a brand's advertising activity in each period and are considered a good measure of advertising effort (Dubé & Manchanda, 2005).[3] TV remains one of the most important advertising media in the CPG industry, with a renewed interest from firms after COVID-19 in 2021 and 2022 (Moorman, Ryan, & Tavassoli, 2022), and is arguably less recession-sensitive than other media (van der Wurff, Bakker, & Picard, 2008). In Spain, cumulative TV audiences and percentage of the population following TV relative to other media types (e.g., newspapers, magazines, radio) have been relatively stable between 2001 and 2010 (https://www.ine.es/). Moreover, TV has been the top earner of advertising expenditures in Spain, with a share above 40% between 2001 and 2010 (e.g., 42.2% in 2010, https://iabspain.es/). Of the 153 brands, 48 brands never engaged in TV advertising during that period, 14 of which were private labels. For the remaining 105 brands included in the competitive analysis, we observe advertising activity in 32.9% of the (4-week) periods in our sample.

Brand *promotion* includes various types of promotional effort and is expressed as a "promotional weighted distribution" capturing the number of stores, weighted by their total sales values in the Spanish grocery market, that sell the brand on promotion in a period. Promotions cover price discounts (i.e., a reduction >5% of the brand's regular price for no more than five consecutive weeks), in-store displays, leaflets of special offers, and multi-buy or other special promotional packs, among

[2] Based on nominal gross domestic product of countries in 2010, World Economic Outlook (International Monetary Fund, 2011).

[3] Advertising expenditures, if not acquired from company financial statements, are accessed through media research companies that calculate the monetary values by assuming a constant cost of exposure across different TV channels and brands. However, as is well acknowledged in the industry, larger firms and heavy advertisers get discounts from media buying agencies and advertising rates may change in contractions. Regardless of actual costs, an advertising action is more severe if it reaches a larger audience, making the GRP a more meaningful proxy for the true marketing effort that is independent of the ad prices charged by media agencies.

Table 1
Overview of the brands by category.

Category	# brands total	# brands with adv[a]	% months with adv[b]	Example brands[c]
Bath gel	19	12	11.3%	La Toja, Fa, Sanex, Dove
Laundry detergents	33	22	34.1%	Ariel, Dixan, Skip, Colon
Soft drinks	24	19	32.8%	Coca-Cola, Fanta, Pepsi, Schweppes
Dairy/yoghurt	30	18	45.0%	Danone, Vitalinea, La Lechera, Nestlé
Milk	25	19	32.9%	Asturiana, Kaiku, Lauki
Bottled water	22	15	34.1%	Font Vella, Vichy Catalan, Nestlé Aquarel
TOTAL	**153**	**105**	**32.9%**	

[a] Brands that never advertise are excluded from the analysis.
[b] For brands with advertising, the percentage brand–month combinations with positive advertising spending.
[c] The underlined brand is the market leader in each category, defined as the brand with the highest brand awareness in that category.

others. On average, the 105 brands in the competitive analyses are offered on promotion in 35% of the stores each month, ranging from 0% to 99.7%.

Apart from these key economic and marketing variables, for each brand, the dataset includes a survey-based metric on *brand awareness* over time, expressed as the percentage of respondents who indicated they know the brand, and data on *brand price*, or the price paid per unit (e.g., kilos, liters) by consumers in each period. Table 2 provides details on all the variables in the models, their measurements, and key summary statistics.

4.2. Model-free insights on brand advertising behavior

We observe considerable differences in advertising activity of the 105 brands in the analysis, especially when we compare competitive reactions across economic conditions. As column 2 in Table 3 shows, most brands only advertise about one-third of the time; the percentage of periods with positive advertising by the brands is 32.9%, ranging from 11.3% in the bath gel category to 45.0% in the dairy category. Brand leaders clearly stand out with advertising activity around 80% of the time. Columns 3 and 4 in Table 3 present brand advertising activity when competitive advertising occurred in the previous month. Such advertising "reactions" occur in 33.0% of the expansion periods, but the reaction frequency increases to 40.6% in contractions. Thus, brands are, on average, 7.6% *more likely* to respond to a competitor's advertising in contractions, a substantial increase relative to the 33.0% expansion baseline. This increase occurs in each of the six categories and for almost every moderator group. One exception is again the market leader group, whose advertising reactions are lower in contractions.

Comparing the magnitude of the advertising reactions, expressed as the average GRP for brands that advertise after a competitor advertises, columns 5 and 6 in Table 3 show a value increase from 473 in expansion times to 564 in contraction times, a substantial rise in the average advertising reaction of 19.4%. This rise in advertising reaction intensity occurs for the majority of the categories and for all moderator groups.[4] In combination, these statistics provide first insight that during contractions, the dominant pattern for both the probability and intensity of advertising reactions is to rise, but clear differences exist between categories and brands. The results of our formal analysis allows us to explore whether these differences are meaningful and, more importantly, how the patterns vary across brands.

5. Method

5.1. Model specification

We model both the reaction incidence (i.e., whether a reaction occurs) and the reaction intensity (i.e., the magnitude of the reaction) by a defending brand (d) to an advertising action by a competing brand (c). Our focus on firm dyads as the relevant unit in the competitive analysis is consistent with other work in marketing (e.g., Gijsenberg & Nijs, 2019; Steenkamp et al., 2005) and management (e.g., Kilduff, 2019). Each dyad enters the analysis twice: once as the defending brand and once as the competing brand. This approach can account for individual brand and relational factors that drive competitive moves while leaving open the possibility of asymmetric or unreciprocated rivalry between the brand pairs.

When brand managers observe an advertising action by a competing brand, they first decide whether to respond or not (advertising incidence). The spending magnitude of their reaction (advertising intensity) is then determined conditional on this response. To model this sequential decision process and to account for the censored nature of advertising incidence and

[4] The statistics reported in Table 3, columns 3–6 are only based on observations where competitors advertise in the month before. In line with earlier research (see e.g., Deleersnyder et al., 2009), overall advertising is less common in contractions, but in the few cases where competitors do advertise, other brands respond more often *and* more intensely.

Table 2
Measurement of the variables.

Variable	Measurement	Mean/Freq
Time-variant variables		
Economic contraction ($dCONT_t$)	Dummy = 1 if the Spanish economy is in an economic contraction in period t according to the OECD, 0 otherwise	48.55%
Competitor advertising ($CADV_{c,t}$)	Advertising spending (expressed in GRP) by the competing brand c in period t	138.83
Brand promotion ($PROM_{d,t}$)	Brand promotion intensity expressed as a promotional weighted distribution based on the number of stores in the national market, weighted by their total sales value, that sell brand d on promotion in period t. Apart from price discounts (i.e., reduction > 5% of the brand's regular price for no more than 5 weeks), promotions cover, among others, in-store displays, leaflets of special offers, and multi-buy or special promotion packs.	0.35
Time-invariant brand variables		
Leading brand ($dCLEAD_c/dLEAD_d$)	Dummy = 1 if the competitor brand c or defender brand d has the highest awareness in category, 0 otherwise	4.76%
Brand price positioning ($CPREM_c/PREM_d$)	Price difference with the average category price, determined as the mean price over time of competing brand c or defending brand d less the mean category price across all brands. All prices are expressed in equivalent units.	−0.05
Power difference ($DISTANT_{d,c}$)	Absolute value of the differences in mean brand awareness between competitor c and defender d brands	0.31
Sister brand ($dSISTER_{d,c}$)	Dummy = 1 if brand competitor c and defender d are from the same manufacturer, 0 otherwise	15.89%
Industry competition ($INDCOM_d$)	Industry competition in the category of brand d, defined as the total number of competing brands in the category	26.23

Notes: For dummy variables, we report the percentage of observations with a value = 1 instead of the mean. Means or percentages for time-variant variables are based on all time–brand–competitor observations (N = 171,606), but for time-invariant variables, these are based on the brand observations only (N = 105), except for the power difference and sister brand variables that pertain to the competitor–defender dyads (N = 2,265).

Table 3
Summary statistics on brand advertising behavior.

	Months ADV > 0 (%)	Reaction frequency		Reaction intensity	
		Expansion (%)	Contraction (%)	Expansion (grp)	Contraction (grp)
Total	32.9%	33.0%	40.6%	473	564
PART A – by category					
bath gel	11.3%	6.1%	12.0%	506	468
laundry detergent	34.1%	30.2%	36.1%	398	458
soft drinks	32.8%	28.6%	46.4%	511	705
dairy	45.0%	41.0%	47.9%	715	648
milk	32.9%	31.5%	35.1%	327	359
bottled water	34.1%	37.3%	37.6%	302	393
PART B – by moderator group					
Competing brand					
leader	30.1%	30.3%	37.4%	450	516
follower	33.1%	33.5%	41.0%	477	571
premium	32.3%	33.2%	40.7%	470	587
non premium	33.5%	32.7%	40.4%	476	538
Defending brand					
leader	80.4%	84.8%	79.5%	570	746
follower	30.0%	29.9%	38.1%	456	540
premium	37.1%	39.0%	45.2%	539	641
non premium	29.0%	27.9%	36.2%	394	475
Competitor dependence					
distant competitor	31.2%	27.9%	33.5%	452	526
close competitor	34.7%	37.2%	45.5%	486	584
sister brand	38.7%	45.6%	49.0%	647	692
non sister brand	31.2%	29.9%	38.5%	408	523

Notes: Column 2 presents for the 105 brands the percentage brand-month combinations (overall or within a group) with positive advertising spending. Columns 3–4: given positive advertising spending by the *competitor* in period t-1 (reflecting competitive advertising action), the percentage brand-month combinations where the *defender* responds in period t with positive advertising. Columns 5–6: given positive advertising by a *competitor* in period t-1, the average size of the reaction (expressed in GRP per month) in case the *defender* responds in period t.

intensity variables with many periods of zero spending, we follow Gijsenberg and Nijs (2019) and estimate a two-part model.[5] First, we estimate a probit model for advertising incidence, which takes the form:

$$z_{d,c,t} = \begin{cases} 1 \ if \ z^*_{d,c,t} > 0 \\ 0 \ otherwise \end{cases} \tag{1}$$

$$z^*_{d,c,t} = \beta_1.dCONT_t + \beta_2.lnCADV_{c,t-1} + \beta_3.(dCONT_t.lnCADV_{c,t-1}) + \beta_4.lnPROM_{d,t} + \Gamma.S_t + \beta_5.COPULA_{d,c,t} + \alpha_d + u_{d,c,t} \tag{2}$$

with $d \neq c$; $d = 1, \ldots, D$ is the index for the defending brand; $c = 1, \ldots, C$ is the index for the competing brand; and $t = 1, \ldots, T$ is the time index. Brand advertising decisions are a function of (1) economic conditions ($dCONT_t$), (2) competitive motives contained in the response to competitor advertising in the previous period ($lnCADV_{c,t-1}$), and (3) other internal reasons related to coordinating advertising with other marketing activities, such as price promotions ($lnPROM_{d,t}$). External demand factors related to a linear time trend and seasonal (quarterly) dummies are included in vector S. Second, to allow competitive reactions to vary over the business cycle, we add an interaction term between the contraction dummy and a competitor's prior advertising ($dCONT_t \times lnCADV_{c,t-1}$). By adding this interaction, the estimate β_2 represents the reaction to competitive advertising during economic expansions ($dCONT_t = 0$), and β_3 captures how this competitive reaction *changes* in a contraction ($dCONT_t = 1$). To address potential endogeneity concerns in competitors' advertising decisions that might arise from unobservables that are not accounted for in the model, we include a Gaussian copula term ($COPULA_{d,c,t}$).[6] Finally, we capture brand-specific advertising behavior with brand fixed effects (α_d). We assume that the error term $u_{d,c,t}$ follows a standard normal distribution, with zero mean and the variance set to 1.

Conditional on incidence, we estimate how much managers spend on advertising on the subsample of observations with positive advertising, using the same set of predictors as in the incidence Eq. (2):

$$lnADV_{d,t} | \, z^*_{d,c,t} > 0 = \beta_1{\prime}.dCONT_t + \beta_2{\prime}.lnCADV_{c,t-1} + \beta_3{\prime}.(dCONT_t.lnCADV_{c,t-1}) + \beta_4{\prime}.lnPROM_{d,t} + \Gamma{\prime}.S_t + \beta_5{\prime}.COPULA_{d,c,t} + \alpha_d{\prime} + e_{d,c,t} \tag{3}$$

Given the skewed nature of the advertising GRP and promotion variables, we model the (natural) logarithm of these variables because the distribution is closer to normal (van Heerde, Mela, & Manchanda, 2004). With both the dependent variable (advertising spending) and the focal predictor variables log-transformed in Eq. (3), we arrive at a multiplicative model specification in which the estimate of the competitive reaction can be easily compared between brands and categories with different advertising levels. Note that while the set of predictors in Eqs. (2) and (3) are the same, we allow for separate coefficients for each variable, as they may influence the advertising incidence and intensity decision differently. We assume that the error term for the continuous dependent variable $e_{d,c,t}$ is normally distributed, with zero mean and variance σ^2.

To further understand which factors drive advertising reactions and whether their influence changes over the business cycle, we allow the estimates of the competitive reaction (β_2, β'_2) and those of the interaction with the business cycle (β_3, β'_3) in the incidence (Eq. (2) and intensity (Eq. (3) models to vary with the brand and positioning-related drivers proposed in Fig. 1:

$$\beta^{(\prime)}_{2,d,c} = \gamma_{20} + \gamma_{21}.dCLEAD_c + \gamma_{22}.CPREM_c + \gamma_{23}.dLEAD_d + \gamma_{24}.PREM_d + \gamma_{25}.DISTANT_{d,c} + \gamma_{26}.dSISTER_{d,c} + \gamma_{27}.INDCOM_d \tag{4}$$

$$\beta^{(\prime)}_{3,d,c} = \gamma_{30} + \gamma_{31}.dCLEAD_c + \gamma_{32}.CPREM_c + \gamma_{33}dLEAD_d + \gamma_{34}.PREM_d + \gamma_{35}.DISTANT_{d,c} + \gamma_{36}.dSISTER_{d,c} \tag{5}$$

The brand drivers of competitive reactions relate to the leadership status of the competing ($dCLEAD_c$) and defending ($dLEAD_d$) brand, the price positioning of the competing ($CPREM_c$) and defending ($PREM_d$) brand, the distance between the brands ($DISTANT_{d,c}$), and whether the brands are produced by the same manufacturer ($dSISTER_{d,c}$). Finally, we control for industry differences in competitive reactions by the number of competing brands in the market ($INDCOM_d$). More brands make it more difficult to monitor and respond to each individual competitor. As before, the estimates in Eq. (4) represent the drivers of competitive advertising reactions during expansions ($dCONT_t = 0$), and those in Eq. (5) indicate if and how this reaction changes in contractions ($dCONT_t = 1$).

[5] Prior research has adopted related approaches, such as the Tobit II model, to model strategic decisions comprising a yes/no choice for a certain action and, in the case of a yes, the decision of how much resources to dedicate to it (e.g., van Heerde, Gijsbrechts, & Pauwels, 2008). Our results are highly similar when implementing the Tobit II alternative, as we report in the "Robustness checks" section.

[6] This term is a non-linear transformation of the potentially endogenous regressor lnCADV in our models (for further details, see Rutz & Watson, 2019, p. 490). The instrument-free Gaussian copula approach is increasingly used in marketing studies to address endogeneity concerns (see Papies et al., 2017; for recent applications, see Datta, van Heerde, Dekimpe, & Steenkamp, 2022; Rajavi et al., 2022). As with any approach addressing endogeneity, we realize this method has its limitations (Becker, Proksch, & Ringle, 2022). Note, however, that the results are robust and the inclusion of the copula term hardly changes the model estimates.

5.2. Model estimation

Before taking the ln-transformation, we add the value of 1 to all values to avoid missing data in brand–period combinations with no advertising. We first estimate the models without the drivers in Eqs. (1)–(3) to evaluate whether and how competitive reactions change over the business cycle. After this, we extend the model with the proposed drivers of the competitive reactions. By substituting Eqs. (4) and (5) into Eqs. (1) to (3), we arrive at a single estimation equation. The Gaussian copula approach requires that lnCADV is non-normally distributed, which is the case in both subsamples, as indicated by the Anderson–Darling test ($p < 0.01$). The coefficients for the copula term are statistically significant ($p < 0.10$) only in the advertising intensity models. In line with Papies, Ebbes, and van Heerde (2017)'s recommendation, we therefore remove it again from the incidence models.

6. Results

6.1. Model buildup

We build our models by successively adding blocks of predictions to the baseline advertising incidence and advertising intensity models with only brand fixed effects (M0). Table C1 in Web Appendix C provides the results of the incremental model-building approach, and Table C2 reports the full estimation output for each model (M1–M6 for the incidence (a) and intensity (b) models). The results confirm that competitive motives drive advertising reactions, and these advertising reactions are stronger in bad economic times (model fit improves from M1 to M2 based on the likelihood ratio tests and a decline in the Akaike information criterion [AIC]). Adding the brand drivers to the advertising *incidence* models (M.a) further improves model fit in each step. In the advertising *intensity* models (M.b), the lowest values for the (residual) likelihood ratio (−2resLL) and AIC are in M4b, consistent with many insignificant three-way interactions in the full model M6b. These results indicate that the proposed drivers determine managers' decision to react, but they are less relevant in explaining reaction intensity in M6b where the three-way interactions should be interpreted with care. More important, all estimates remain stable in sign, magnitude, and significance when we successively add interactions to the models (see Web Appendix C, Table C2).

6.2. Model results

The residuals $e_{c,d,t}$ in M2b and M6b (full model) approximate the normal distribution, and we detected no systematic trends over time in the residual plots. Columns 2 and 3 in Table 4 report the unstandardized coefficients for the advertising incidence (M2a) and intensity (M2b) models without the brand drivers, while columns 4 and 5 report the full incidence (M6a) and intensity (M6b) models extended with the drivers of competitive reactions. The results for the controls in the models are plausible. Apart from seasonal patterns (Dquart) and a general trend (Trend) in advertising activity, which often mimic fluctuations in grocery demand, the results confirm that managers' advertising decisions are also based on other internal motivations. Brand advertising and promotion activities in a given period are often used in a synergetic way, with managers combining both instruments (β_4 is significant positive in all four models). Consistent with prior research (Deleersnyder et al., 2009), brands engage in advertising less often during contractions ($\beta_1 < 0$, $p < 0.01$, in the advertising incidence equations M2a and M6a). But if brands do advertise in contractions, the budget is much larger (significant and positive β'_1 in the advertising intensity models M2b and M6b).

6.2.1. Competitive advertising reactions and their change over the business cycle

The results in Table 4 show that brands systematically react to competitors' advertising campaigns given the significant positive estimate for β_2 in all 4 models. This result provides evidence that next to internal motivations, competitive motives drive brand advertising decisions. More importantly, during contractions, brands become more aggressive with the advertising instrument: they react more often (M2a: $\beta_3 = 0.015$, $p < 0.01$) *and* more intensely (M2b: $\beta'_3 = 0.010$, $p < 0.05$) to a competitor's action. These findings are in line with H1 but clearly contradict H2; that is, despite shrinking ad budgets, brands do react intensely to competitors' advertising and become more aggressive in contractions. The possible loss in market position in contractions seems to pressure managers to more closely follow competitors, in line with advertising escalation tendencies (Metwally, 1978).

To give meaning to the size of the increase in advertising reaction probability and intensity, in Fig. 2, we present the predicted values with and without competitive advertising based on the estimates of the full models with 105 brand fixed effects (M6a and M6b, respectively) in the base quarter (Q1). To determine the mean advertising incidence and intensity in the *absence* of a competitive action, we take the mean fixed effects and imputing in the models a value of zero for competitive advertising, the mean values for all other continuous predictors and a value of zero for dummies. In the *presence* of competitive advertising, the same approach is used but we impute the (ln-transformed) mean competitive advertising based on observations with competitive advertising (mean CADV = 164.25). To facilitate the interpretation, these predictions are reconverted back into advertising probabilities (i.e., by taking the inverse of the cumulative normal density of the predicted values) and advertising intensity expressed in the original GRP values (i.e., by taking the exponent of the predicted lnADV

Table 4
Model results.

Parameter		Advertising incidence M2a	Advertising intensity M2b	Advertising incidence M6a	Advertising intensity M6b
dCONT	(β_1)	-0.037^{***}	0.168^{***}	-0.034^{***}	0.170^{***}
CADV-1	(β_2)	0.005^{**}	0.025^{***}	0.098^{***}	0.143^{***}
CADV-1 × dCONT	(β_3)	0.015^{***}	0.010^{**}	0.045^{***}	0.007
CADV-1 × dCLEAD	(γ_{21})			0.0002	−0.010
CADV-1 × dCONT × dCLEAD	(γ_{31})			-0.012^{*}	−0.009
CADV-1 × CPREM	(γ_{22})			-0.005^{*}	−0.002
CADV-1 × dCONT × CPREM	(γ_{32})			0.004	0.003
CADV-1 × dLEAD	(γ_{23})			0.045^{***}	0.018^{*}
CADV-1 × dCONT × dLEAD	(γ_{33})			-0.103^{***}	-0.036^{***}
CADV-1 × PREM	(γ_{24})			-0.011^{***}	0.0001
CADV-1 × dCONT × PREM	(γ_{34})			0.016^{***}	−0.008
CADV-1 × DISTANT	(γ_{25})			0.023^{**}	−0.009
CADV-1 × dCONT × DISTANT	(γ_{35})			-0.096^{***}	0.025
CADV-1 × dSISTER	(γ_{26})			0.007	−0.005
CADV-1 × dCONT × dSISTER	(γ_{36})			−0.008	0.005
CADV-1 × INDCOM	(γ_{27})			-0.004^{***}	-0.004^{***}
PROM	(β_4)	0.328^{***}	0.427^{***}	0.329^{***}	0.425^{***}
Dquart2		0.379^{***}	0.052^{***}	0.376^{***}	0.049^{***}
Dquart3		0.194^{***}	-0.041^{**}	0.183^{***}	-0.050^{***}
Dquart4		-0.331^{***}	-0.418^{***}	-0.335^{***}	-0.419^{***}
Trend		-0.006^{***}	-0.002^{***}	-0.006^{***}	-0.002^{***}
Copulas term for CADV-1	(β_5)	NO	-0.020^{**}	NO	-0.024^{***}
Brand fixed effects		YES	YES	YES	YES
Number of observations (N)		171,606	56,498	171,407	56,444
Number of brands		105	105	105	105
AIC		150,095	199,441	149,640	199,329

Notes: A two-part model is estimated, with the advertising incidence model a probit (binary dependent variable [DV]) estimated on the full sample of observations, and conditional on incidence, a multiplicative reaction model of advertising intensity (DV = lnADV) estimated on the subsample of observations with positive advertising. The marketing variables ADV, CADV-1, and PROM are ln-transformed in the models. A copulas term is added to account for endogeneity in competitive advertising. The estimate turns out significant only in the intensity models and thus, is removed again from the incidence models. Estimates are unstandardized coefficients.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$ (two-sided tests).

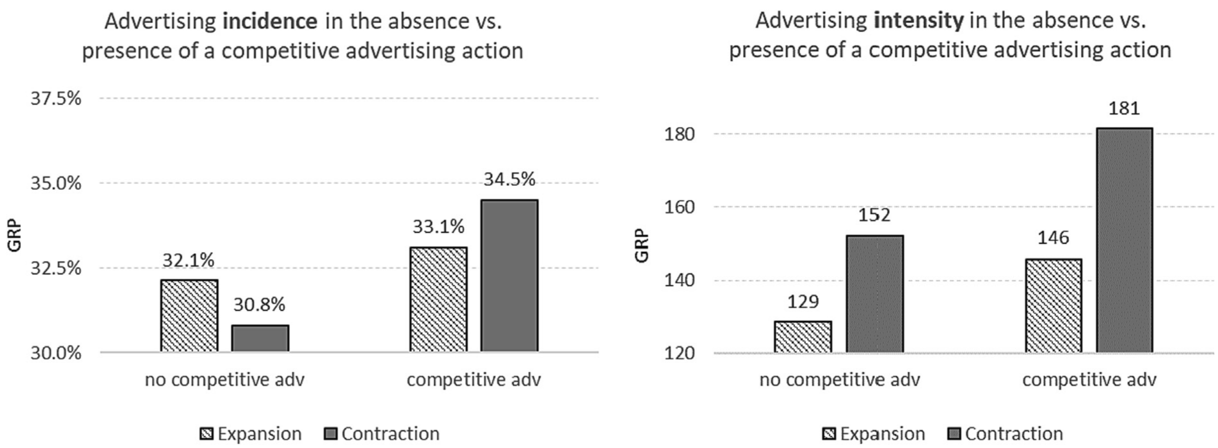

Fig. 2. Predicted advertising incidence and intensity across economic conditions.
Notes: Predicted values for advertising incidence and intensity are derived based on the estimates of the full models with 105 brand fixed effects (M6a and M6b, respectively) in the base quarter (Q1). The average advertising incidence and intensity in the *absence* of a competitive action are determined by taking the average across all fixed effects and imputing in the models a value of zero for competitive advertising, mean values for all other continuous predictors, and zero for dummies. In the *presence* of competitive advertising, the same approach is used but we impute the (ln-transformed) mean competitive advertising based on all observations with competitive advertising (average CADV = 164.25 GRP). To express the advertising incidence in probabilities, the inverse of the cumulative normal density of the predicted value in the incidence model is taken. Similarly, the exponent of the predictions in the intensity model will express advertising intensity again in its original GRP values.

values). In line with earlier research findings (e.g., Deleersnyder et al., 2009), Fig. 2 shows that brands are less likely to advertise in contractions in the absence of competitive advertising: they advertise in 30.8% of the contraction months compared to 32.1% of the expansion months. But when brands face competitive advertising, the probability to advertise will increase. In expansions, the probability rises from 32.1% to 33.1%, so a modest 1% rise in advertising is observed in response to competitors' actions. In contractions, however, a much larger increase in the reaction probability of 3.7% is observed, in which the lower contraction base probability of 30.8% rises to 34.5%. For advertising intensity, there is a clear contraction main effect with more intense advertising in bad times. But this increase is again substantially larger in the presence of competitor advertising: in expansions, it rises from an average value of 129 GRPs to 152 GRPs in the absence of competitive advertising (+18%) compared to a rise from 146 GRPs in expansions to 181 GRP in contractions (+24%) in response to competitors' actions. In combination, the fewer advertising campaigns in contractions will be much bigger in response to competitor's advertising.

6.2.2. Brand drivers of competitive reactions across economic conditions

To understand which brand characteristics underlie competitive reactions and whether different brands respond across alternative economic phases, we turn to the results of the full models with interactions (M6a and M6b in Table 4). To interpret these 3-way interactions, we compare the predicted reaction probabilities and intensity between expansions and contractions for high and low levels of the moderators using the same approach outlined before. These predicted values are visualized in Figs. D1 and D2 in Web Appendix D. First, brands do not react more or more intensely *to the market leader* than to other competitors in expansion periods, given the non-significant interaction with the competitor leader dummy dCLEAD in both models (M6a: γ_{21}; M6b: γ'_{21}). However, in line with H3a, the three-way interaction CADV × dCLEAD × dOECD is significant and negative (M6a: γ_{31} = –0.012, $p < 0.10$), consistent with a higher reaction probability to follower brands in contractions. This is also evident in Fig. D1 in Web Appendix D where the bars for reactions to leaders versus followers only differ in contractions. In contrast with H3b, we find no difference in the advertising reaction intensity to the leader versus follower brands in contractions (M6b: γ_{31} *ns*). Second, brands are less likely to respond *to premium brands* than to value brands (M6a: γ_{22} = –0.005, $p < 0.10$), and this response difference prevails across economic conditions since there is no significant change in contractions (M6a: γ_{32} *ns*). In terms of response intensity, we find no difference based on the competitor's brand price positioning, not even in contractions when consumers are less willing to pay a premium (M6b: γ'_{22} and γ'_{32} *ns*). Thus, there is no support for H4a and H4b.

Third, although brands respond similarly to market leaders and followers in expansions, we find that responses *by brand leaders* differ from those by other competitors. As expected, leaders are more aggressive defenders than non-leading brands, given that they react more often (M6a: γ_{23} = 0.045, $p < 0.01$) and more intensely (M6b: γ'_{23} = 0.018, $p < 0.10$). This behavior, however, reverses in contractions: leaders are no longer more aggressive than other brands, given the significant negative interaction with the contraction dummy in both the incidence (M6a: γ_{33} = –0.103, $p < 0.01$) and intensity (M6b: γ'_{33} = –0.036, $p < 0.01$) models. To illustrate the size of these differences, the advertising reaction incidence in expansions by brand leaders is 42.0%, while follower brands respond only 33.2% of the time. In contractions, brand leaders respond even less often than follower brands, with a reaction probability of 25.3% against 35.6% by follower brands that face a competing advertising action (see Appendix D Fig. D1). Predicted advertising intensity is no different between leaders and followers in contractions with average intensity values of 195 and 194 GRPs, respectively. Thus, contrary to H5a and H5b, leaders become less aggressive in contractions.

Fourth, the likelihood of a reaction *by premium-tier brands* also differs from value brands, but the reaction intensity is not related to brands' price positioning. As expected, premium brands are less defensive toward competitors' actions (M6a: γ_{24} = –0.011, $p < 0.01$) given their distinct positioning in the market with more loyal customers, which can protect them from competitors' actions. The average reaction probability by premium brands in expansions is 31.6% compared to 34.9% for value brands. In contractions, however, they become more defensive (M6a: γ_{34} = 0.016, $p < 0.01$) with an average reaction probability by premium brands of 36.4% compared to 34.9% for value brands. This is in line with H6a. A comparable difference in reaction intensity by premium brands is absent, both in expansions (M6b: γ'_{24} *ns*) and contractions (M6b: γ'_{34} *ns*). Thus, H6b is not supported.

Fifth, also the distance between competing brands drives the reaction incidence but not the reaction intensity. The higher reaction likelihood *between distant competitors* observed in expansions (M6a: γ_{25} = 0.023, $p < 0.05$) reverses again in contractions (M6a: γ_{35} = –0.096, $p < 0.01$), suggesting that, in line with H7a, competitive distance is less influential and brands respond more often to *any* competitor in bad times, not just to a subset of brands with a particular positioning in the perceptual space. The diminished impact of distance on reaction intensity proposed in H7b is not supported (M6b: γ'_{35} *ns*). Finally, in line with our reasoning, advertising reactions do not differ *between sister brands* compared with brands from other suppliers (M6a: γ_{26} *ns*; M6b: γ'_{26} *ns*), and this does not change in contractions (M6a: γ_{36} *ns*; M6b: γ'_{36} *ns*). Thus, H8a and H8b are not supported.

Industry factors further shape competitive advertising response: a competitive reaction to each individual brand is both less likely (M6a: γ_{27} = –0.004, $p < 0.01$) and less intense (M6b: γ'_{27} = –0.004, $p < 0.01$) with more competitors in the market. Overall, these results provide evidence that the probability and intensity of competitive advertising reactions differ over the business cycle. In addition, several brand characteristics (e.g., brand leadership, price positioning, and competitor distance) determine the responses to competitor's advertising actions but they mainly influence reaction incidence and seem to work differently in good and bad economic times.

6.3. Qualitative feedback from practitioners

To complement the findings and gain additional insights into competitive reactions of CPG brands over the business cycle, we conducted 10 key informant interviews with knowledgeable and experienced marketing executives in Turkey. These follow-up interviews included managers in diverse roles in the advertising ecosystem (e.g., brand managers, advertising and media planners, media buying representatives). We approached these executives (75% female, 16.7 years of experience on average) via our own network. The interviews were guided by a structured set of questions, and we explicitly asked whether reaction to competitors' advertising changed in contractions. To help managers visualize the economic environment and reflect on their experiences, we provided short scenarios capturing alternative business cycle phases (expansion vs. contraction) and competitive reaction patterns (e.g., increase–increase/increase–decrease/decrease–decrease).

Overall, managers agreed that in contractions, brands follow competitors' actions more closely with more in-sync (increase–increase) competitive reactions. One manager gave the example of a main beverage brand following media plans during expansions but reacting aggressively in contractions. In line with our empirical results, managers also confirmed that leaders take more aggressive actions to defend their positions but were agnostic about how this would change in contractions. These insights from experts validate our econometric results and help contextualize the findings.

6.4. Robustness checks

We performed several robustness checks to ensure the stability of our findings to the model specification, the sample, and estimation approach. Our results were robust across these additional analyses, which we report in Web Appendix E. Moreover, we further checked whether brands systematically use promotions as an alternative instrument in reaction to competitors' advertising. To determine whether brands shift (some of) their reactions to the less costly promotion instrument in contractions, we estimated a model with brand promotion as the dependent variable and checked whether it was higher with (more) competing advertising in the past month and if this changed in contractions. Given the non-censored and continuous nature of the promotion variable (see Table 2), we estimated an ordinary least squares regression with the same predictors as in Eq. (2), except for the own promotion variable which we replaced with the corresponding advertising efforts of the defending brand. The results show that brands do not systematically respond to competitors' advertising actions with promotions in good times, given the non-significant estimate associated with previous month competitive advertising ($\beta_{\text{CADV-1}} = 0.001$, $p > 0.10$). However, we find that in contractions, brands do react to competitors' advertising with more promotions ($\beta_{\text{CADV-1} \times \text{dCONT}} = 0.003$, $p < 0.01$). This result further confirms that brands become more aggressive in contractions and that reactions are not restricted to the same advertising tool.

7. Diagnostic tool to map changes in brand competition

7.1. Brand competitive aggressivity and competitive receptivity metrics

Our key insights into general (changes in) brand reaction patterns across industries may not be as useful to managers working in a particular industry. To uncover the competitive dynamics between individual brands in a specific category and the changes in competitive interactions when economic conditions deteriorate, managers can determine for each brand dyad in an industry the advertising reaction elasticity in both directions. These elasticities are obtained by regressing over-time advertising of each brand on the advertising spending of a competing brand in the previous period, using the multiplicative model specification with the same predictors and controls as in our main analysis (see Eq. (2):

$$lnADV_t = \beta_0 + \beta_1.dCONT_t + \beta_2.lnCADV_{t-1} + \beta_3.(dCONT_t.lnCADV_{t-1}) + \beta_4.lnPROM_t + \beta_5.COPULA_t + \Gamma.S_t + v_t \quad (6)$$

By estimating Eq. (6) for each brand with every competitor in a category with N brands that advertise,[7] we obtain a matrix with (N × N)-N advertising reaction elasticities, with each $\beta_2^{i,j}$ the response of brand *i* to an advertising action by competitor *j* in expansion periods. This reaction elasticity (1) can differ from the reciprocal elasticity of brand *j* in response to the advertising actions by brand *i* (i.e., $\beta_2^{i,j} \neq \beta_2^{j,i}$) and (2) can change in a contraction to $\beta_2^{i,j} + \beta_3^{i,j}$.

With these (N × N)-N advertising reaction elasticities, we can summarize the competitive position for each brand in the market in two metrics of brand competition. In line with the clout and vulnerability metrics introduced by Kamakura and Russell (1989) to summarize the competitive impact on brand performance (sales or share), we construct competitive *aggressivity* and *receptivity* metrics for each brand to summarize the competitive interactions between brands. The competitive *aggressivity* summarizes how intense brand *i* responds to the actions of its competitors, and it is the sum of all N – 1 cross-reaction elasticities of brand *i* on each competing brand *j*'s actions:

[7] As before, brands that never advertise will not react to competitors' advertising and thus drop out of the analysis.

$$\text{Competitive}\, aggressivity_i = \sum_{\substack{j=1 \\ j \neq i}}^{N-1} \beta_2^{i,j} \tag{7}$$

where $\beta_2^{i,j}$ is the cross-reaction elasticity of brand i to advertising actions by brand j in the previous period. Given that cross-reaction elasticities are positive when competitive actions are followed but turn negative when competitive reactions are avoided, the aggressivity metric can take negative values. Steenkamp et al. (2005) define reaction avoidance by stepping back when a competitor steps forward as "accommodation." Brands with greater competitive aggressivity will react more intensely to competitors' actions. Conversely, the competitive *receptivity* reveals how competing brands collectively respond to actions by brand i, and it is the sum over all N – 1 cross-reaction elasticities by brand j to actions by brand i:

$$\text{Competitive}\, receptivity_i = \sum_{\substack{j=1 \\ j \neq i}}^{N-1} \beta_2^{j,i} \tag{8}$$

where $\beta_2^{j,i}$ is the cross-reaction elasticity of brand j to advertising actions by brand i in the previous period. This metric can again take both positive and negative values; brands with higher competitive receptivity face more intense reactions from other brands to their actions.

Given that we allow the reaction elasticities in Eq. (6) to change in a contraction, we can also determine both summary metrics in contraction times for each brand by using the cross-reaction elasticity $\beta_2 + \beta_3$ instead of only β_2 in Eqs. (7) and (8). A comparison of a brand's reaction metrics across economic conditions can help brand managers anticipate which specific brands will become more (or less) aggressive and which brands face more (or less) reactions by others across economic cycles. As such, managers can better anticipate reactions to their own actions and identify opportunities to strengthen their market position.

7.2. Brand aggressivity and receptivity results

To illustrate the potential insights from these new statistics, Fig. 3 shows the competitive aggressivity and receptivity metrics, both in expansions and contractions, for 8 of the 15 brands that advertise in the bottled water category. Several findings stand out. First, we find a clear change in the aggressivity of many brands when the economic conditions deteriorate: the most aggressive brands (e.g., brand 4 and brand 7) hardly respond in contractions, while brand 12, which was not responsive in favorable times, becomes the most aggressive brand in contractions in this market.

Second, in this industry, the market leader brand 4 is clearly the most aggressive advertiser with the highest aggressivity score among all brands in expansions; however, competitors should not fear the leader in contractions. At the same time, brands rarely respond to the leader, and this does not change in contractions given its competitive receptivity close to zero regardless of economic conditions.

Third, premium brand 14, which was most receptive to reactions from almost all brands in good times, is no longer targeted by its competitors in contractions. This has clear implications to its management: bad economic times open a window of opportunity to strengthen its position, as competing brands no longer follow its moves. At the same time, although the brand hardly responds in favorable times, it turns aggressive when the economy deteriorates. By contrast, brand 17 with a below-average price in the category faces hardly any reactions in good times, but this brand becomes a key target with the highest receptivity score in contractions. Thus, while none of the brands responded to it, its moves are closely followed when the economic tide turns.

Fourth, further considering the price–quality positioning of brands, we find that especially premium-priced brands that were either overly submissive (e.g., brand 9) or neutral (e.g., brand 14) become more aggressive in contractions. In turn, lower-priced brands (e.g., brands 5 and 17), with below-average receptivity scores in good times, are more often targeted in contractions. This finding supports our intuition that during contractions, lower-priced brands become more attractive to consumers and therefore become more threatening alternatives. These four insights illustrate how competitive aggressivity and receptivity, as well as the changes in these metrics, can guide managers in their advertising decisions when economic conditions change.

8. Discussion

Despite shrinking budgets, brands advertise more aggressively in contractions. Evidence for this comes from TV advertising activity of a large sample of CPG brands across six categories in Spain over a 10-year period characterized by severe economic swings. TV advertising has traditionally been the dominant medium in these markets to communicate with a large audience in an economically efficient way. Interest in TV advertising has rebounded in recent years, with more firms investing again in traditional media after a decade of decline (Moorman et al., 2022). TV advertising is also closely monitored by competitors, making it a fertile setting to elicit responses to competitor actions. Overall, this study shows that the state of the economy has a clear and sizable influence on brands' responses to competitors' advertising actions. Consistent with earlier research (e.g., Deleersnyder et al., 2009), brands engage in advertising less often in contractions where TV ads are observed

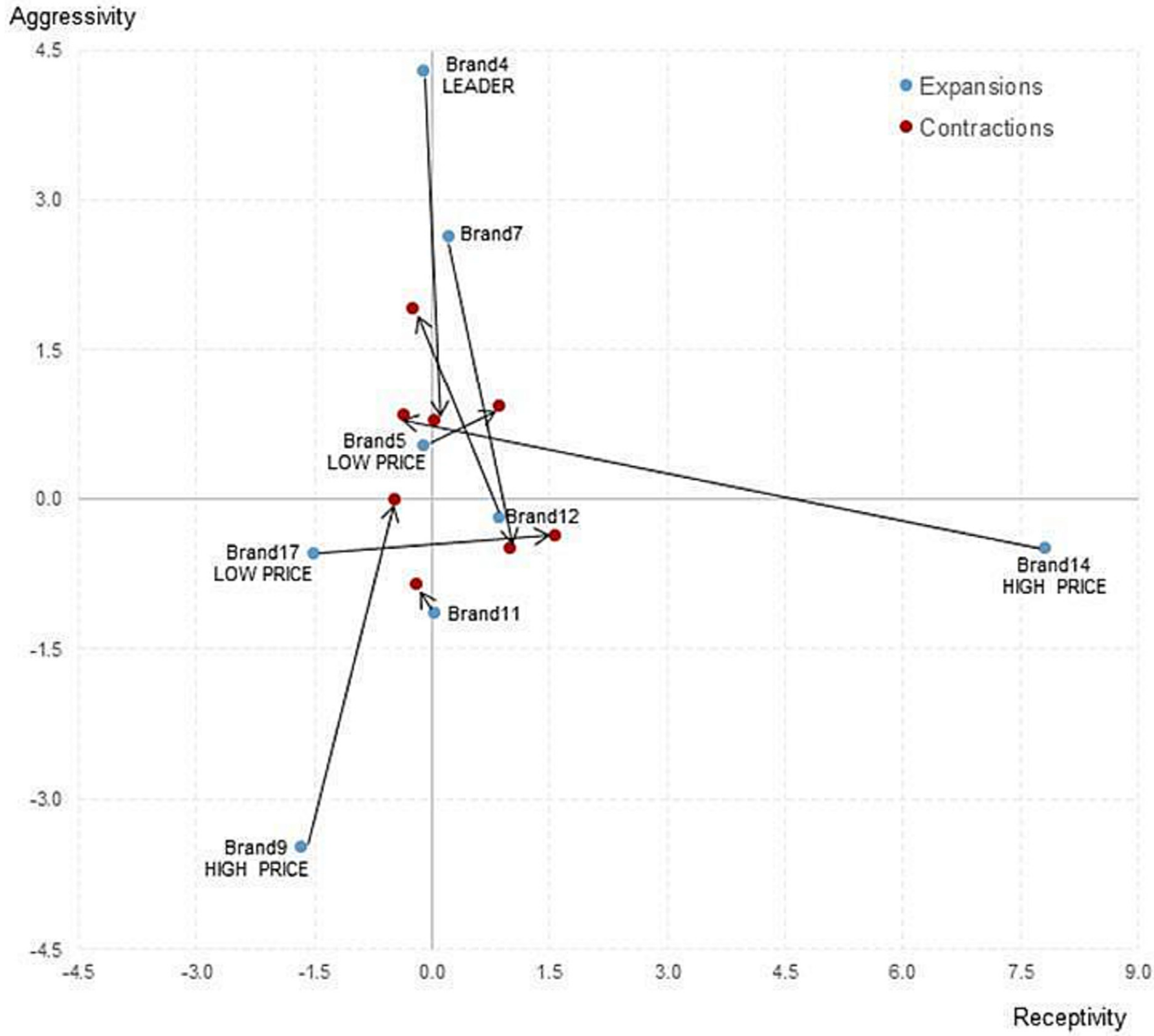

Fig. 3. Brand aggressivity and receptivity across economic conditions in the bottled water category.
Notes: The lines connecting aggressivity and receptivity show each brand during regular times (blue dots) and contractions (red dots). The bottled water category has 15 advertising brands, but only 8 brands are shown here to avoid clutter. The other brands showed similar behavior to that of the brands in the figure. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

approximately 30.8% of the time compared to 32.1% in prosperous economic times. These advertising frequencies are averages in the *absence* of competitive campaigns. But when competitors advertise, brands are more likely to follow this behavior with a reaction likelihood of 34.5%, an increase of 3.4%. Advertising reactions occurred not only more frequently, during contractions, they are also more intense, given that the magnitude of an advertising reaction increased by 19.1%, from an average of 152 GRPs without competitive advertising to a reaction corresponding to 181 GRPs if a competitive TV advertisement is observed. While we indeed expected the higher reaction probability (H1), the higher reaction intensity is less intuitive and counter to our expectation in H2. These results clearly extend research on competitive interactions that find advertising reactions not to be common (Gijsenberg & Nijs, 2019; Steenkamp et al., 2005) using data covering mainly good economic times. We show that such reactions are more prevalent and that competitors become more aggressive during adverse economic times.

Given that advertising budgets generally decrease in tandem with shrinking demand (Deleersnyder et al., 2009; Lamey et al., 2012) and are scrutinized more closely in contractions, our findings suggest that advertising in good times is driven more by other (internal) motivations, while competitive motives become a key driver of brand advertising in bad economic times. Initial evidence of this shift in focus from brand building to more competitive advertising motives is evident in our data: when we add the interaction between the economy and brand own promotion (in addition to that between the economic state and competitive advertising) to our base model in Eq. (3), the estimate is significantly negative ($\beta_{PROMO \times dCONT}$ = –0.041, p = 0.02), in line with the lesser importance of other brand marketing communications in allocating advertising money in bad times.

Marketing studies increasingly urge managers to advertise more in bad times (Deleersnyder et al., 2009; Lamey et al., 2012; Rajavi et al., 2022; Steenkamp & Fang, 2011). Our findings show that doing so also provokes competitors to respond accordingly more often and more intensely in contractions. We caution brands that more aggressive responses in bad times could make advertising less effective. The extent to which competitive reasoning plays a role in advertising decisions vis-à-vis internal motives may even explain the contradictory findings on lower advertising effectiveness in van Heerde et al. (2013), which is based on UK data in which more and more severe contractions occurred, than in Steenkamp and Fang (2011), which is based on US data under moderate contractions.

Finally, advertising leverage may backfire depending on certain brand characteristics. Our results show that different CPG brands respond differently across business cycle phases. Although market leaders are among the most aggressive competitors in favorable times, they respond less frequently in contractions. Premium-priced brands, in contrast, are unlikely to respond in good times, but they become aggressive when many consumers turn to cheaper alternatives to economize on their grocery expenditures (Kamakura & Du, 2012). Keep in mind that brands become more responsive to any type of competitor advertising in bad markets, not just to a subset of brands as in good times.

8.1. Managerial implications

Anticipating reactions from rivals is fundamental to practitioners. Given that competitive interferences diminish advertising effectiveness (Danaher et al., 2008), strategically scheduling advertising when competitors are less likely to respond pays off. At the same time, competitive interactions are not always rational (Kilduff, 2019), and firms face difficulties anticipating competitive advertising reactions and interpreting competitive signals in a noisy environment (Clark & Montgomery, 1996). This study provides managers a practical approach and offers a set of clear guidelines on when and which competitors will retaliate against their brands. Furthermore, it cautions brand managers not to be misled by the large reductions in advertising spending in contractions, as this does not discourage competitors from responding.

Also, different brands will retaliate in bad times. Although the threat from market leaders diminishes, especially premium brands are more eager to defend their position and will respond more often to competitors' advertising in contractions. Moreover, while competition in good times is restricted to a subset of brands, brands need to account for and insulate themselves from any type of competitor in bad markets. Finally, consistent with prior research (Gijsenberg & Nijs, 2019), we show rivalry between sister brands owned by the same parent firm even in contractions, suggesting that advertising decisions are left to the discretion of individual brand managers. Especially when advertising budgets are under pressure, funding advertising competition between sister brands may not be desirable from a firm perspective. Alternatively, if the internal competition is not cannibalizing but rather enabling cross-selling and/or contributes to brand-building objectives (Mason & Milne, 1994), optimization of advertising spending is advisable at the brand level. During contractions, demand shrinks, but through actions and re-actions similar to regular competition, marketing executives can target separate segments and execute unique strategies with sister brands to increase overall firm sales at the category level (Kekre & Srinivasan, 1990). Either way, we recommend that firms involve general management in budgeting decisions to manage internal competition and to make best use of scarce resources.

To provide managers with more refined and actionable insights into which competitors likely respond and how their responses change over the business cycle, we introduced a tool based on two new metrics (receptivity - aggressivity) to evaluate competitive interactions for each brand in good and bad markets. We showcased for an example category how managers can recognize a window of opportunity to improve their position in a less cluttered advertising market.

8.2. Future research

A natural next step is whether more and stronger competitive reactions in contractions are indeed justified and contribute positively to firm profitability and survival, not only during but also after a contraction. Without sales or profit data, we could not answer such normative questions. Furthermore, future research should expand the set of reaction instruments and include other common and emerging advertising media (e.g., in the digital space). While TV advertising remains one of the largest and most effective media in CPG markets, in contractions, competitive reactions also occurred with price reductions, and prior studies have already revealed reactions with other marketing instruments, such as new product introductions (Luoma, Falk, Totzek, Tikkanen, & Mrozek, 2018). Similarly, capturing more refined and faster competitive dynamics, which our monthly data were unable to detect, would be insightful. Future research should also explore how advertising content changes (or should change) when brands suddenly compete against different (cheaper) brands in contractions. The effectiveness of alternative advertising communications in which brands emphasize their price–quality position rather than quality levels and image in TV ads during contractions would be another fruitful area for research.

Research on competitive dynamics is evolving in various disciplines of business, such as supply chains (Hofer, Barker, D'Oria, & Johnson, 2022) and innovation (Chih-Yi & Bou-Wen, 2021). Our research broadened our understanding of interfirm rivalry and identified the context where competitive interactions are more common. We hope our study sparks renewed interest in competitive interactions between brands and stimulates managers to better account for competitors' behavior, especially during tough economic times.

Data availability

The authors do not have permission to share data.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

We thank Koen Pauwels for providing the dataset and for his guidance on earlier versions of the paper. We also appreciate the input from the participants of the Tilburg Christmas Camp 2019, in particular Peter Leeflang, Maarten Gijsenberg, and Insan Tunali for their gracious and helpful feedback. This research did not receive any funding from agencies in the public, commercial, or not-for-profit sectors.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijresmar.2023.11.001.

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