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Advertising spending patterns and competitor impact

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A B S T R A C T

In most industries, brand managers do not advertise continuously. Instead, advertising is switched on and off systematically, a phenomenon often referred to as pulsing. Moreover, spending levels vary considerably across periods when brands do advertise. Surprisingly, this variety in advertising spending patterns as observed in practice, as well as competitor impact on these patterns and their sales outcomes, have received relatively little empirical attention. In this paper we focus on two core aspects of observed advertising patterns: *incidence* and *magnitude*. Insights are based on the analysis of advertising spending for 370 CPG brands in 71 product categories over a four-year period. We also collected feedback from practitioners dealing with advertising across a wide range of firms. We first empirically establish that pulsing is the dominant form of advertising scheduling. Observed patterns, in turn, are largely driven by television and print advertising. Next, we show that, after accounting for a wide range of other possible drivers, advertising in-sync with competitors is more common than out-of-sync. However, the results suggest that competitive reasoning plays only a relatively minor role in advertising decisions. Finally, we show that, across a wide range of real-world scenarios, investing in top-of-mind awareness through maintenance advertising insulates brands from competitors' actions and boosts sales.

1. Introduction

Advertising remains one of the most visible and frequently used marketing instruments. In 2016, the world's 25 largest advertisers collectively spent $133.5 billion (Advertising Age, 2018). The largest advertiser was Procter & Gamble, with $10.5 billion. Other heavy spenders in the CPG sector included Unilever ($8.6 billion), L'Oréal ($8.3 billion), Anheuser-Bush InBev ($5.9 billion) and Coca-Cola ($4.0 billion). In the car industry, Volkswagen and General Motors spent $6.7 billion and $5.3 billion each, while Samsung Electronics and Sony Corp. spent $9.9 billion and 3.4 billion, respectively. In relative terms, Shimp (2010) reports that, across nearly 200 categories of B2C and B2B products and services, advertising expenditures are on average 3% of firm sales, albeit with considerable variation across companies. Procter & Gamble reported 17% for its US operations, and for L'Oréal and Estée Lauder the percentage exceeded 30%.

Given this prominent position in marketing investments, it should come as no surprise that advertising has been the subject of a large body of research (see e.g., Tellis and Ambler (2007) for a review). Within this research, two important streams can be distinguished. First, an extensive *empirical* literature has focused on quantifying the impact of advertising on sales or market share. Sethuraman, Tellis, and Briesch (2011) compiled 751 short-term brand-level elasticities and 402 long-term advertising elasticities

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from 56 studies in that tradition, and report an average short-run (long-run) elasticity of 0.12 (0.24). Second, a *normative* literature has studied — among other things — under what conditions pulsing, as opposed to even spending, is an optimal advertising strategy (see e.g., Feinberg, 1992; Naik, Mantrala, & Sawyer, 1998; Sasieni, 1971; Villas-Boas, 1993).

However, the actual advertising spending patterns observed in practice have received relatively little empirical attention. Such patterns are characterized by two aspects: the timing and magnitude of advertising actions. Whereas several normative studies (Freimer & Horsky, 2012; Park & Hahn, 1991) provide guidance to brand managers about optimal competitive advertising timing, i.e., in-sync or out-of-sync, the second aspect, magnitude, and the extent to which it should be based upon competitive reasoning has largely been ignored (see e.g., Aravindakshan & Naik, 2015). In addition, these studies do not address the large variety in advertising behavior observed in practice, nor the extent to which brand manager account for competitors' actions when designing their own. The latter, in turn, is not without importance given the profound impact competitors' advertising actions can have on brands own advertising effectiveness (see e.g., Danaher, Bonfrer, & Dhar, 2008).

The relevance of this topic and the variety in observed behavior is also reflected in discussions with managers. While some state that "*continuity is a top driver*", others argue that "*brand decisions should be shaped by the actions and interests of their end consumers*", thus hinting at more concentrated pulses. In addition, while some advocate preempting competitors to "*make [the consumer] stock up beforehand*" (out-of-sync), others propose that "*when under attack, [one should] defend the high ground*" (in-sync), and a third group of managers state that competitors' actions have limited impact on advertising decisions. These statements demonstrate substantial variation in advertising reasoning, possibly driven by a lack of understanding of the relative benefits of different advertising patterns on brand performance.

This study aims to address the following research questions:

- To what extent are the competitive advertising *incidence* patterns as suggested in the normative literature observable in practice?
- To what extent do advertising incidence patterns differ across traditional media?
- To what extent are observed patterns in advertising *incidence* and *magnitude* driven by competitors' actions?
- Which (non-)competitive advertising pattern is most successful in generating sales across a broad range of real-world competitive settings?

To answer these questions we analyze the weekly incidence and magnitude of advertising expenditures aggregated across traditional media for 370 CPG brands in 71 product categories over a four-year period. We augment these data with media-disaggregated monthly data for 162 CPG brands in 37 product categories over an eighteen-year period and qualitative feedback from practitioners. First, we determine the prevalence in practice of advertising incidence patterns derived from normative literature. We then use a descriptive approach to determine the extent to which advertising incidence and magnitude are driven by competitors' actions. Finally, we use simulation to determine the relative impact of different advertising patterns on brand performance across a broad range of real-world competitive settings.

In our analyses, we focus on traditional media. While, overall, digital advertising now accounts for about 1/3 of all advertising expenditures, thereby matching TV advertising (Advertising Age, 2018), in the CPG industry brands still strongly rely on the latter (MAGNA, 2018), with twice as much being spent on TV advertising compared to digital (eMarketer, 2017). Traditional media, in addition, are still considerably more efficient in generating sales (IRI, 2017). Major CPG producers like Procter & Gamble and Unilever are even shifting budgets back to traditional media because of the low perceived effectiveness and efficiency of digital advertising to increase sales (Johnson, 2018).

2. Background

2.1. Advertising spending patterns

In many industries, brands do not advertise continuously nor are advertising spending levels consistent over time. Instead, managers systematically switch advertising on and off (e.g., Doganoglu & Klapper, 2006; Dubé, Hitsch, & Manchanda, 2005; Naik et al., 1998), a phenomenon often referred to as pulsing. Moreover, spending levels vary considerably across periods when brands advertise. Fig. 1 provides examples of such behavior.

The three upper panels show the weekly expenditures for three soft-drink brands in the UK. Brand A is a frequent and heavy advertiser (100% of weeks, average spending of £371,481 per advertising week). In contrast, brand C advertises 42% of the time and spends only £45,950 on average per advertising week. Brand B takes an intermediate position: it advertises less often than brand A (61% of weeks, mainly in spring and summer) but spends more than brand C (£119,987 on average per advertising week). The bottom panels of Fig. 1 show three brands in the UK cleanser market. Again, we observe considerable variability in both the timing and magnitude of advertising actions.

These advertising patterns also illustrate that advertisers must make two decisions: (i) *when* to advertise, and (ii) *how much* to spend (Danaher et al., 2008; Tellis & Ambler, 2007), a duality encountered in many investment decisions (see e.g., Bar-Ilan & Strange, 1999).

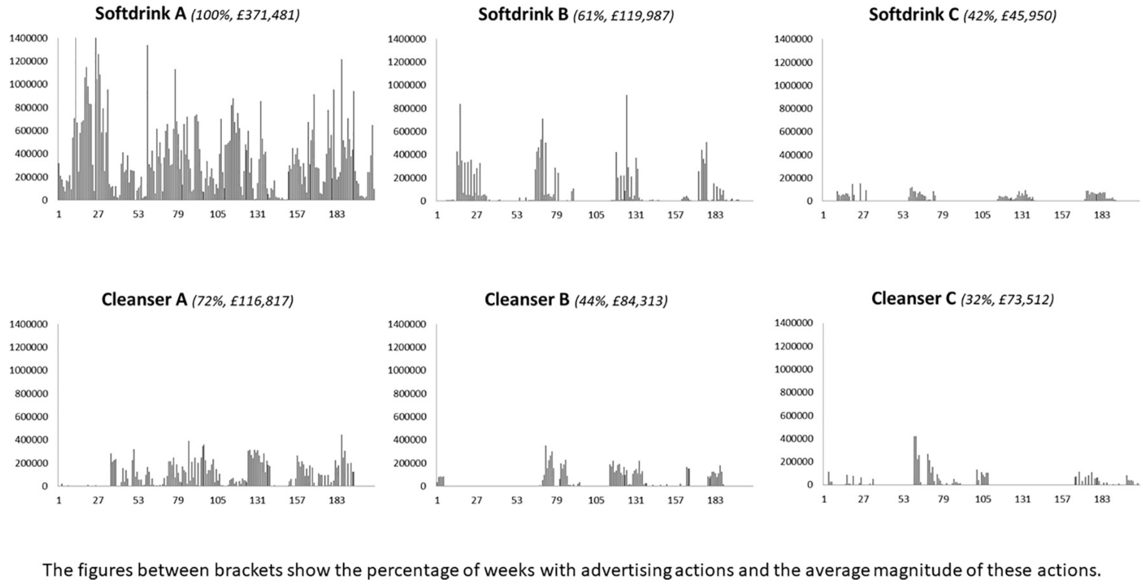

Fig. 1. Advertising spending patterns in 2 UK CPG categories.

2.2. Normative literature on advertising spending patterns

Over the past decades, a wide stream of research has focused on the optimality of different types of advertising scheduling patterns. Over the years, the preponderance of prescriptions from normative studies has shifted from constant advertising schedules (Sasieni, 1971, 1989; Zielske, 1959) to pulsing (e.g., Mahajan & Muller, 1986). For example, Katz (1980) and Aravindakshan and Naik (2011) introduced learning and forgetting effects, while Aravindakshan and Naik (2015) discussed the impact of memory effects. Mesak (1992) and Naik et al. (1998) added, respectively, wear-out effects and quality restoration. Park and Hahn (1991), Villas-Boas (1993), Dubé et al. (2005), and Freimer and Horsky (2012), in turn, expanded the scope of this work to competitive settings.

Based on discussions with industry experts, Dubé et al. (2005) posit that "managers track their own *and their competitors'* advertising efforts" (p. 116, italics added) when deciding on advertising tactics. How competitors should schedule their advertising campaigns relative to one another is, however, less clear. On the one hand, Villas-Boas (1993) argues that advertising out-of-sync with competitors may increase effectiveness as it is easier to raise consumers' consideration level for a firm's products when the consideration level for competitors' products is low. Freimer and Horsky (2012), in contrast, show that for sales retention levels δ within the range of values found in previous literature ($0.46 < \delta < 0.73$) it is optimal for brands to advertise in-sync rather than out-of-sync.

While conceptually elegant, these normative studies do not address a number of issues related to the actual implementation of the advocated strategies. First, empirical advertising patterns are often neither purely pulsing nor purely even advertising but on a continuum between these extremes. Second, guidelines are provided for a single brand in a stylized setting, potentially ignoring environmental factors that can systematically affect advertising decisions. Third, these studies mainly focus on the timing of advertising actions and ignore spending levels (Aravindakshan and Naik (2015) is a notable exception in a non-competitive setting).

2.3. Empirical literature on advertising spending effectiveness

An extensive stream of econometric studies has focused on measuring the *effectiveness of advertising*. Performance is treated as a function of advertising expenditures in so-called single equation models (e.g., Lambin, Naert, & Bultez, 1975). These models treated advertising as an independent variable, without investigating how spending patterns were determined. Simultaneous equation models, starting with Bass (1969) and including work by Hanssens (1980), as well as VAR models (e.g., Dekimpe & Hanssens, 1995), in turn, treat advertising also as an endogenous variable.

The latter type of studies not only allows for feedback effects, where past performance influences current spending, but also for *competitive interactions* (see e.g., Steenkamp, Nijs, Hanssens, & Dekimpe, 2005). Advertising competition, and in particular, in-sync advertising, has been shown to negatively affect advertising elasticities (Danaher et al., 2008). In practice, brand advertisers have been found to avoid (Danaher et al., 2008), trump (Metwally, 1978), or simply ignore each other (Steenkamp et al., 2005).

Although empirical research has tried to explain variation in patterns across brands and categories, none distinguish between two key components of advertising management: (1) the decision to advertise, or not, at time *t* (incidence) and (2) conditional on the decision to advertise, how much to spend (magnitude). This distinction is important since the factors that influence both decisions, like for example competitors' advertising actions, could have different weights. Furthermore, little or no attention has been given to the relative performance implications of different advertising spending patterns. Finally, previous studies show a bias towards large and frequently advertised brands. Such data pruning can significantly affect inference (Zanutto & Bradlow, 2006).

2.4. Heterogeneity across brands

Brands can show considerable heterogeneity in advertising spending patterns and response to competitors. We focus on two common interactions: a) between same-owner brands, and b) between market leaders and followers.

2.4.1. Same-owner brands

Firms owning multiple brands in the same product category face possible cannibalization issues (e.g., Copulsky, 1976). Such brands may cooperate rather than compete (Solomon & Hymowitz, 1987), avoiding in-sync advertising to reduce self-generated clutter.

However, the risk of cannibalization can be strongly reduced if each brand focuses on a specific niche (e.g., Mason & Milne, 1994) to better serve heterogeneous consumer needs (e.g., Kekre & Srinivasan, 1990). A brand portfolio may include flagship brand leaders and “protective flankers” to deter competitive entry and fight same-profile competitors (see e.g., Aaker, 1991; Aaker, 2004; Aaker & Joachimsthaler, 2000). P&G, for example, markets Tide (fully synthetic, strong cleaning power) as its leading brand, but also sells Gain (fully synthetic, great smell) and Cheer (budget detergent) in the US clothing detergent market. Similarly, in the UK they sell Ariel (fully biological, main brand in most non-US markets), Fairy (fully synthetic), Daz (low-price alternative to Ariel, same product as Tide in the US) and Bold (low-suds biological).

In such portfolios, same-owner brands are no direct competitors, and are managed independently to compete directly with other brands in same market segments. In such settings, same-owner brands may choose to advertise in-sync to limit category-reminder benefits from spilling over to competitors.

2.4.2. Leader versus follower

Smaller follower brands face a double jeopardy as they have fewer customers who are less loyal (e.g., Ehrenberg, 1972) making it difficult to challenge market leaders. To grow, these brands can use advertising to increase mental availability and acquire new customers (e.g., Riebe, Wright, Stern, & Sharp, 2014; Sharp, 2010). Leaders, in turn, can protect their position by keeping mental availability high through intense advertising (Sharp, 2010).

Firms' reactions to competitive actions are shaped by their ability and motivation to react, as well as by the visibility of these actions (Chen, 1996; Chen & MacMillan, 1992). Actions by leaders are likely to draw more attention. However, as advertising budgets are often determined on a percentage of sales basis (e.g., Allenby & Hanssens, 2005; Smith, Grimm, Gannon, & Chen, 1991), followers may lack the resources to react. They may also be less motivated to react if they believe it is too hard to change brand attitudes held by the leader's loyal customer base.

Reactions to actions by followers may differ for leaders and co-followers. Such actions may draw less attention from leaders due to followers' smaller advertising budgets (e.g., Allenby & Hanssens, 2005; Smith et al., 1991). Although market leaders have the required resources to react, their strong brand equity and established position in consumers' minds (e.g., Kent & Allen, 1994) may reduce motivation to advertise in-phase with weaker brands. That said, market leaders often have many challengers and strong incentives to maintain vigilant and defend their competitive position (Bowman & Gatignon, 1995; Dutton & Jackson, 1987). Co-followers, in turn, are likely to closely monitor direct competitors (see e.g., Debruyne & Reibstein, 2005). Co-followers may have similar capabilities and strong incentives to react when acquiring customers from each other is easier than from the market leader.

Table 1
Overview of included product categories and example brands.

Product class	Number of categories	Example categories	Example brands
Food	24	Breakfast cereals	Kellogg's
		Savory snacks	Pringles
		Yoghurt	Danone
Beverages	19	Lager	Heineken
		Mineral water	Evian
		Softdrinks	Coca-Cola
Personal care	18	Cleansers	Oil of Olay
		Dentifrice	Colgate
		Shampoo	L'Oreal
Household care	10	Household cleaners	Flash
		Liquid detergents	Fairy
		Machine wash products	Ariel
Total number	71		370

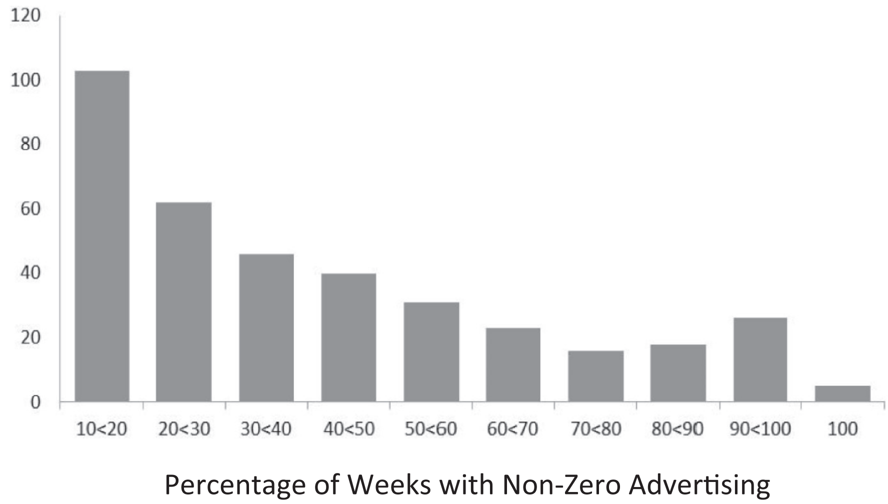

Fig. 2. Histogram of advertising frequencies.

3. Data

3.1. Focal dataset: weekly media-aggregated data

The key empirical analyses presented in this paper are based on data from a large number of CPG categories in the United Kingdom. The data cover a wide range of food, beverage, personal care, and household care products and provide a representative sample of the goods found in a typical supermarket. An overview of the product categories and the number of brands is given in Table 1.[1]

We obtained four years (2002–2005) of weekly total advertising spending data (208 weeks) from NielsenMedia. These expenditures are aggregated across television, radio, print, direct mail, outdoor, and cinema advertising. We study brands that were available in the market for the full four years and that advertised in at least 10% of the weeks in our dataset (395 brands in 96 categories). However, in 25 categories only 1 brand met the threshold, precluding estimation of competitive behavior. These categories were consequently removed resulting in a total of 370 brands in 71 categories. Same-owner brands were found in 30 of these categories.

In contrast to many previous studies, we include both small and large brands, resulting in an average market share of 7.4% (standard deviation: 9.6). Adopting the selection rules applied by Steenkamp et al. (2005), i.e., advertising in at least 12.5% of the weeks and a top-three market share in the category, would have reduced the number of brands in our study from 370 to only 150. We focus on national brands, as private labels are typically not advertised at the category level (e.g., Lamey, Deleersnyder, Steenkamp, & Dekimpe, 2012).[2]

Information on volume sales and prices come from Kantar Worldpanel UK.[3] Data from this panel have been used in prior research (e.g., Gijsenberg, 2017). Panel members scan all fast-moving consumer goods purchases on a daily basis. These purchases can be made at mom-and-pop stores and drugstores up to large supermarket chains like Asda, Sainsbury's, and Tesco. This information is then aggregated over the >17,000 British households in this consumer panel. A correct representation of the full population is obtained by weighing along the following dimensions: region, social grade, household size, housewife age, and family makeup.

Although all 370 brands advertised in at least 10% of weeks, considerable variability exists in advertising behavior. On average, brands advertised 86 out of 207 weeks (41.5% of the time) with a standard deviation of 55 weeks. Average spending per advertising week was £94,010, with a standard deviation of £79,366.

We use this dataset in Section 4 to establish advertising spending patterns, in Section 5 to establish competitor impact on advertising incidence and magnitude, and in Section 6 for a simulation analysis.

3.2. Additional dataset: monthly media-disaggregated data

We also obtained over 17 years (January 1993–October 2010) of monthly advertising data for 162 brands in 37 categories from NielsenMedia. Expenditures in this dataset are not aggregated across media, but split out over television, radio, print, direct mail, outdoor, and cinema advertising.

We use this dataset in Section 4 to judge the extent to which the advertising spending patterns based on weekly advertising data can also be extracted from monthly or quarterly data. In addition, this dataset also allows us to judge to what extent the observed overall patterns are driven by specific media types.

[1] A more detailed description of the included categories, including descriptive statistics, is provided in web Appendix A.
[2] Private label brands were considered in the derivation of variables such as market share change.
[3] We gratefully thank AiMark for providing access to the data.

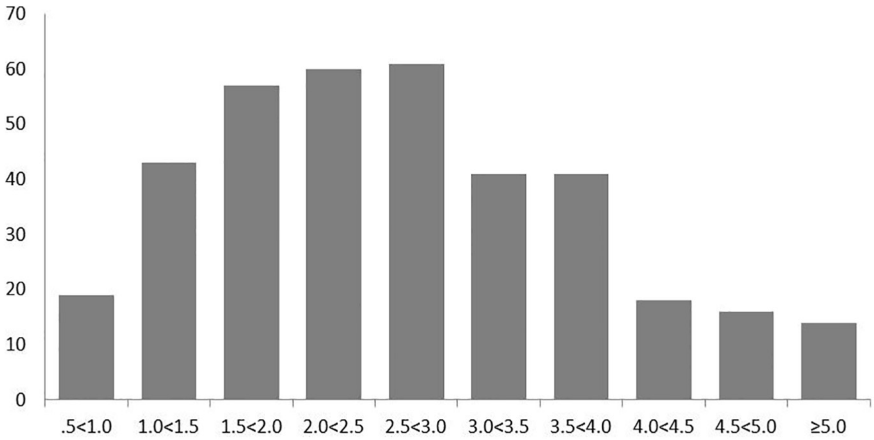

Fig. 3. Histogram of number of brands with coefficient of variation in advertising expenditures.

3.3. Qualitative feedback from practitioners

We not only had access to the two quantitative datasets described above, but also to qualitative feedback from practitioners. To obtain this feedback, we invited 50 managers from a wide range of major CPG producers, (online/offline) retailers, media firms, advertising agencies, marketing research agencies, and marketing consultancy firms to share their thoughts on our work. In total, 13 managers (response rate of 26%) agreed to provide feedback. Of these 13, 7 (54%) are women. These practitioners all qualify as middle or senior level managers, and had up to 29 years of relevant experience, with an average of 10 years. All aforementioned types of firms are represented, with 5 of the managers being employed by major CPG producers, 3 by (online/offline) retailers, 2 by marketing consultancy firms, and 1 manager by a media firm/advertising agency/marketing research agency each, respectively.

Upon their agreement to cooperate, we asked the practitioners to comment on the outcomes of our analyses regarding the impact of competitors on brands' advertising spending decisions, thereby drawing from their own professional experience. We use this feedback in Section 5 to establish the external validity of our approach and findings.

4. Establishing spending patterns

4.1. Observed spending patterns

In our data only 5 brands have non-zero advertising levels in each week. By definition, only those 5 brands could potentially apply even advertising strategies. Of the brands selected for our analysis (i.e., brands that advertise in >10% of weeks) the majority (57%) advertise in fewer than 40% of weeks. Fig. 2 provides a histogram of the advertising frequencies.

For each brand we also calculated the coefficient of variation in advertising expenditures over time. Values greater than one occur when the standard deviation in advertising expenditures is larger than the mean. A histogram of the coefficient of variation values across brands is presented in Fig. 3. None of the 370 included brands has a coefficient of variation equal to zero. Hence none of the 5 continuous advertisers spends evenly.

Together, Figs. 2 and 3 provide strong evidence that pulsing is the dominant type of advertising pattern in the categories we study. Not only are there many weeks without advertising for almost all brands, the variation in expenditures is very high as well. Neither of these results would be expected if continuous even advertising schedules were used.

A visual inspection of the advertising spending patterns of the included brands allows for a more detailed view on actual advertising patterns. We therefore plot all individual advertising spending series, and, based on previous literature, distinguish the following patterns in the graphs (Mahajan & Muller, 1986)[4]:

- Even spending: Continuous advertising at a (mostly) equal level.
- Pulsing with maintenance spending: Switching between periods of a) high and b) low levels of advertising, possibly with short interruptions. Pulsing can be categorized as Campaigning (multi-week advertising periods), Spikes (one-week advertising periods), or Mixed.
- Flighting[5]: Switching between periods of a) high and b) zero advertising. Flighting can again be categorized as Campaigning, Spikes, or Mixed.
- Chattering: High-frequency switching between a) one-week high advertising and b) subsequent one or more weeks of zero advertising.

[4] Graphs showing the advertising patterns for a sample of the included brands in the focal dataset, together with the assigned pattern type, are provided in web Appendix B.

[5] We use the term “flighting” to refer to pure pulsing strategies without maintenance advertising, thus avoiding confusion with pulsing with maintenance.

Table 2
Distribution of advertising pattern types — weekly data.

Type of pattern	Percentage of brands Individual brands ($n = 370$)	Percentage of brands Same owner in category ($n = 45$)
Even	0.0%	0.0%
Pulsing with maintenance	38.9%	35.6%
Campaigning	26.2%	15.6%
Spikes	3.0%	4.4%
Mixed	9.7%	15.6%
Flighting	57.3%	64.4%
Campaigning	29.5%	37.8%
Spikes	7.8%	2.2%
Mixed	20.0%	24.4%
Chattering	3.8%	0.0%

The distribution of spending pattern types is presented in Table 2. As mentioned before, even though 5 of the 370 studied brands advertise every week, none of them does so at an even level (Even: 0%). While 3.7% of brand engage in chattering-like behavior the vast majority of brands show either flighting (57.3%) or pulsing with maintenance spending (39.0%). Within both pulsing patterns, campaigning and mixed schedules are dominant, with relatively few firms engaging in spiked behavior. As such, these observation indicate that, similar to Dubé et al. (2005), many brands in our data alternate between a) periods of high, and b) periods of continued (maintenance; e.g., soft-drink A and cleanser A in Fig. 1) or non-continued (hence: no maintenance; e.g., soft-drinks B and C and cleansers B and C in Fig. 1) low (but not zero) advertising.

Under the assumption that same-owner brands in a category may show a higher likelihood of even spending patterns when evaluated jointly, we repeated the analysis for this subset of brands. The results for the 45 shared-owner-category combinations in our data are also shown in of Table 2. Overall, patterns are quite similar to the individual brand analysis. There are, however, relatively fewer (*more*) cases of campaigning pulsing with (*without*) maintenance spending (15.6% vs 26.2%; 37.8% vs 29.5%). At the same time, there are more cases of mixed pulsing with maintenance (15.6% vs 9.7%) and fewer cases of spiked flighting (2.2% vs 7.8%). Most importantly, even though the variation is slightly down compared to the individual brand analysis (1.77 vs 2.70), same-owner brands do not show a higher likelihood of even spending.

4.2. Impact of temporal aggregation on observed spending patterns

Temporal aggregation could either mask or create specific patterns, i.e., analyzing data at the weekly level may produce different patterns compared to monthly or quarterly data. We therefore judge the robustness of the patterns reported above by comparing them to the patterns based on monthly and quarterly aggregated data from the 162 brands included in the additional dataset, thereby aggregating across media. The distribution of these patterns is shown in Table 3.

Overall, monthly advertising patterns are very similar to the weekly patterns. At the more detailed level, deviations from the weekly patterns are in the same range as in the case of the same-owner analysis, with relatively fewer (*more*) cases of campaigning pulsing with (*without*) maintenance spending (19.1% vs 26.2%; 36.4% vs 29.5%). Conversely, we find relatively more (*fewer*) cases of mixed pulsing with (*without*) maintenance spending (18.5% vs 9.7%; 14.8% vs 20.0%). Aggregating at the quarterly level, on the other hand, shows considerably strong deviations from the observed weekly patterns. This level of time aggregation seems too coarse to address our research questions.

Table 3
Distribution of advertising pattern types — additional data.

Type of pattern	Percentage of brands Monthly ($n = 162$)	Percentage of brands Quarterly ($n = 162$)
Even	0.0%	0.0%
Pulsing with maintenance	38.9%	54.9%
Campaigning	19.1%	15.4%
Spikes	1.2%	4.9%
Mixed	18.5%	34.6%
Flighting	58.0%	45.1%
Campaigning	36.4%	24.1%
Spikes	6.8%	6.8%
Mixed	14.8%	14.2%
Chattering	3.1%	0.0%

Table 4
Distribution of advertising pattern types in different media and relative prominence of media.

Type of pattern	Total (n = 162)	TV (n = 145)	Print (n = 159)	Outdoor (n = 116)	Radio (n = 118)	Cinema (n = 67)	Direct mail (n = 35)
Even	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Pulsing with maintenance	38.9%	41.4%	40.9%	19.8%	28.0%	13.4%	0.0%
Campaigning	19.1%	21.4%	21.4%	1.7%	12.7%	7.5%	0.0%
Spikes	1.2%	2.8%	1.3%	2.6%	2.5%	0.0%	0.0%
Mixed	18.5%	17.2%	18.2%	15.5%	12.7%	6.0%	0.0%
Flighting	58.0%	53.1%	59.1%	80.2%	72.0%	86.6%	100.0%
Campaigning	36.4%	29.7%	22.6%	19.0%	31.4%	77.6%	22.9%
Spikes	6.8%	3.4%	8.8%	23.3%	13.6%	4.5%	37.1%
Mixed	14.8%	20.0%	27.7%	37.9%	27.1%	4.5%	40.0%
Chattering	3.1%	5.5%	0.0%	0.0%	0.0%	0.0%	0.0%
Relative prominence (across all 162 brands)							
25th pctile	% of advertising periods	35.57%	46.67%	0.00%	0.00%	0.00%	0.00%
Median		62.50%	63.72%	5.00%	5.71%	0.00%	0.00%
75th pctile		81.04%	81.79%	15.34%	18.57%	3.68%	0.00%
Average		56.22%	63.24%	10.20%	11.72%	4.21%	0.89%
25th pctile	% of advertising spending	62.40%	5.93%	0.00%	0.00%	0.00%	0.00%
Median		77.89%	10.90%	2.93%	0.42%	0.00%	0.00%
75th pctile		87.42%	20.79%	8.32%	1.59%	1.44%	0.00%
Average		68.51%	21.41%	6.56%	1.68%	1.36%	0.48%

4.3. Observed spending patterns across media

It seems plausible that advertising spending patterns may differ across media. Having established the consistency in patterns based on monthly versus weekly temporal aggregation, we analyze the monthly spending patterns across the different individual media for the 162 brands included in the additional dataset. The distribution of patterns as well as the relative prominence of the different media is shown in Table 4.

Television and print advertising are the most important media used, both in terms of incidences (56.22% and 63.24% respectively) and spending (68.51% and 21.41% of total advertising spending respectively). Advertising spending patterns for these media, in addition, strongly resemble the overall patterns depicted in Tables 2 and 3. The four other media, in turn, are less often used and account for a much lower percentage of overall advertising spending. Maintenance advertising is also less often found in these media, and even fully absent in the case of direct mail. None of the media shows even advertising, and only TV shows chattering-like patterns (5.5% of the brands using TV).

In the past decades, Integrated Marketing Communication (see e.g., Naik, 2007) has gained increasing importance as a paradigm in advertising. Combining different media in an integrated strategy should benefit brands. Table 5 provides insights on the extent to which both the incidence and advertising spending in the different media are related to the aggregate advertising numbers. In addition, it provides the same type of insights on their relation to TV advertising, given the dominance of the latter form of advertising in the total advertising figures.

TV and print advertising show much stronger relations with the overall advertising figures than the other media, with average phi coefficients of 0.60 and 0.57 and average Pearson correlations of 0.91 (0.93) and 0.35 (0.40), respectively. While especially TV advertising has a strong relation with the overall advertising spending figures, the phi coefficients are rather similar. Hence, while

Table 5
Relation of individual media advertising with total and TV advertising.

Relation with total (TV) advertising	TV	Print	Outdoor	Radio	Cinema	Direct mail
Advertising incidence (phi coefficient)						
25th pctile	0.47	0.41 (*−0.01*)	0.11 (*−0.00*)	0.10 (*−0.02*)	0.06 (*−0.03*)	0.03 (*−0.04*)
Median	0.60	0.57 (*0.09*)	0.17 (*0.07*)	0.16 (*0.05*)	0.09 (*0.07*)	0.06 (*0.02*)
75th pctile	0.72	0.73 (*0.19*)	0.25 (*0.15*)	0.27 (*0.12*)	0.17 (*0.15*)	0.09 (*0.07*)
Average	0.60	0.57 (*0.11*)	0.20 (*0.08*)	0.20 (*0.06*)	0.12 (*0.08*)	0.06 (*0.02*)
Advertising spending across all weeks (Pearson correlation)						
25th pctile	0.90	0.19 (*−0.02*)	0.16 (*−0.01*)	0.03 (*−0.02*)	0.06 (*−0.03*)	0.03 (*−0.05*)
Median	0.95	0.30 (*0.06*)	0.35 (*0.05*)	0.11 (*0.02*)	0.15 (*0.03*)	0.12 (*−0.02*)
75th pctile	0.98	0.43 (*0.16*)	0.51 (*0.18*)	0.21 (*0.11*)	0.28 (*0.11*)	0.22 (*0.03*)
Average	0.91	0.35 (*0.08*)	0.36 (*0.10*)	0.13 (*0.05*)	0.18 (*0.06*)	0.14 (*−0.00*)
Advertising spending conditional upon incidence (Pearson correlation)						
25th pctile	0.92	0.20 (*−0.08*)	0.46 (*−0.13*)	0.10 (*−0.14*)	0.13 (*−0.39*)	0.20 (*−0.29*)
Median	0.97	0.34 (*0.03*)	0.66 (*0.06*)	0.32 (*0.06*)	0.46 (*0.01*)	0.64 (*0.01*)
75th pctile	0.99	0.52 (*0.16*)	0.93 (*0.40*)	0.69 (*0.30*)	0.71 (*0.38*)	0.88 (*0.21*)
Average	0.93	0.40 (*0.06*)	0.63 (*0.14*)	0.36 (*0.08*)	0.35 (*0.01*)	0.52 (*0.01*)

Note: The phi coefficient is equivalent to the Pearson correlation coefficient for two binary variables.

Table 6
Relation between brands' actions.

Relation between brands' actions: overall (*same owner*)	Incidence Phi coefficient[a]	Magnitude Pearson correlation[b]
25th pctile	−0.02 (*−0.02*)	−0.08 (*−0.09*)
Median	0.06 (*0.05*)	0.03 (*0.02*)
75th pctile	0.16 (*0.19*)	0.16 (*0.13*)
Average	0.08 (*0.08*)	0.05 (*0.03*)

[a] For the incidence analysis, brands with continuous advertising were excluded.
[b] For the magnitude analysis, dyads without competitor advertising were excluded.

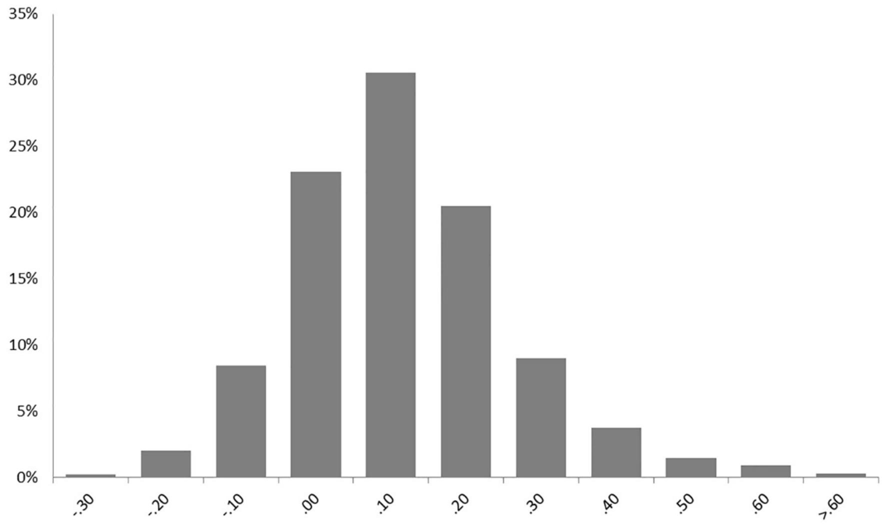

Fig. 4. Distribution of phi coefficient (overall, dyadic basis, symmetric, $n = 1274$).

usage as such may be related in the same way to the overall figures, the higher TV advertising rates are clearly driving the spending relations.

Simultaneous usage of TV and other media appears to be relatively limited. Average phi coefficients never exceed 0.11 (print), and Pearson correlations are similarly low. These findings show that integrated marketing communications do not appear to be a wide-spread phenomenon among the brands in this dataset. Relations among advertising in the different media are positive, but on the low side. Hence, media are used together for advertising campaigns, but likely not in a systematic way.

5. Establishing competitor impact

5.1. Model-free insights

To obtain initial insights on the extent to which both incidence and magnitude of advertising for the 370 brands in our focal dataset are related to competitors' actions, we calculate two model-free advertising overlap measures: the phi coefficient for advertising incidence, and the Pearson correlation for advertising magnitude conditional upon incidence. Both measures are calculated for each brand dyad in a category. Results are reported in Table 6.

Overall, in 66.3% of dyads, the phi coefficient is positive. The average value of the coefficient, however, is only 0.08. Consequently, while there is a tendency to advertise in-sync with competitors (i.e., at the same time), this tendency is relatively weak. Interestingly, same-owner brands' behavior does not deviate from the overall picture, providing first evidence for the fact that these brands are not forced to avoid each other when advertising. By nature of this measure, any reported relations are symmetric. Fig. 4 shows the distribution of the phi coefficient across all included dyads. Even though there is considerable heterogeneity, most coefficients lie within the −0.10 to 0.20 interval.

For advertising magnitude, we looked at the correlation between competitors' advertising expenditures. The measure is based upon the weeks in which a focal brand in the dyad advertised. Consequently, each brand appeared twice in the analysis: once as the focal brand and once as a competitor brand.[6] In 56.2% of the included dyads, the Pearson correlation is

[6] Correlations could not be calculated for dyads without advertising overlap so these were excluded from the analysis.

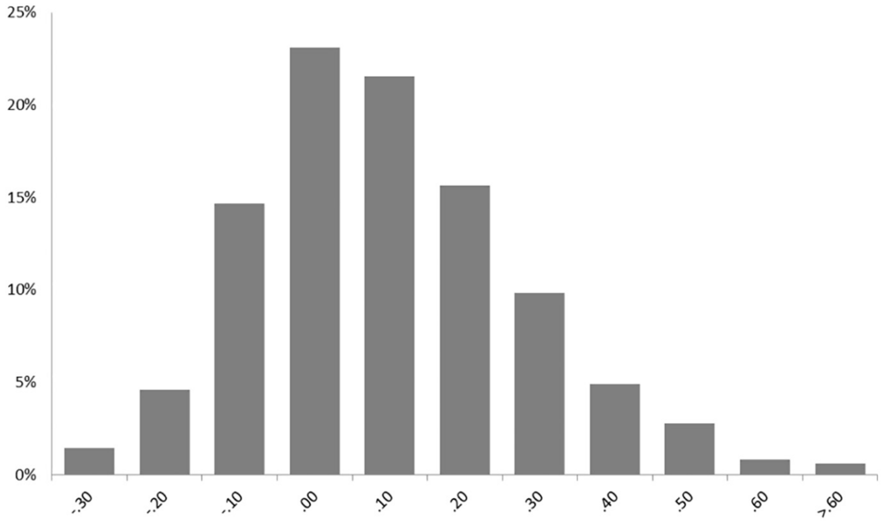

Fig. 5. Distribution of Pearson correlation conditional on advertising (overall, dyadic basis, asymmetric, $n = 2532$).

positive. The average correlation, however, is only 0.05. Similar to advertising incidence, there thus appears to be a tendency to retaliate to competitors (respond with higher advertising when the competitor has higher advertising), but this retaliation is relatively weak on average. Same-owner brands once again show a similar profile, although the reactions seem weaker overall. Fig. 5 shows the distribution of the Pearson correlation coefficient across all included dyads. Similar to the phi coefficient, we see considerable heterogeneity, with most values between −0.10 and 0.20.

5.2. Partial correlations

The measures presented above provide initial insights on the association between the advertising by different brands. However, the observed links may be the consequence of other factors than only competitive considerations. To obtain more accurate estimates of competitive interaction, we need to account for these additional factors.

5.2.1. Empirical model

For each brand dyad in a category (see e.g., Steenkamp et al., 2005), we estimate a two-part model (see e.g., Donelson & Hopkins, 2016).[7] We first model competitive interaction with regard to advertising incidence. Next we model the role of these interactions with regard to the spending magnitude conditional on advertising incidence (see e.g., Bar-Ilan and Strange (1999) or Gielens and Dekimpe (2007) for similar reasoning in investment decisions). The general form of this model is

$$y^*_{1i} \mid y^*_{2i} > 0 = \mathbf{x}'_{1i}\beta_1 + u_{1i} \tag{1}$$

$$y^*_{2i} = \mathbf{x}'_{2i}\beta_2 + u_{2i} \tag{2}$$

where

$$y_{1i} = \begin{cases} y^*_{1i} & if\ y^*_{2i} > 0 \\ 0 & if\ y^*_{2i} \le 0 \end{cases} \tag{3}$$

In this model, Eq. (2) is a logistic regression for incidence. Eq. (1), in turn, is a linear regression for magnitude, conditional on incidence, estimated using subsample OLS.[8] Eq. (3) specifies the relevant condition.

We build up to a full model by adding 4 blocks of explanatory variables consecutively. The first block contains a set of intra-year factors that are perhaps the most obvious alternative explanation for correlation in competitors' advertising behavior (e.g., Gijsenberg, 2017; Villas-Boas, 1993). Competing brands may advertise together during high demand periods, e.g., soft

[7] An alternative approach would be to specify a game-theoretical model that assumes optimal behavior. While we acknowledge the value of such an approach, there are several reasons why we believe it is not appropriate for this research. First, formulation and estimation of this type of model could easily become infeasible given the number of brands and categories in our dataset. Second, both the results of our analyses and the feedback from managers showed that competitive reasoning is limited. As game theoretic models are highly dependent on underlying assumptions, giving too much weight a priori to competitive factors could easily lead to erroneous conclusions. Finally, managers indicated that advertising decisions are hardly ever the result of a formal optimization approach.

[8] High degrees of correlation between the $\mathbf{x}'_{1i}$ and $\mathbf{x}'_{2i}$ (0.88, on average) and high degrees of censoring (68/37/15% of the brands have >50/75/85% zero observations) indicate that subsample OLS is appropriate (Puhani, 2000).

drink brands mainly advertising in spring and summer. As one manager phrased it: "*When dealing with seasonal products, you will be advertising at the same time as your competitor, regardless of any deliberate competitive reactions*". Therefore, we start with a set of controls, capturing *holiday*, intra-year demand cycle (*CatDemCycle* see Gijsenberg, 2017), and *trending* behavior in advertising decisions.

The second block of variables contains competitor variables. These account for competitor incidence (*CompIncidence*) in the incidence equation and competitor adspend (*CompAdspend*) in the magnitude equation, respectively. The coefficients for these focal variables will provide insights on competitive reasoning. We also control for the advertising pressure by the other brands in the category (*CompAdPressure*).

Next, we add a set of variables that capture the internal advertising reasoning of the firm. Because firms tend to what they know (e.g., Nijs, Srinivasan, & Pauwels, 2007), future advertising patterns will likely copy past patterns. Similarly, the time until the next pulse is likely dependent on the observed time difference between previous pulses. We thus add *Time Since Previous Pulse* (*TSPP*), defined as the number of weeks since the previous advertising pulse. We add two variables to flexibly capture a build-up and decline in pressure to advertise similar to the Adstock concept (e.g., Broadbent, 1984). The first variable ($TSPP \leq TSPP^{prev}$) is defined as the elapsed time relative to the length of the previous interval and equals one beyond that duration. When a new campaign starts, values remain constant, and a new counting cycle starts when the campaign has ended. The second variable ($TSPP > TSPP^{prev}$) equals the ratio of elapsed to the length of the previous interval time minus 1 once the current interval is longer than the previous and takes a value of zero before. We account for the *Previous Time In Pulse* (TIP^{prev}) in a similar manner. The variable ($TIP \leq TIP^{prev}$) is defined as the elapsed time in the new pulse relative to the previous pulse duration until the duration is equal, and set to one beyond that point. The second variable ($TIP > TIP^{prev}$) equals the ratio of elapsed to previous duration minus 1 once the current pulse is longer than the previous one and takes a value of zero before. After the pulse has ended, values remain constant, and a new counting cycle starts when a new pulse has started. We also include lagged dependent variables in both equations (i.e., *PrevIncidence* and *PrevAdspend*).[9]

Finally, we account for short-term deviations in performance and other marketing mix decisions that may drive advertising behavior. As shown by e.g., Allenby and Hanssens (2005), advertising decisions are often based upon previous performance. Good performance creates additional resources, while bad performance calls for efforts to regain lost ground. We account for this by including Δ*MarketShare*, the one-period lagged first difference of the log-transformed brand volume sales over a moving window of previous 26 weeks (cfr. Franses & Koop, 1998). We also include *Price*, as price changes are often coordinated with advertising efforts.

5.2.2. Model estimation

As mentioned before, we estimate brand competition in dyads (see e.g., Steenkamp et al., 2005), in which we investigate the effect of competitive advertising actions by one specific competitor through the *CompIncidence* and *CompAdspend* variables.[10] The parameter estimates for these variables capture the influence of a competitor's actions on the advertising decisions of the focal brand. In our analyses, we allow for asymmetries by including each brand twice in the dyad: once as focal brand, once as competitor. For example, brand A might always advertising in-sync with brand B, but brand B need not always advertise in-sync with brand A.

We combine the individual-brand-dyad estimates using the added-Z method (Rosenthal, 1991) to arrive at general across-brand insights on the significance of variables. To account for the fact that some of the variables are the same in dyads with the same focal brand, we a) calculate the within-brand average parameters for these variables, b) determine the associated standard deviations and significance levels, and c) apply the added-Z method to these brand-specific across-dyad average parameters and significance levels. The added-Z method thus allows us to combine individual estimates and create generalizable insights in a straightforward way (e.g., Gijsenberg, 2017; Van Heerde, Gijsenberg, Dekimpe, & Steenkamp, 2013). The reported parameter values are the across-dyad uncertainty-weighted parameter estimates.

5.2.3. Overall incidence insights

The overall results across all types of dyadic interactions for the incidence equation are given in Table 7. While the addition of competitor variables in Model 2 increases the average pseudo R^2 by 0.057, adding internal reasoning related variables in Model 3 shows a much stronger effect with an increase in average pseudo R^2 of 0.441, thus nearly quadrupling the explanatory power. In addition, the hit rate for incidence nearly doubled from 0.483 to 0.849, while including competitor variables only increased the hit rate by 0.062. These differences in relative impact are in line with findings by Montgomery, Moore, and Urbany (2005) who show that current competitive behavior is mentioned as a driver of advertising decisions only about half as often as internal factors. As such, internal reasoning plays a much more important role in advertising incidence decisions compared to competitive reasoning, as was also confirmed in the feedback from the practitioners.

After accounting for various possible drivers of advertising incidence, we still find a small significant overall positive effect ($\overline{\beta}_4 = 0.351$, $p < .01$) of competitor incidence on the own advertising incidence in Model 4. Hence, overall, brands show some tendency to advertise in-sync with competitors. When looking at individual dyads, we see that in 85.8% of cases, reactions were not significant, while in 11.2% of cases there was a significant in-sync reaction (retaliation) and in 3.0% a significant out-of-sync reactions

[9] We make abstraction of the underlying optimization process, if any (see also footnote 7).

[10] We estimate our models at the weekly level, not at the pulse level. Tactical advertising decisions are usually made at the weekly level (e.g., Danaher, 2007; Vakratsas & Ambler, 2007). As already indicated by Steenkamp et al. (2005) brands can and do adjust their advertising at the weekly level. Not accounting for this by analyzing the data at the pulse level could consequently lead to misleading conclusions.

Table 7
Overall incidence equation results.

		Expected sign	Model 1	Model 2	Model 3	Full model 4
			Weighted beta	Weighted beta	Weighted beta	Weighted beta
Intercept	$\overline{\beta}_0$	≠0	*−0.411******	*−1.858******	*−4.517******	−3.724***
Holiday	$\overline{\beta}_1$	≠0	*−0.036******	*−0.023***	*−0.167******	−0.178***
CatDemCycle	$\overline{\beta}_2$	≠0	*1.042******	*0.673******	*0.737******	0.821***
Trend	$\overline{\beta}_3$	≠0	*−0.073******	*−0.063******	*0.243******	0.091***
CompIncidence	$\overline{\beta}_4$	>0		*0.287******	*0.342******	0.351***
CompAdPressure	$\overline{\beta}_5$	>0		*0.164******	*0.186******	0.188***
$TSPP \le TSPP^{exp}$	$\overline{\beta}_6$	>0			*3.408******	3.677***
$TSPP > TSPP^{exp}$	$\overline{\beta}_7$	≠0			*−0.006***	−0.011***
$TIP \le TIP^{exp}$	$\overline{\beta}_8$	<0			*−4.498******	−4.649***
$TIP > TIP^{exp}$	$\overline{\beta}_9$	≠0			*0.089******	0.092***
PrevIncidence	$\overline{\beta}_{10}$	≠0			*5.047******	5.145***
ΔMarketShare	$\overline{\beta}_{11}$	≠0				0.640***
Price	$\overline{\beta}_{12}$	≠0				0.390***
Average pseudo R^2			0.087	0.144	0.585	0.606
Average AIC			0.971	0.934	0.723	0.547
Average hit rate			0.773	0.789	0.913	0.918
Average hit rate incidence (ones)			0.421	0.483	0.849	0.860
% in-sync				63.6%	62.3%	62.6%
% out-of-sync				36.4%	37.7%	37.4%
% in-sync sig				19.7%	11.6%	11.2%
% out-of-sync sig				6.1%	3.2%	3.0%
% not sig				74.2%	85.2%	85.8%

Tests are one-sided if clear directional effects are expected, two-sided if not (Rosenthal, 1991). Deviations from 100% are due to rounding.
** $p < .05$.
*** $p < .01$.

Table 8
Overall magnitude equation results.

		Expected sign	Model 1	Model 2	Model 3	Full model 4
			Weighted beta	Weighted beta	Weighted beta	Weighted beta
Intercept	$\overline{\beta}_0$	≠0	*10.133******	*8.976******	*8.149******	7.087***
Holiday	$\overline{\beta}_1$	≠0	*0.080******	*0.071******	*0.052******	0.052***
CatDemCycle	$\overline{\beta}_2$	≠0	*1.020******	*0.814******	*0.631******	0.587***
Trend	$\overline{\beta}_3$	≠0	*−0.192******	*−0.154******	*−0.179******	−0.182***
CompAdspend	$\overline{\beta}_4$	>0		*0.014******	*0.015******	0.015***
CompAdPressure	$\overline{\beta}_5$	>0		*0.100******	*0.096******	0.097***
$TSPP \le TSPP^{exp}$	$\overline{\beta}_6$	>0			*0.040***	0.055***
$TSPP > TSPP^{exp}$	$\overline{\beta}_7$	≠0			*0.002***	0.001
$TIP \le TIP^{exp}$	$\overline{\beta}_8$	<0			*−0.322******	−0.308***
$TIP > TIP^{exp}$	$\overline{\beta}_9$	≠0			*−0.019******	−0.019***
PrevAdspend	$\overline{\beta}_{10}$	≠0			*0.108******	0.104***
ΔMarketShare	$\overline{\beta}_{11}$	≠0				0.016
Price	$\overline{\beta}_{12}$	≠0				−0.035*
Average R^2			0.149	0.215	0.392	0.424
Average AIC			0.832	0.812	0.758	0.759
Average RMSE			1.514	1.452	1.300	1.261
Average MAPE			0.145	0.138	0.120	0.116
% in-sync				59.9%	60.5%	60.5%
% out-of-sync				40.1%	39.5%	39.5%
% in-sync sig				11.4%	9.8%	9.8%
% out-of-sync sig				5.0%	4.0%	4.4%
% not sig				83.6%	86.2%	85.8%

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

(accommodation). In their reactions, practitioners were equally mixed on this point, with slightly more in agreement with in-sync compared to out-of-sync.

5.2.4. Overall magnitude insights

The overall results for the magnitude equation are given in Table 8. Similar to the incidence equation, internal factors have a much stronger role in observed spending compared to competitor factors, with increases in R^2 of 0.177 vs 0.066, and decreases of the MAPE of 0.018 and 0.007, respectively. This finding was strongly confirmed by practitioners who stressed the importance of internal reasoning over competitor reasoning in spending decisions, with one manager even stating that "*share of voice is irrelevant for media decisions*".

It should consequently come as no surprise that, after accounting for various drivers of advertising magnitude, we find only a very small but significant positive effect ($\overline{\beta}_4 = 0.015$, $p < .01$) of competitor spending on focal brand (i.e., in-sync). As the advertising variables were log-transformed, we can interpret the coefficient as an elasticity: a 1% increase in competitor advertising increases the focal brand's advertising spending by 0.015%, on average, keeping all other variables in the model constant. When looking at individual dyads, we see that in 85.8% of cases, reactions were not statistically significant. In 9.8% of cases there was significant in-sync reaction (retaliation) and in 4.4% or cases significant out-of-sync reaction (accommodation). Similar to incidence, practitioners' reactions were mixed on this point.

5.2.5. Insights for specific types of responses

The dyad-based estimation of the two-part model also allows for the analysis of specific types of responses. Brands reacting to a competitor with the same owner are slightly less likely to advertise at the same time (weighted incidence competitor beta of 0.329) compared to cases in which the competitor had a different owner (weighted incidence competitor beta of 0.353). Conditional upon incidence, the influence of competitor spending on the focal brands' magnitude is even more similar (weighted magnitude competitor beta of 0.016 and 0.015 for same/other owner, respectively). Brands with a same owner thus seem to compete with each other in almost the same way they would with brands from other firms. Practitioner feedback confirms this insight. They add that same-owner brands in a category most often are positioned differently: "*If all brands have reasons to exist, they appeal to different audiences…*" As such, cannibalization risks are small and each brand develops a strategy for its own target audience.

A second response type is based on the relative market power of brands. Reactions by the market leader[11] to followers are stronger (incidence: 0.385; spending: 0.022) compared to reactions by followers to actions by market leaders (incidence: 0.322; magnitude: 0.018). Market leaders monitor smaller competitors and fiercely defend their leading positions. As practitioners put it: "*[it is] hard work to stay on top, so challengers are monitored closely.*" and "*Arrogance of market leaders to ignore followers is a dangerous trap*".

Reactions by followers to other followers take somewhat of a middle position regarding incidence reactions (incidence: 0.350). Interestingly, the magnitude reaction elasticity is the smallest of the three types of interactions (magnitude: 0.014). Most likely these brands have limited resources and cannot spend as much in response to (follower) competitor actions as market leaders could.

6. Competitive scheduling impact simulation

Inspired by the work of Guyt and Gijsbrechts (2014) on the impact of different promotional agendas with varying degrees of in-sync vs out-of-sync competitive scheduling on brands' sales, we performed a simulation to compare the impact of multiple advertising spending patterns characterized by different levels of competitive scheduling on brands' sales. We need not rely on a specific stylized setting, but rather we can use the richness of our dataset to explore effects across a wide range of real-life situations, thus adding to the external validity of our findings.

6.1. Methodology[12]

The first step of the simulation analysis consists of estimating a market-response model, linking (competitor) advertising and price to brand sales.[13] This model should allow for a) asymmetric effects of advertising increases and decreases (a condition for other patterns than even spending to arise as optimal even in the absence of an S-shaped response function, see e.g., Simon, 1982), b) interaction effects of own brand and competitor advertising to account for effects of in-sync competitor advertising (e.g., Danaher et al., 2008; Freimer & Horsky, 2012), as well as c) differential immediate and long-term effects.

[11] We define the market leader as the brand with the highest average market share over the four-year period. Market leadership was very stable, with 95% of brands having the largest share at the start of the data still having the largest share at the end.

[12] A detailed description of the different simulation steps is provided in web Appendix C.

[13] This approach tackles some of the limitations and paths for future research described by Freimer and Horsky (2012). While well-known advertising models like the Nerlove-Arrow or Vidale-Wolf model are very valuable in their analysis of stylized settings in which only advertising is changed, such models do not account for, for example, price changes or other drivers of brands' sales. As such, these models may overstate advertising effects and cannot capture the reality brand managers face when making advertising decisions. Reduced-form market response models, on the other hand, have a proven track record in explaining and forecasting brands' sales with regard to all kinds of marketing mix decisions and external influences (see e.g., Hanssens, 2015; Hanssens, Parsons, & Schultz, 2001; Leeflang, Wieringa, Bijmolt, & Pauwels, 2013).

Table 9
Included advertising pattern scenarios.

Type of pattern	When	Amount
Even	All weeks	$AB_b/52$
Pulsing with maintenance		
In-sync, rectangular spend	Non-pulse weeks	$[\mu_{b,i} * AB_b]/52$
	Pulse weeks	$[\mu_{b,i} * AB_b]/52 + [(1 - \mu_{b,i}) * AB_b]/T_k$
In-sync, matching spend	Non-pulse weeks	$[\mu_{b,i} * AB_b]/52$
	Pulse weeks	$[\mu_{b,i} * AB_b]/52 + \pi_{k,t} * [(1 - \mu_{b,i}) * AB_b]$
Out-of-sync, rectangular spend	Non-pulse weeks	$[\mu_{b,i} * AB_b]/52$
	Pulse weeks	$[\mu_{b,i} * AB_b]/52 + [(1 - \mu_{b,i}) * AB_b]/(52 - T_k)$
Flighting		
In-sync, rectangular spend	Non-flight weeks	0
	Flight weeks	$[AB_b]/T_k$
In-sync, matching spend	Non-flight weeks	0
	Flight weeks	$\pi_{k,t} * [AB_b]$
Out-of-sync, rectangular spend	Non-flight weeks	0
	Flight weeks	$[AB_b]/(52 - T_k)$
Chattering	Non-advertising weeks	0
	Advertising weeks	$[AB_b]/26$

Note: AB_b represents the total advertising year budget of the focal brand b; T_k represents the number of advertising weeks of the competing brand k; $\mu_{b,i}$ represents the percentage maintenance advertising of the focal brand b on an annual basis resulting in the highest sales increase in scenario i; $\pi_{k,t}$ represents the relative advertising spend in week t of the competing brand k as percentage of the total annual spend of that brand.

To address all these issues in one parsimonious model, we adopt an Error Correction Model (ECM). See, e.g., Van Heerde et al. (2013) for an elaborate discussion of the ECM. The model is given by

$$\begin{aligned}\Delta \ln Sales_{bt} &= \alpha_{b0} + \alpha_{b1} Trend_t + \alpha_{b2} Qrtr2_t + \alpha_{b3} Qrtr3_t + \alpha_{b4} Qrtr4_t \\ &+ \beta^{sr}_{b1} \Delta \ln Adv_{bt} + \beta^{sr}_{b2} \Delta \ln Adv^{+}_{bt} + \beta^{sr}_{b3} \Delta \ln Adv_{bt} * \Delta \ln CompAdv_{bt} \\ &+ \beta^{sr}_{b4} \Delta \ln CompAdv_{bt} + \beta^{sr}_{b5} \Delta \ln Price_{bt} + \beta^{sr}_{b6} \Delta \ln CompPrice_{bt} \\ &+ \Pi_b \left[\ln Sales_{bt-1} - \begin{pmatrix} \beta^{lr}_{b1} \ln Adv_{bt-1} + \beta^{lr}_{b2} \ln Adv^{+}_{bt-1} \\ + \beta^{lr}_{b3} \ln Adv_{bt-1} * \ln CompAdv_{bt-1} \\ + \beta^{lr}_{b4} \ln CompAdv_{bt-1} \\ + \beta^{lr}_{b5} \ln Price_{bt-1} \\ + \beta^{lr}_{b6} \ln CompPrice_{bt-1} \end{pmatrix} \right] + \varepsilon_{bt}\end{aligned} \tag{4}$$

ECM models relate the change in a dependent variable (here: $\ln Sales_{bt}$) to the changes in a set of explanatory variables (short-term effects) as well as to the deviations from the long-term equilibrium between the dependent variable and the explanatory variables (long-term effects). Such equilibria may exist between cointegrated non-stationary variables, but also between stationary variables.

In our model, $\ln Adv_{bt}$ represents the focal brand's advertising in a given week t, and $\ln Adv^{+}_{bt}$ the focal brand's advertising in a given week t, provided that advertising increased compared to previous week, thus capturing the possibly asymmetric effects of advertising increases vs decreases. We specify competitor advertising $\ln CompAdv_{bt}$ as total within-category competitor advertising, as this is the actual advertising competition each brand faces when deciding on competitive scheduling and spending. Competitor pricing $\ln CompPrice_{bt}$, in turn, is defined as the average price across all brands in the category. All variables are included in natural logarithms, thus also taking into account decreasing returns. Finally, we control for trending and quarterly seasonal effects.

A basic condition for the estimation of this type of model is that all included series are stationary. Given their superior power compared to individual brand unit root tests, we apply panel data unit root tests with an intercept and trend (Im, Hashem Pesaran, & Shin, 2003; Levin, Lin, & Chu, 2002). We find that all series are (trend) stationary at the 5% level. We estimate the model for each brand on the first 3 years (155 weeks) of observations.[14] The model showed good explanatory and predictive performance, with an average R^2 of 0.543, MAPE of 0.044, and GMRAE of 0.491, the latter well below the critical value of 1.

In the second step, we use the model to generate a baseline sales forecast for each brand for the final year (52 weeks) using the observed own and competitor advertising and price series for that band, but setting the brands' advertising to zero (see Guyt & Gijsbrechts, 2014). As the model forecasts the first-differenced log-transformed sales series, we back-transform these series to actual sales levels, and calculate cumulative sales over the 52-week period.

In a third and final step, we use the model to forecast the sales outcomes of a set of alternative advertising strategies using the total amount actually spent in the last year of the data. We then compare the sales forecasts in different scenarios to the baseline zero-advertising forecast. We refer to Table 9 for an overview of the different strategies.

A stylized example of the scenarios, together with a fictitious competitor advertising schedule, is depicted in Fig. 6. In all scenarios, both brands spend \$1000 k on advertising.

[14] We do not apply endogeneity corrections given the detrimental impact of such corrections on predictive performance (see e.g., Ebbes, Papies, & Van Heerde, 2011).

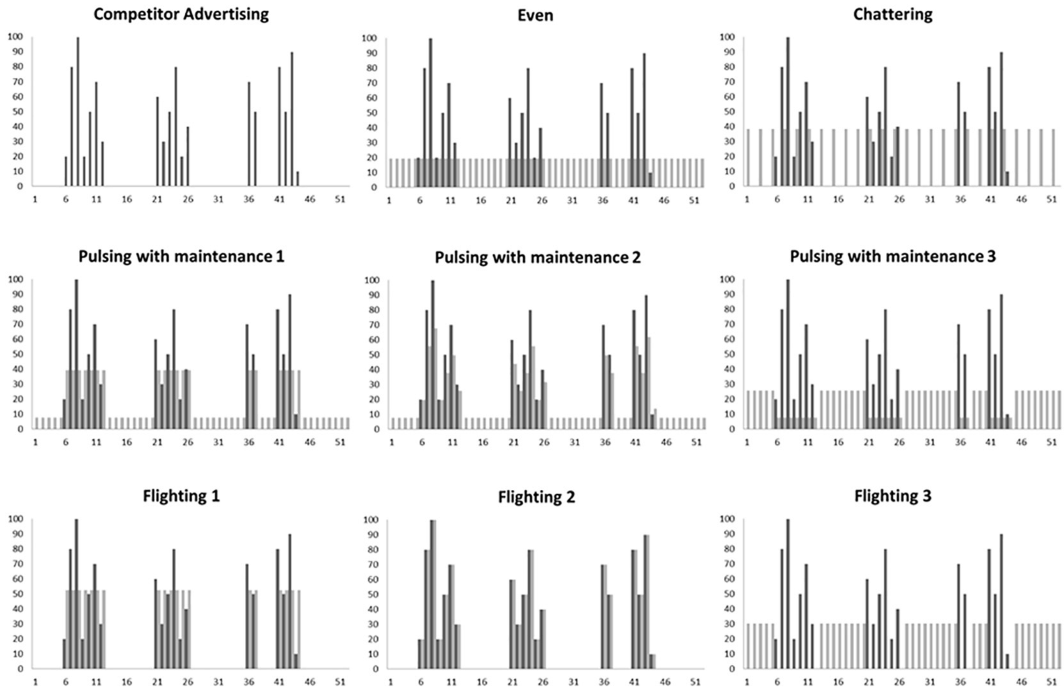

Fig. 6. Alternative advertising scenarios.

The scenarios can either be competitive or non-competitive. Non-competitive scenarios are analyzed on an overall basis, making abstraction of individual competitors. Conversely, we analyze all competitive scenarios on a dyad base, in which the advertising pattern is dependent on one specific competing brand. As a consequence, the resulting patterns can be asymmetric between the brands in a dyad, depending on their position. However, as in the ECM, we take the full competitive advertising pressure into account as competitor advertising. For these dyads, competing brands are required to advertise min 10% and max 90% of the time in order to obtain sufficient variation in the incidence decision.

We first analyze two fundamentally non-competitive schedules: even advertising (even amount every week), and chattering (even amount every other week). In addition, we look into three possible pulsing strategies, with varying degrees of competitive scheduling: in-sync with the competitor with the same (rectangular[15]) amount in each week of advertising (partly competitive); in-sync with the competitor thereby spending a same relative percentage as the competitor (fully competitive); fully opposite timing compared to the competitor thereby spending the same (rectangular) amount in each week of advertising (partly competitive). We analyze these three strategies twice: once as pure flighting strategies without maintenance advertising (i.e., full budget is spent on pulsing and hence subject to competitive scheduling) and once as hybrid strategies in combination with maintenance advertising (i.e., part of the budget is spent on pulsing and thus subject to competitive scheduling). In the latter case, we allow the percentage of the total budget spent on maintenance advertising (i.e., the baseline of each week, to which pulses are added) to vary between 10 and 50%.

6.2. Simulation results

Table 10 shows the simulation results for the different scenarios.[16] Overall, out-of-sync flighting scenarios generated significantly ($p < .01$) higher sales lift (+3.70%) compared to in-synch flighting with rectangular (+1.16%) or matching spend (+1.67%). Sales lifts for the flighting scenarios, however, are significantly smaller compared to pulsing-with-maintenance (+9.81/9.53/9.63%) or even spending (+9.32%) scenarios ($p < .01$). Even with only 10% of the budget assigned to maintenance advertising, pulsing-with-maintenance scenarios outperformed flighting scenarios in over 60% of cases. The highest sales lift for pulsing-with-maintenance scenarios was obtained by spending about 1/3 of the budget on maintenance advertising. Interestingly, differences among pulsing-with-maintenance scenarios and with the even spending scenario were not statistically significant ($p > .10$).

This overall picture is largely maintained across different settings (i.e., same owner, leader vs follower, follower vs leader, and follower vs follower).[17] For example, flighting and chattering scenarios are always inferior to the pulsing-with-maintenance or

[15] See Feinberg (1992).

[16] To ensure robust insights we removed extreme forecasts using Tukey's (1977) formula: Lower fence = Q1 − 3 ∗ (Q3 − Q1); Upper fence = Q3 + 3 ∗ (Q3 − Q1). For a recent application in Marketing, see Ptok, Jindal, and Reinartz (2018).

[17] One difference is that for Follower vs Leader there is no significant difference between performance for flighting with out-of-sync, rectangular spend (+2.12%) and in-sync, matching spend (+2.36%).

Table 10
Simulation results.

Type of pattern	Overall	Same owner	Leader vs follower	Follower vs leader	Follower vs follower
Even	+9.32%	+8.99%	+12.37%	+8.57%	+8.57%
Pulsing with maintenance					
In-sync, rectangular spend	+9.81%	+9.70%	+12.09%	+8.19%[a]	+9.67%[b]
In-sync, matching spend	+9.53%	+7.69%	+13.45%	+6.78%[a]	+9.18%[a]
Out-of-sync, rectangular spend	+9.63%	+9.28%	+11.80%	+7.81%[a]	+9.53%[b]
Flighting					
In-sync, rectangular spend	+1.16%[c]	+0.60%[c]	+2.10%[c]	+0.45%[c]	+1.09%[c]
In-sync, matching spend	+1.67%[c]	+0.62%[c]	+1.62%[c]	+2.12%[d]	+1.62%[c]
Out-of-sync, rectangular spend	+3.70%	+3.74%	+3.84%	+2.36%	+3.85%
Chattering	+3.21%	+3.02%	+3.54%	+3.12%	+3.12%
Pulsing with maintenance: Average level of maintenance advertising with highest sales results					
In-sync, rectangular spend	36.81%	38.42%	42.32%	37.41%	35.87%
In-sync, matching spend	37.42%	35.94%	45.44%	37.49%	35.92%
Out-of-sync, rectangular spend	36.65%	38.20%	42.40%	37.06%	35.71%

Note: In all interaction types, even and pulsing-with-maintenance strategies result in significantly higher sales effects compared to flighting and chattering strategies ($p < .01$). In all interaction types, none of the even and pulsing-with maintenance strategies result in significantly different sales effects ($p > .10$).
[a] Significantly different from pulsing with maintenance by leader ($p < .01$).
[b] Significantly different from pulsing with maintenance by leader ($p < .05$).
[c] Significantly different from out-of-sync flighting ($p < .01$).
[d] Not significantly different from out-of-sync flighting.

even scenarios. It is interesting to note, however, that market leaders, in line with e.g., the reasoning by Sharp (2010), achieve higher lift from pulsing-with-maintenance compared to followers (e.g., +12.09% vs +8.19%, $p < .01$).

7. Discussion

7.1. Summary of findings

In contrast to the large body of literature devoted to advertising effectiveness, advertising spending patterns and the role of competitor impact in this matter have received relatively little empirical attention. To the best of our knowledge ours is the first large-scale investigation on the influence of competitive factors on both the incidence and magnitude of advertising actions and their sales outcomes.

Our results first of all demonstrate that the vast majority of observed advertising patterns can be categorized as pulsing patterns, as most brands alternate advertising pulses (multi-week campaigns possibly combined with one-week spikes) with extended periods without any or with low maintenance advertising expenditures. The high coefficient of variation in ad spending for the majority of brands further supports this result. Feedback from practitioners showed that most brands lack the resources to engage in continuous advertising. They prefer to concentrate spending during seasonal demand peaks (see also Gijsenberg, 2017). Weak top-of-mind awareness, in turn, requires stronger efforts to create effects among consumers, adding to the peakedness of the patterns.

Observed patterns appear mixed, and seem far from the stylized patterns recommended by normative literature. Interestingly, the prevalence of observed patterns is similar when comparing weekly to monthly time aggregation. Observed patterns, in addition, are mainly driven by TV and print advertising, which should not come as a surprise given that they account for the vast majority of both advertising incidence and spending.

Model-free evidence shows that both advertising incidence and magnitude are positively related to competitors' actions, although the effects are small. Model-based evidence, accounting for intra-year demand factors, internal reasoning, short-term deviations, and other marketing decisions, confirms this positive overall relation between both advertising incidence and magnitude on the one hand, and competitors' actions on the other. While same-owner brands are slightly less likely to advertise at the same time, their competitive spending patterns are no different from other brands. Market leaders, in addition, fiercely defend their position, and show much stronger reactions to followers (both incidence and spending) than vice versa. These reactions are also stronger than those observed between followers.

Overall, we find a small but statistically significant effect of competitive actions in both incidence and magnitude decisions. This confirms the results from Montgomery et al. (2005), who find that current competitive behavior is mentioned by managers only about half as often as internal factors when it comes to advertising decisions.

Same-owner brands in a category appear to enjoy considerable autonomy in advertising scheduling. Observed patterns do not add up to even amounts at the category level, and these brands also show positive reaction coefficients, both regarding incidence and magnitude. This is in line with a "house of brands" strategy in which each brand is tailored to a specific target audience, has a clear and unique positioning, and should consequently develop its own communication and advertising strategy and tactics. They may react somewhat less strongly to each other compared to other brands, possibly as a consequence of "cascading" or hierarchical strategies, in which the strongest brands get preferential treatment in e.g., negotiations with media on timing of their advertising (they choose first), without, however, barring the other brands from advertising at the same time.

Market leaders fiercely and effectively defend their position. As they have much to lose they show strong response to actions by followers. Followers, however, show much weaker response to market leader actions. As such, they may regard leaders as *untouchables* that benefit from strong loyalty and involvement of their many buyers (see e.g., Ehrenberg, 1972; Sharp, 2010), thus rendering their response as futile before even starting it. It is consequently not surprising that these followers focus mainly on their fellow followers when making advertising decisions, and mainly compete among each other for the remaining parts of the market. This result confirms earlier work by Debruyne and Reibstein (2005) who show that brands mainly focus on direct competitors.

Finally, our simulation demonstrates that, out-of-sync flighting strategies generate higher sales returns compared to in-sync flighting. However, performance from flighting strategies is inferior compared to pulsing-with-maintenance and even spending scenarios. As such, these findings confirm the reasoning by Sharp (2010) and practitioners that a continuous presence fosters “mental availability” and brand performance.

7.2. Managerial implications

While advertising has traditionally been regarded as a field where much is decided by gut feeling with little accountability and structure (“half the money I spend on advertising is wasted, however, I do not know which half”), our research provides some clear suggestions to managers about designing more effective advertising spending patterns.

Normative literature on advertising scheduling has mostly focused on “pure” strategies in stylized settings. As a result, recommendations were limited to either even or pulsing strategies, hardly touching upon advertising magnitude, especially in competitive settings. Our simulation, based on a wide range of real-world settings, takes into account spending magnitude and demonstrates the value of maintenance advertising or even spending. Sustained support appears fruitful as it builds and maintains a brand’s “mental availability” among customers and seems to limit sensitivity to the relative timing of own and competitor advertising pulses which do not play a significant role in the sales outcomes.

Brands can even boost performance without spending more as our recommendations are built upon fixed budgets across all scenarios. We show that, while maintenance levels of approximately 1/3 of the total budget generate the highest sales for pulsing-with-maintenance, 10% maintenance spending is already sufficient to outperform pure flighting strategies in the majority of cases.

While our results show that sales outcomes of even spending are not significantly different from pulsing-with-maintenance, brands might still use pulses to counter competitors' actions (Danaher et al., 2008) or to enhance visibility in high demand periods. Quoting Sun Tsu, one senior practitioner stated that one should “*defend the high ground when under attack*”. Our results show that doing so is not counterproductive, but may not lift sales compared to focusing on continuity and top-of-mind awareness. It is interesting to note that the same senior practitioner, quoting Ehrenberg (2000), also stated: “*continuity is a top driver as FMCG products are bought all year round […] looking at penetration as a key driver*”.

Earlier work by Montgomery et al. (2005) showed limited competitive reasoning among practitioners. Interestingly, our results show that this need not be detrimental to brand performance. In fact, firms may experience a triple benefit from focusing less on competitive schedules and more on maintenance spending as this can result in a) greater advertising lift, b) lower sensitivity to competitive advertising, and c) a reduced need for competitive monitoring.

7.3. Conclusion

Our research is one of the first large scale studies to investigate brands' advertising spending patterns and competitor impact. It resulted in a set of intriguing empirical generalizations and managerial recommendations, but also uncovered some avenues for future research. We hope to inspire additional work in some of the following areas.

First, in our main dataset advertising expenditures are aggregated across media. Investigating the extent to which reactions occur in the same or different media as part of Integrated Marketing Communication strategies (e.g., Naik & Raman, 2003) appears a promising path for future work. In addition, such research could also integrate newer online media (e.g., social media advertising).

Second, while our research was limited to national brands, analyzing private-label brand advertising spending patterns is increasingly important given the rise of these brands. While originally focused mainly on low prices, retailers in recent years have developed tiered strategies with economy, standard, and premium private labels (Geyskens, Gielens, & Gijsbrechts, 2010). The latter in turn, have become direct competitors to A-brands and will likely adopt different advertising spending patterns than private labels had in the past.

Third, our work focuses on brand-initiated advertising. However, retailer-initiated advertising is often used to support promotional agendas developed through collaboration by retailers and producers (see e.g., Guyt & Gijsbrechts, 2014). The extent to which retailer-initiated advertising follows similar patterns and experiences similar competitive forces is yet to be determined.

Finally, extending our analysis to service industries and durables appears warranted given the fierce (advertising) competition in, for example, the telecom industry and the longer purchase cycles in, for example, the consumer electronics industry. While longer purchase cycle could have a profound effect on observed advertising patterns, competitive intensity could alter the nature of competitive interplay. Evaluating these speculations could add considerably to our knowledge and understanding of advertising spending patterns and competitor impact.

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Appendix A, B, and C. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijresmar.2018.11.004.

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