university of groningen / faculty of economics and business

2018004-MARK

Advertising Timing: In-Phase or Out-of-Phase with Competitors?

Maarten J. Gijsenberg
Vincent R. Nijs

SOM is the research institute of the Faculty of Economics & Business at the University of Groningen. SOM has six programmes:

- Economics, Econometrics and Finance
- Global Economics & Management
- Innovation & Organization
- Marketing
- Operations Management & Operations Research
- Organizational Behaviour

Research Institute SOM
Faculty of Economics & Business
University of Groningen

Visiting address:
Nettelbosje 2
9747 AE Groningen
The Netherlands

Postal address:
P.O. Box 800
9700 AV Groningen
The Netherlands

T +31 50 363 7068/3815

www.rug.nl/feb/research

university of groningen

faculty of economics and business

Advertising Timing: In-Phase or Out-of-Phase with Competitors?

Maarten J. Gijsenberg
University of Groningen, Faculty of Economics and Business, Department of Marketing
m.j.gijsenberg@rug.nl

Vincent R. Nijs
Rady School of Management, UC San Diego, USA

Advertising Timing: In-Phase or Out-of-Phase with Competitors?

Maarten J. Gijsenberg[a]

Vincent R. Nijs[b]

[a] Department of Marketing, Faculty of Economics and Business, University of Groningen, PO Box 800, 9700 AV Groningen, The Netherlands. Email: M.J.Gijsenberg@rug.nl. ***Corresponding Author.***

[b]Rady School of Management, UC San Diego. Otterson Hall 3W116, 9500 Gilman Drive #0553, La Jolla, CA 92093-0553, USA

Acknowledgments. The authors thank Marnik Dekimpe, Jan-Benedict Steenkamp and AiMark for providing access to the data.

Advertising Timing: In-Phase or Out-of-Phase with Competitors?

Abstract

In many industries, brands systematically switch advertising on and off, a tactic often referred to as pulsing. The appropriate timing of these pulses in a competitive environment is an issue of debate. While some research suggests that advertising out-of-phase with the competition is most effective (e.g., Danaher, Bonfrer, & Dhar, 2008; Villas-Boas, 1993), others argue that timing advertising in-phase with the competition is more profitable (e.g., Freimer & Horsky, 2012; Park & Hahn, 1991). While previous research has extensively studied the performance consequences of advertising spending, much less is known about (1) what drives managers' decisions on when to advertise and (2) if these decisions are in line with normative theory. The primary aim of this study is therefore to determine if, and to what extent, the competitive advertising timing patterns suggested in the normative literature are observable in practice.

In this paper, we investigate the timing of advertising expenditures for 370 CPG brands in 71 product categories over a four-year period. We first establish empirically that pulsing is indeed the dominant form of advertising scheduling. Next, we show that advertising in-phase with competitors is more widespread than out-of-phase. Finally, we show that the extent to which advertising is in-phase depends on brands' relative position with regard to advertising effectiveness, price positioning, and market power in the competitive interaction.

Key-words: Advertising, Pulsing, Timing, Competition

1. INTRODUCTION

Advertising remains one of the most visible and frequently used marketing instruments. In 2014, the world's 25 largest advertisers collectively spent $73.68 billion (Advertising Age, 2016). The largest advertiser was Procter & Gamble, with $10.13 billion. Other heavy spenders in the CPG sector included Unilever ($7.39 billion), L'Oréal ($5.26 billion), and Coca-Cola ($3.28 billion). In the car industry, Toyota Motor Company and General Motors spent $3.19 billion and $2.85 billion each, while Samsung Electronics and Sony Corp. spent $1.91 billion and 2.35 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 reports 17% for its US operations, and for L'Oréal and Estée Lauder, this percentage is no less than 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 from 56 studies in that tradition, and report an average short-run (long-run) elasticity of .12 (.24). Second, a *normative* literature has studied – among other – under what conditions pulsing (as opposed to even spending) is an optimal advertising strategy (see e.g., Feinberg, 1992; Sasieni, 1971; Villas-Boas, 1993).

However, advertising spending patterns as observed in practice have received relatively little empirical attention. Whereas several normative studies (Freimer & Horsky, 2012; Park & Hahn, 1991) provide guidance to brand managers about optimal competitive advertising scheduling – in-phase or out-of-phase –, little is known about how companies actually time their actions. The primary aim of this study is therefore to investigate if, and to what extent, the competitive advertising timing patterns suggested in the normative literature are observable in practice.

To achieve this aim we analyze the timing of advertising expenditures for 370 CPG brands in 71 product categories over a four-year period. First, we investigate the volatility in brands' advertising spending and provide insights on the extent to which pulsing is adopted in practice. Then we develop a measure of in-phase versus out-of-phase behavior to provide model-free evidence on timing decisions in a competitive environment. Finally, we formulate an empirical model to control for seasonality, trends, and brand characteristics to establish robust estimates of competitive in-phase /out-of-phase behavior. By estimating brand-specific effects across a large number of categories we are able to uncover empirical generalizations. It also allows us to study boundary conditions by investigating differences across brands with regard to their in-phase/out-of-phase behavior relative to competitors in advertising timing. Note that our empirical approach is descriptive; we therefore do not impose any particular structure on the competitive process.

The paper is organized as follows: We first discuss pulsing in advertising scheduling, and provide arguments for in-phase and out-of-phase timing of advertising actions. Next, we present the data used in our analyses, provide evidence on the usage of pulsing schemes by brands, and present model-free insights on the extent to which brands advertise in-phase with competitors. We subsequently present model-based insights on the extent of in-phase advertising and discuss across-brand differences. We end with a discussion of the results and implications for scholars and practitioners.

2. ADVERTISING PATTERNS

2.1. Pulsing

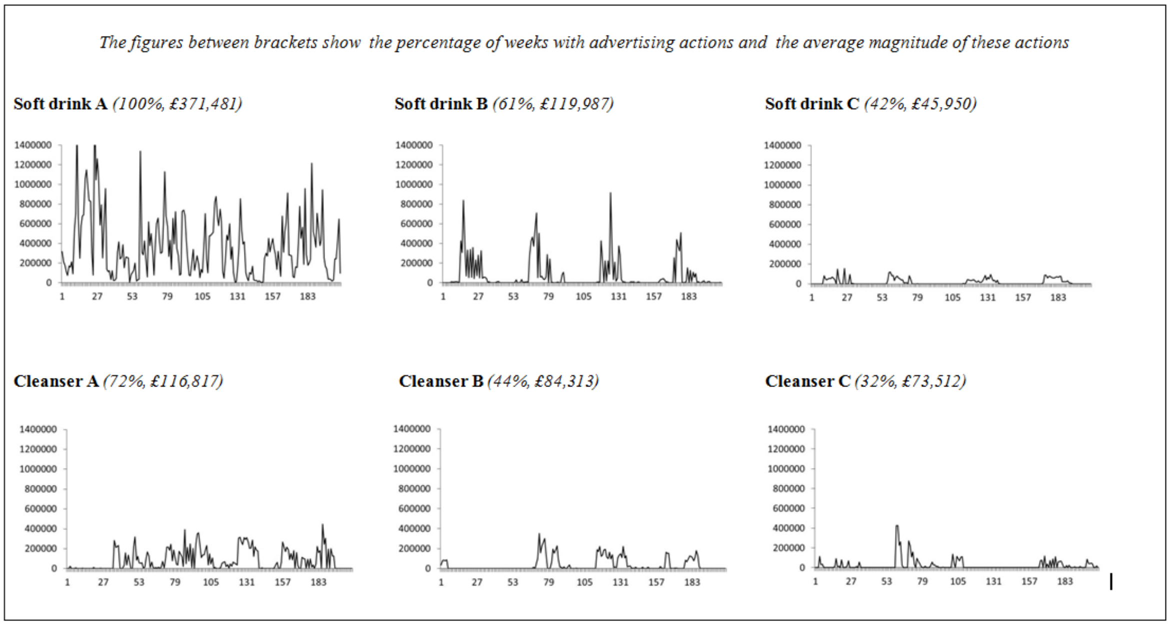
Over the past decades, a wide stream of research has focused on the optimality of different types of advertising scheduling patterns. The following patterns have been suggested:

- Constant/even spending, i.e., advertising at a mostly equal level in each time period
- Pulsing: Switching between periods of high and zero advertising. Note that spending levels my stay at a similar level for multiple period (e.g., an advertising campaign)
- Pulsing with maintenance spending: Switching between periods of high and low advertising.
- Chattering: High-frequency switching between high and zero spending.

Over the years, the preponderance of the prescriptions from normative studies on the optimal timing of advertising has shifted from constant advertising schedules (Sasieni, 1971; 1989; Zielske, 1959) to pulsing advertising schedules (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, Mantrala, and Sawyer (1998) added, respectively, wear-out effects and quality restoration. Park and Hahn (1991), Villas-Boas (1993), Dubé, Hitsch, and Manchanda (2005), and Freimer and Horsky (2012), in turn, expanded the scope of this work to competitive settings. Pulsed advertising (with or without maintenance spending) is now generally considered to be the optimal choice for firms. Pulses that last for several weeks are called campaigns (Doganoglu & Klapper, 2006).

Pulsing has not only been shown to be optimal in most scenarios, there is also anecdotal and some empirical evidence to indicate managers use pulsing in practice (e.g., Dogangoglu & Klapper, 2006; Dubé et al., 2005; Naik et al., 1998). Figure 1 provides an illustration of pulsing, i.e., brands switching advertising on and off, in two different categories in our data.

Figure 1. Weekly Advertising Expenditures for Three Brands
in the UK Soft Drink and Cleanser Markets



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), while brand C is situated at the other end of the spectrum. It advertises 42% of the time and spends only £45,950 per advertising week on average. Brand B takes an intermediate position: it advertises less often than brand A (61% of weeks, mainly in spring and summer), but spends a larger amount during campaigns than C (£119,987 per advertising week on average). The bottom panels of Figure 1 show three brands in the UK cleanser market. Again, we observe considerable variability.

Based on the aforementioned limited empirical evidence on the use of pulsing in practice, together with the fact that normative literature considers pulsing optimal in most instances, we expect that pulsing is the dominant form of advertising in practice.

2.2. In-Phase Versus Out-Of-Phase Advertising Timing

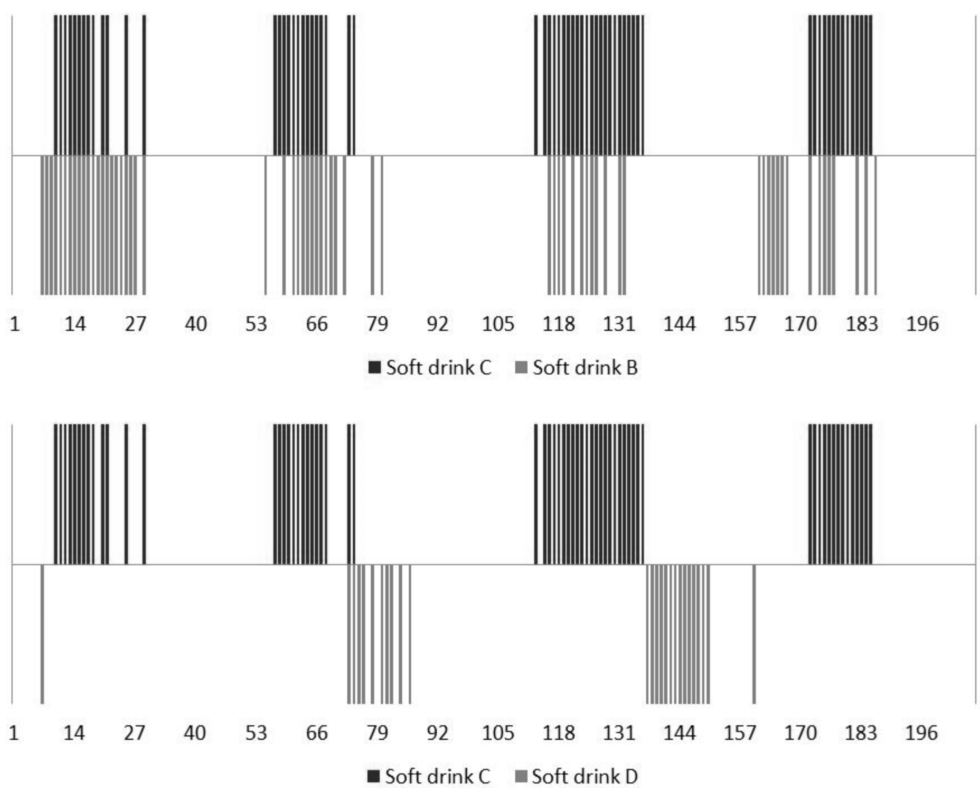
If companies adopt pulsing policies, they still must decide on the timing of their own advertising actions while taking into account the timing of competitors' actions. Previous research has shown that managers indeed consider their competitors' actions in marketing decisions (Montgomery, Moore, & Urbany, 2005). 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 how to adjust their advertising tactics. How competitors should schedule their advertising campaigns relative to one another is, however, less clear.

Advertising out-of-phase 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 (Villas-Boas, 1993). Danaher, Bonfrer, and Dhar (2008) show that the negative effects of competitive interference on sales can be quite strong as a focal brand's advertising elasticity is halved when competitors advertise in the same week (i.e., in-phase).

Freimer and Horsky (2012), in contrast, show that for sales retention levels within the range of values found in previous literature ($.46 < \delta < .73$) it is optimal for brands to advertise in-phase rather than out-of-phase. This could be because it is more difficult for brands to retain their market share when they do not advertise in-phase with competitors (Metwally, 1978). Furthermore, although the findings by Danaher et al. (2008) suggest a brand can achieve sales benefits by advertising out-of-phase, they speculate that some brands advertise in-phase to interfere with and thus “blunt the sword” of competitors’ advertising efforts.

Figure 2 shows how timing choices can differ for brands in the UK soft drinks category. The figure shows the advertising actions of brands B and C from figure 1, and a third brand D with lower-frequency advertising. Whereas the advertising actions of brands B and C appear to be in-phase, brands C and D seem to avoid advertising at the same time (i.e., out-of-phase behavior).

Figure 2. Advertising Timing of Three Brands in the UK Soft Drinks Category



This example shows that, in practice, we can find both in-phase and out-of-phase advertising. Which of both types of behavior dominates in practice remains an empirical question that requires rigorous study. Given opposing arguments from previous literature, we thereby do not formulate a priori hypotheses.

2.3. Impact of Relative Competitive Position

Based on previous research and anecdotal evidence provided above, we expect considerable heterogeneity in the *extent* to which brands advertise in-phase or out-of-phase with their competitors. This heterogeneity is the likely outcome of the relative position of the brands in their competitive interaction, as firms' reactions to competitive actions are largely shaped by their ability and motivation to react, as well as by the visibility of the actions (Chen, 1996; Chen & MacMillan, 1992).

When brands achieve higher *advertising effectiveness*, advertising becomes a potent tool in competitive interactions and may be used to preserve market share against brands that are also able to achieve high levels of advertising effectiveness (see e.g., Metwally, 1978). Reacting with advertising is relatively easy and effective for these brands while at the same time the motivation to react is high, leading to more severe and active reaction behavior (Chen & MacMillan, 1992). Brands with lower advertising effectiveness, in turn, are less likely to use their relatively "blunt swords" to react to effective advertisers, but may still decide to advertise in-phase with other low-effectiveness advertisers to further limit their influence (see e.g., Danaher et al., 2008). While the ability to respond effectively may not be high, the motivation still is. Strong reactions by highly effective brands to other highly effective brands and by low-effectiveness brands to other low effectiveness brands would also be in line with findings by Debruyne and Reibstein (2005) who show that competitive interactions are stronger the more the actors are alike.

The (competitive) use of advertising, however, may also be linked to the *price* positioning of the brand in the category. Premium brands are characterized by high quality, high prices, and a strong brand image (and resulting brand equity) usually built by advertising (see e.g., Keller, 1993). These premium brands cater to the less price-sensitive segments (e.g., Gijsenberg, 2017), and consequently do not compete on price. In their interactions with other premium brands, they are therefore more likely to use non-price forms of competition like advertising. We consequently expect more intense competitive advertising interactions and in-phase behavior among premium brands. Value brands, in turn, cater to the more price-sensitive segments, and are more likely to use their marketing budgets for price-oriented actions rather than advertising in their competitive interactions with other value brands. In-phase advertising behavior is therefore likely less intense among value brands.

Brand strength or *market power*, as expressed by brand size (market share) has been identified as a key characteristic in advertising decisions (e.g. Patti & Blasko, 1981; Lynch & Hooley, 1990). Stronger brands such as market leaders benefit from high brand equity (e.g., Keller, 1993; 2007) and may feel less need to react by advertising in-phase with weaker brands as the former already have an established position in consumers' minds (e.g., Kent & Allen, 1994). This finding is also consistent with Steenkamp et al. (2005) who argue that an aggressive (i.e., in-phase) response to smaller brands is less likely as their actions may be less noticeable (Chen & MacMillan, 1992). Followers, on the other hand may feel a stronger urge to react in-phase to the actions of stronger player's more visible actions (Chen & MacMillan, 1992) and may rely on the leaders' knowledge on how to be successful, including when to advertise.

3. DATA

The empirical analyses presented in this paper are based on a large set of CPG categories in the United Kingdom. The data cover a range of food, beverages, personal care, and household care products and thus provide a good sample of the goods offered in a typical supermarket. An overview of the included product categories, along with the number of included brands is given in Table 1.

Table 1. Overview of Included Product Categories

Product Class	Number of Categories	Example Categories	Example Brands
Food	25	Breakfast cereals Savory snacks Yoghurt	Kellogg's Pringles Danone
Beverages	18	Lager Mineral water Softdrinks	Heineken Evian Coca-Cola
Personal care	18	Cleansers Dentifrice Shampoo	Oil of Olay Colgate L'Oreal
Household care	10	Household cleaners Liquid detergents Machine wash products	Flash Fairy Ariel
Total number	71		370

We obtained four years (2002-2005) of weekly total advertising spending data from NielsenMedia. These expenditures may include 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. This provided us with 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. In contrast to 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 brands. We focus on national brands, as private labels are typically not advertised at the category level (e.g., Lamey et al., 2012).[1]

Information on volume sales and prices come from Kantar Worldpanel UK[2]. Data from this panel have been used in prior research (e.g., Van Heerde et al., 2013). Members of the panel receive a scanning device that they subsequently use to scan, on a daily basis, all the fast-moving consumer goods purchases they take home. 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 more than 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 the weeks, considerable variability exists in their 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 equal to £94,010, with a standard deviation of £79,366.

4. MODEL-FREE INSIGHTS

4.1. Observed Spending Patterns

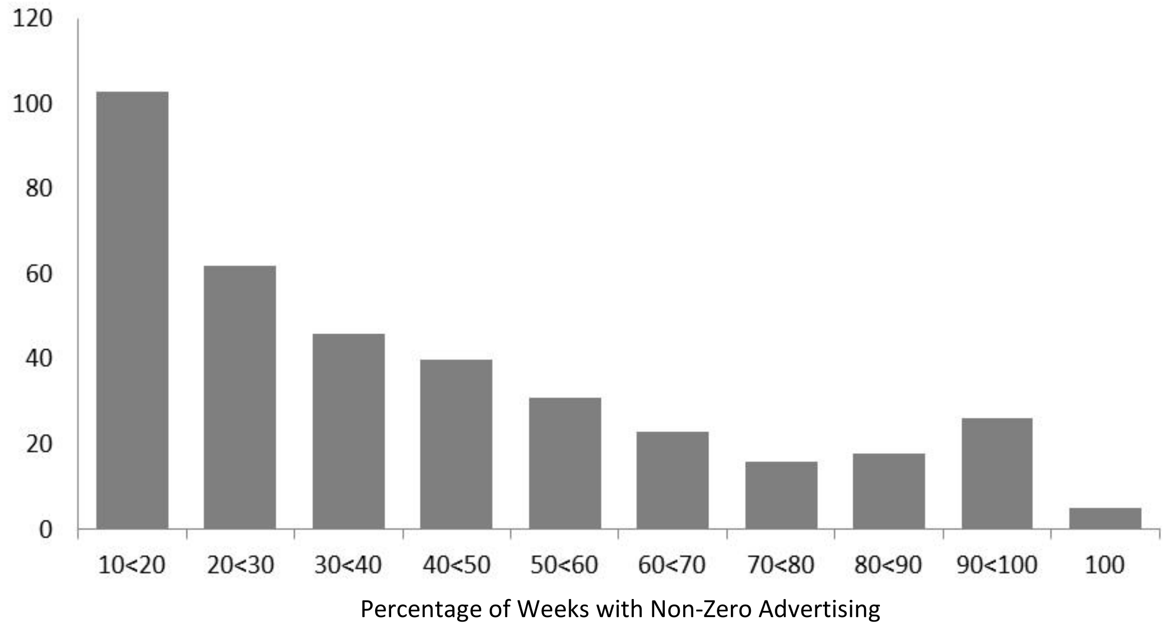
In our data only 5 brands have non-zero advertising levels in each week. Of the brands selected for our analysis (i.e., brands that advertise in more than 10% of weeks) the majority (57%) advertise in fewer than 40% of weeks. Figure 3 provides a histogram of the advertising

[1] Private label brands were considered in the derivation of variables such as concentration level and market share change.

[2] We gratefully thank AiMark for providing access to the data.

frequencies.

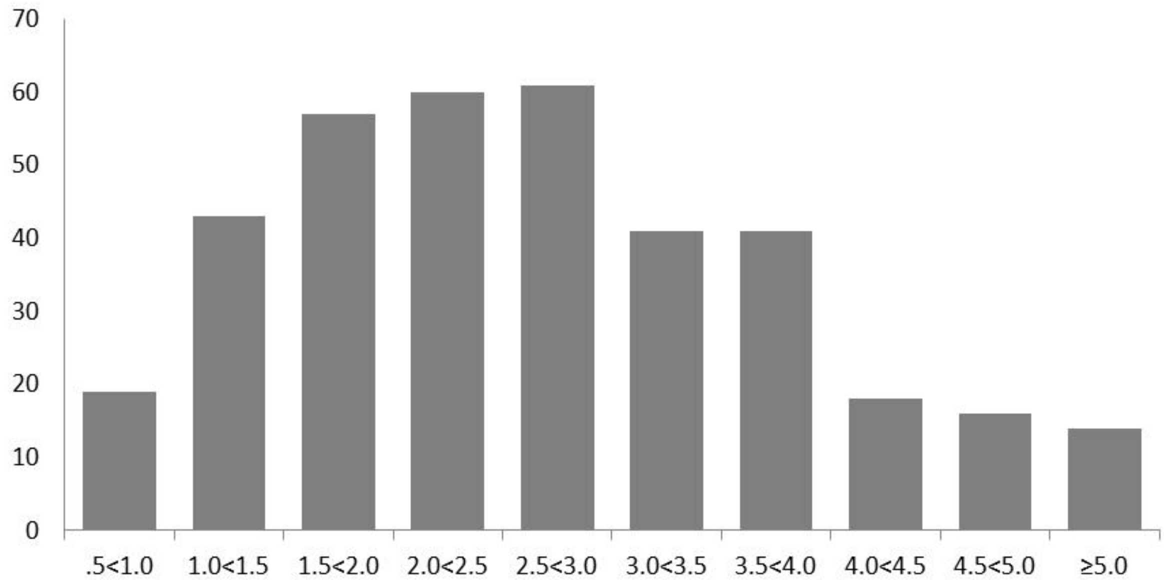
Figure 3. Histogram of Advertising Frequencies



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 Figure 4.

Together, Figures 3 and 4 give 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 constant advertising schedules were used.

Figure 4. Histogram of Number of Brands with Coefficient of Variation
in Advertising Expenditures



A visual inspection of the advertising spending patterns of the included brands allows for a more detailed view on actual advertising patterns. We thereby base ourselves upon previous literature, and distinguish between the following patterns:

- Even spending: Permanent advertising at a mostly equal level.
- Pulsing with maintenance spending: Switching between periods of high and continued low levels of advertising. Pulsing can be categorized as Campaigning (multi-week advertising periods), Spikes (one-week advertising periods), or Mixed.
- Pulsing without maintenance spending: Switching between periods of high and non-continued (low for one or a few weeks, then zero) or zero advertising. Pulsing can again be categorized as Campaigning, Spikes, or Mixed.
- Chattering: High-frequency and regular switching between one-week high advertising and subsequent (one-week or multiple-week) zero advertising.

The distribution across types of spending patterns is presented in Table 2. Even though 5 of the included brands advertise every week, none of them does at an even level (Even: 0%). On the other end of the spectrum, 3.7% of brand engage in chattering-like behavior. Confirming the insights reported above, the vast majority of brands show either pulsing without maintenance spending (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.

Table 2. Distribution across Types of Advertising Patterns

Type of Pattern	**Percentage of Brands**
Even	**.0%**
Pulsing with maintenance	**39.0%**
Campaigning	26.1%
Spikes	3.1%
Mixed	9.8%
Pulsing without maintenance	**57.3%**
Campaigning	29.5%
Spikes	7.9%
Mixed	19.9%
Chattering-like	**3.7%**

Table 2 indicates that many brands in our data alternate between periods of high and periods of continued (maintenance) or non-continued (hence: not maintenance) low (but not zero) advertising (e.g., Brand B in the soft drinks market in Figure 1). Dube et al. (2005) show similar patterns in their data and suggest that the non-continued lower advertising levels may be attributable to “make good” weeks where the ad publisher was unable to achieve previous GRP targets. Since weeks with low levels of advertising outside of defined campaigns are of less interest in understanding competitive interactions between brands, we adapt the regular-vs-promotion-price algorithm proposed by Van Heerde (1999) to identify advertising campaigns. In each week *t*, we identify two conditions:

1. If a brand is not in a campaign in week *t*: $Pulse_{b,t} = 0$

   If $Adv_{b,t+1} > (1+\alpha) * \overline{Adv}_{b,t+1}$ and $Adv_{b,t+1} > \delta * \overline{\overline{Adv}}_{b}$, then $Pulse_{b,t+1} = 1$ else $Pulse_{b,t+1} = 0$.

2. If a brand is in a campaign in week *t*: $Pulse_{b,t} = 1$

   If $Adv_{b,t+1} \leq (1-\alpha) * \overline{Adv}_{b,t+1}$, then $Pulse_{b,t+1} = 0$ else $Pulse_{b,t+1} = 1$.

where $\overline{Adv}_{b,t+1}$ equals the average advertising spending in the previous 26 weeks (from *t*-25 to t) by brand b and α represents the threshold factor which is set to .1. $\overline{\overline{Adv}}_{b}$ equals the average advertising spending over the whole four-year period by brand b, and δ represents a second threshold factor which is set to .5.[3] Subsequent results are robust to the choice of the threshold levels.

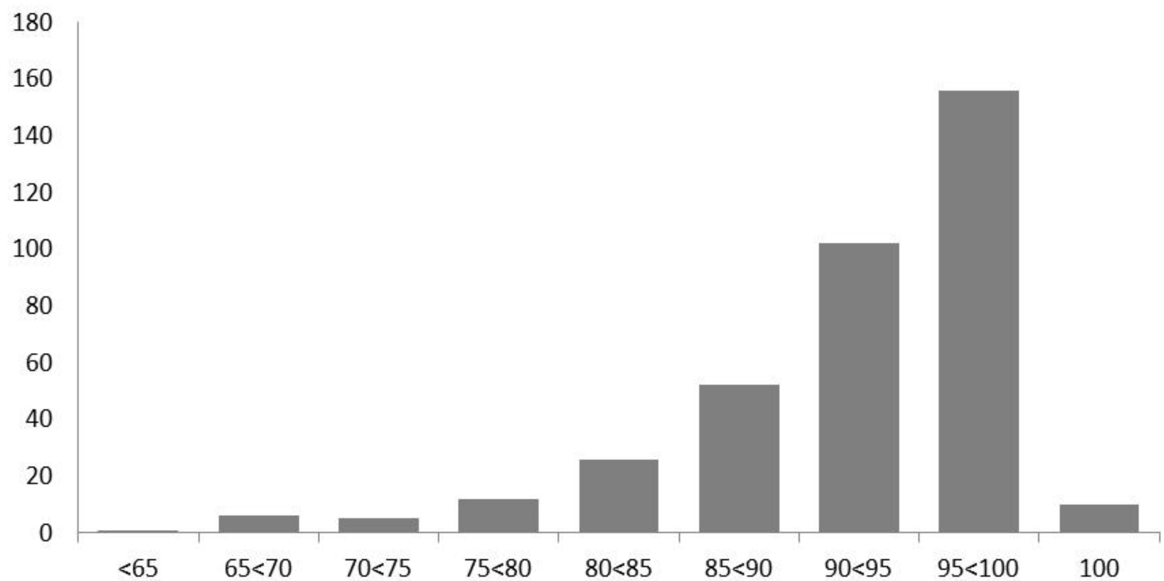
In order for a brand to be considered entering a campaign, its advertising spending in a specific week should be at least 10% higher than the average over the previous half year; in order for the brand to be considered leaving a campaign, its advertising spending in a specific week should be at least 10% lower that the average over the previous half year. To prevent minor changes (in absolute terms) during extended periods of low-spend advertising from being classified as campaigns, we introduce the additional requirement that, to be classified as a campaign, an advertising action should also exceed a certain minimum absolute threshold. This threshold is specified as δ times the overall average advertising action by that brand.

Figure 5 shows the relationship between brand advertising and the proportion of

[3] Reported values are based on a grid search.

expenditures that is classified as a campaign by the algorithm described above. Overall, 92% of expenditures are considered campaign behavior. In section 5.2 we discuss the robustness of our main results to alternative specifications of the algorithm.

Figure 5. Histogram of Number of Brands with the Percentage of Advertising Expenditures that are Part of a Campaign



4.2. In-Phase Versus Out-Of-Phase Advertising Timing

To obtain initial insights on in-phase versus out-of-phase behavior of individual brands' advertising, we calculate a model-free measure of advertising overlap. We start with the naïve random model described by Morrison (1969). If brands A and B advertise independently, the expected % of weeks with advertising by both brands is $p_{AB}^{exp} = p_A * p_B$, where brand A advertises p_A % of weeks and brand B advertises p_B% of weeks. We compare the expected percentage of overlapping weeks to the observed percentage of overlapping weeks where the observed % of weeks with advertising by both brand A and B is p_{AB}^{obs}, and $Phase_{AB} =$

$p_{AB}^{obs}/p_{AB}^{exp}$.

When the phase measure equals 1, the observed number of weeks with advertising by both brand A and B equals the expected number based on an independence model and no apparent systematic competitive behavior is present. When the phase measure tends towards 0, fewer weeks with advertising by both brands are observed than expected, and competitive advertising behavior seems to be out-of-phase. As the phase measure exceeds 1, the number of weeks with advertising by both brands exceeds what would be expected if advertising was independent, suggesting competitors may be advertising in-phase.[4]

Figure 6. Distribution of Phase Statistic

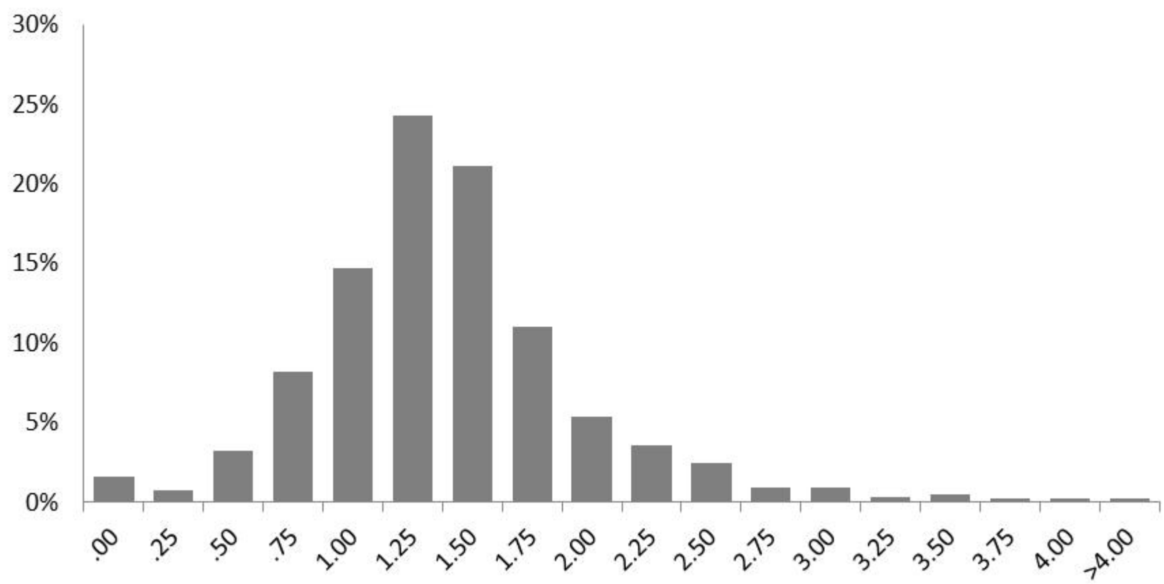


Figure 6 shows the distribution of the model-free phase measures. The graph shows the strong heterogeneity among brands with regard to in-phase versus out-of-phase timing of their advertising actions. In the vast majority of the cases (71.4%), the measure exceeds 1, suggesting

---

[4] The upper limit is not fixed to a specific absolute value, but is determined by the percentage of weeks brands A and B are advertising. The theoretical absolute upper limit is reached when two brands A and B each advertise only once, but in exactly the same week. As we require brands to advertise at least 10% of the time, the theoretical upper limit is .10/(.10*.10) = 1/.10 = 10.

in-phase advertising behavior. In the remaining cases (28.6%), the measure is less than 1 indicating out-of-phase behavior, with 1.6% of the cases showing no overlap in advertising actions (i.e., the phase measure is equal to 0). The resulting average value of 1.280 (standard deviation = .583) suggests a tendency to schedule advertising in-phase with competitors.[5]

5. MODEL-BASED INSIGHTS

5.1. Methodology

5.1.1. Empirical model

The phase measure presented above provides initial insights on the extent of advertising overlap between competitors. However, this overlap, i.e., in-phase behavior, may be due to factors that are not linked to competitive considerations in advertising decisions. To obtain better estimates of competitive interactions, we analyze the advertising interactions of brands dyads within the same category (see e.g., Steenkamp et al., 2005). In our analyses, we allow for asymmetries in the relationships (e.g., brand A always advertising in-phase with brand B, but brand B not always advertising in-phase with brand A) by including each brand twice in the dyad: once as focal brand, and once as competitor.

We use a binary logit model and include a set of factors to explain advertising-timing decisions. An advertising decision by brand *b* in dyad d during week *t* is described as:

$$(1) \qquad Pulse_{db,t} = \begin{cases} 1 & if\ Pulse^*_{db,t} > 0 \\ 0 & if\ Pulse^*_{db,t} \leq 0 \end{cases}$$

The latent variable $Pulse^*_{dbt}$ is modeled as follows:

[5] For the three soft drink brands presented in figure 2, the measure equals 2.072 for brands B and C, and .249 for brands C and D, confirming the observed in-phase and out-of-phase behavior, respectively.

$$Pulse^{*}_{db,t} = \beta_{0,db} + \beta_{1,db}Holiday_t + \sum_{i=1}^{12} \beta_{2,i,db}Period_{i,t} + \beta_{3,db}Trend_t$$

$$+\beta_{4,db}CompPulse_{db,t} + \beta_{5,db}CompAdPressure_{dbt,}$$

$$+\beta_{6,db}[TSPP \leq TSPP^{prev}]_{b,t} + \beta_{7,db}[TSPP > TSPP^{prev}]_{b,t} \tag{2}$$

$$+\beta_{8,db}[TIP \leq TIP^{prev}]_{b,t} + \beta_{9,db}[TIP > TIP^{prev}]_{b,t}$$

$$+\beta_{10,db}\Delta MarketShare_{b,t-1} + \varepsilon_{db,t}$$

Intra-year factors are perhaps the most obvious alternate 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 drink brands mainly advertising in spring and summer (brands B and C in Figure 1). Therefore, we start with a set of time control variables, capturing *holiday* and *seasonality* effects as well as possible *trending* behavior in advertising decisions. Our baseline model (Model 1) contains only these control variables. We add competitive factors *CompPulse and CompAdPressure* in Model 2. The former is a dummy variable that is equal to 1 if the competing brand in the dyad advertises, 0 otherwise. As such, this variable is the focal variable of interest when investigating the in-phase versus out-of-phase scheduling of the advertising actions of the focal brand with regard to the competitor in the dyad. The second competitive factor is a continuous variable representing the total advertising spending by all other brands in the category that are not included in the dyad, representing the remaining competitive advertising pressure we need to control for.

In Model 3, we add the *Time Since Previous Pulse (TSPP),* defined as the number of weeks since the previous advertising pulse. We allow for different effects if the elapsed time since the previous pulse is smaller or larger than the previous interval between two pulses to allow the model to flexibly capture a build-up and decline in pressure to advertise similar to the

Adstock concept (e.g., Broadbent, 1979; 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. *Previous Time In Pulse (TIP^{prev})* is defined in a similar manner as the length of previous advertising pulse. We allow for different effects if the elapsed time since the start of the pulse is smaller or larger than the previous observed duration. The first variable *($TIP \leq TIP^{prev}$)* is defined as the elapsed time in the new campaign relative to the previous campaign 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 campaign is longer than the previous one and takes a value of zero before. After the campaign has ended, values remain constant, and a new counting cycle starts when a new campaign has started.

Finally, in the Full model we account for short-term deviations in performance that may drive advertising behavior. Δ*MarketShare* is the first difference of the log-transformed brand volume sales over a moving window of previous 26 weeks (cfr. Franses & Koop, 1998).

5.1.2. Model estimation

To obtain an accurate view of in-phase and out-of-phase behavior in advertising actions, we estimate brand competition in pairs (see e.g. Steenkamp et al., 2005), in which we investigate the effect of competitive advertising actions by one specific competitor through the *CompPulse* variable. The parameter estimate for this variable indicates the direction and relative impact of a competitor's actions on the advertising decisions of the focal brand, and hence the extent of in-phase versus out-of-phase behavior.

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, 2014; 2017; van Heerde et al., 2013). The reported parameter values are the across-dyad uncertainty-weighted parameter estimates.

5.1.3. Categorizing brands and exploring heterogeneity in competitive interactions

As we argued above, heterogeneity may exist in the extent to which brands advertise in-phase with competitors, depending on their own and their competitor's relative position in the competitive interaction. We therefore investigate the impact of the focal brands' advertising effectiveness (high or low advertising elasticity[6]), price positioning (premium or value) and market power (market leader or follower) relative to their competitor in the interaction on the extent to which the focal brand advertises in-phase with the competitor.

For advertising effectiveness (*price positioning*) we apply a median split per category. Within each category, brands can be categorized as low-effective (*value*) on these dimensions if their value is below the median value and high-effective (*premium*) otherwise. This, in turn,

[6] The advertising elasticities are estimated using a brand level partial adjustment model that accounts for own and competitors' advertising and pricing. The model is described in more detail in Appendix A.

yields four types of competitive interactions: (1) high-effective versus high-effective (*premium versus premium*), (2) high-effective versus low-effective (*premium versus value*), (3) low-effective versus high-effective *(value versus premium*), and (4) low-effective versus low-effective (*value versus value*). For market power, we look within each category at the average market share over the whole four-year period. The brand with the highest average share is considered the market leader, while the other brands in the category are considered followers. This then yields three types of competitive interaction: (1) leader versus follower, (2) follower versus leader, and (3) follower versus follower. Using the same methodology as presented in the previous section, we compare the uncertainty-weighted parameter estimates for the different types of interactions for each of the three factors.

5.2. Substantive Insights

5.2.1. Estimation results

Table 3 shows the estimation results for the four alternative model specifications. For each of the models we show the median (1) pseudo-R^2, (2) BIC values, (3) hit rates, and (4) pulse (one-observation) hit rates, as well as the across-dyad uncertainty-weighted parameter estimates and significance levels based on the added Z-method (e.g., Gijsenberg, 2014; 2017; Van Heerde et al., 2013). For the full model we also show the added Z-scores in Table 3.

Table 3. Overall Across-Brand Parameter Estimates

		Expected sign	Model 1 Weighted beta		Model 2 Weighted beta		Model 3 Weighted beta		Full Model 4 Weighted beta		Full Model 4 Z score
Intercept	$\bar{\beta}_0$	$\neq 0$	*-1.372*	***	*-3.420*	***	*-2.538*	***	-2.676	***	-10.811
Holiday	$\bar{\beta}_1$	$\neq 0$	*.118*	***	*.095*	***	*-.034*		-.076	**	-2.335
Period1	$\bar{\beta}_{2,1}$	$\neq 0$	*.502*	***	*.421*	***	*-.113*		-.094		-.398
Period2	$\bar{\beta}_{2,2}$	$\neq 0$	*.683*	***	*.494*	***	*.637*	***	.620	***	4.365
Period3	$\bar{\beta}_{2,3}$	$\neq 0$	*.391*	***	*.205*	***	*.400*	***	.360	***	2.747
Period4	$\bar{\beta}_{2,4}$	$\neq 0$	*.347*	***	*.114*	**	*-.055*		-.049		-.375
Period5	$\bar{\beta}_{2,5}$	$\neq 0$	*.588*	***	*.349*	***	*.740*	***	.745	***	6.072
Period6	$\bar{\beta}_{2,6}$	$\neq 0$	*.526*	***	*.343*	***	*.576*	***	.503	***	4.185
Period7	$\bar{\beta}_{2,7}$	$\neq 0$	*.426*	***	*.228*	***	*.345*	***	.330	***	2.679
Period8	$\bar{\beta}_{2,8}$	$\neq 0$	*.374*	***	*.191*	***	*.346*	***	.419	***	3.198
Period9	$\bar{\beta}_{2,9}$	$\neq 0$	*.319*	***	*.113*	**	*.240*	**	.104		.792
Period10	$\bar{\beta}_{2,10}$	$\neq 0$	*.187*	***	*.030*		*.047*		.000		.106
Period11	$\bar{\beta}_{2,11}$	$\neq 0$	*.455*	***	*.278*	***	*.125*		.107		.755
Period12	$\bar{\beta}_{2,12}$	$\neq 0$	*.437*	***	*.233*	***	*.058*		.078		.909
Trend	$\bar{\beta}_3$	$\neq 0$	*.074*	***	*.073*	***	*-.125*		-.108		-.507
CompPulse	$\bar{\beta}_4$	> 0			*.182*	***	*.141*	***	.139	***	4.574
CompAdPressure	$\bar{\beta}_5$	> 0			*.207*	***	*.197*	***	.215	***	25.362
$TSPP \leq TSPP^{exp}$	$\bar{\beta}_6$	> 0					*1.755*	***	1.814	***	34.070
$TSPP > TSPP^{exp}$	$\bar{\beta}_7$	$\neq 0$					*.044*	***	.038	***	7.546
$TIP \leq TIP^{exp}$	$\bar{\beta}_8$	< 0					*-4.138*	***	-4.236	***	-81.404
$TIP > TIP^{exp}$	$\bar{\beta}_9$	$\neq 0$					*.024*	***	.016	*	1.689
ΔMarketShare	$\bar{\beta}_{10}$	$\neq 0$							3.254	***	9.005
25th pctile Pseudo R^2			.172		.230		.506		.519		
Median Pseudo R^2			.264		.312		.656		.671		
75th pctile Pseudo R^2			.360		.427		.831		.863		
Median BIC			1.232		1.228		1.041		1.064		
Median Hit Rate			.821		.840		.929		.936		
Median Hit Rate Pulses (Ones)			.381		.481		.828		.840		
% In-Phase					53.8%		52.2%		51.8%		
% Out-of-Phase					46.2%		47.8%		48.2%		
% In-Phase sig					16.9%		11.9%		11.7%		
% Out-of-Phase sig					8.4%		8.1%		8.0%		
% not sig					74.7%		80.0%		80.4%		

* $p < .10$; ** $p < .05$; *** $p < .01$. Tests are one-sided if clear directional effects are expected ,two-sided if not (Rosenthal, 1991). Deviations from 100% are due to rounding.

To evaluate the robustness of our findings with regard to the choices of threshold values in the campaign-identifying algorithm, we estimated four rival models with different threshold values. The first rival model sets $\alpha = .05$ (vs .10); the second rival model uses a moving average of 13 weeks instead of 26; the third rival model uses a δ of .25 (vs .50); and the final rival model uses a δ of 1.00 (vs .50). Differences in parameters across models for our focal variables are small and significance levels are stable, establishing robustness of our findings. Detailed results are included in Appendix B.

5.2.2. Drivers of advertising timing decisions.

The estimates for Model 4 show that brands' advertising timing decisions are affected by competitors' actions, with both *CompPulse* ($\bar{\beta}_4 = .139$, $p < .01$) and *CompAdPressure* ($\bar{\beta}_5 = .215$, $p < .01$) showing a significant positive effect. Moreover, the positive effect of *CompPulse* – an advertising action by the competitor brand having a positive effect on the odds of an advertising action by the focal brand – confirms our earlier model-free findings that brands are more likely to advertise in-phase with each other, in line with the findings of Freimer and Horsky (2012).

Estimates from Model 4 also show that, in addition to competitive pressures, internal dynamics play an important role in brands' timing decisions. The longer the time since the previous campaign the stronger the pressure to start a new one as shown by the significant positive effect of $TSPP \leq TSPP^{prev}$ ($\bar{\beta}_6 = 1.814$, $p < .01$). However, once beyond the previous interval ($TSPP > TSPP^{prev}$) the pressure growth levels off ($\bar{\beta}_7 = .038$, $p < .01$), indicating a tendency to schedule campaigns at regular intervals. Similarly, the longer a brand is in a campaign the stronger the pressure to stop as shown by the significant negative effect of $TIP \leq TIP^{prev}$ ($\bar{\beta}_8 = -4.236$, $p < .01$). Campaigns seem not only to be scheduled at regular intervals but also to have similar durations. Once beyond the previous duration ($TIP > TIP^{exp}$), however, the pressure to stop the campaign diminishes ($\bar{\beta}_9 = .016$, $p < .10$).

Even though both competitive and internal factors seem to drive advertising pulsing decisions, short-term factors also have a significant impact. Changes in market share have a positive effect on the decision to advertise ($\bar{\beta}_{10}$ = 3.254, *p* < .01). It appears that in our data, advertising is not used to make up for weakening positions in the market, but instead is used to reinforce strengthening performance. This pattern is consistent with a percentage-of-sales decision rule to set advertising budgets (Miller & Pazgal, 2007).

5.2.3. Relative impact of different drivers.

The gradual build-up of our models helps to illustrate the relative importance and explanatory power of the different types of factors. Adding competitive factors to model 1 increases the median pseudo R^2 by .048 and increases the correct prediction of pulses by .100. However, internal factors appear to play a more important role in brands' advertising pulsing decisions as the median pseudo R^2 increases by .344 and the correct prediction of pulses goes up by .347 from model 2 to model 3. These differences in relative impact are in line with the findings by Montgomery et al. (2005) who show that current competitive behavior is mentioned as a driver of advertising decisions only about half as often as internal factors. Finally, short-term factors also add to the explanatory power of the model, albeit modestly. The median pseudo R^2 increases by .015 and the correct prediction of pulses increases by .012 from model 3 to the full model. Most importantly, alternative model specifications have little impact on the size and significance of the competitive influence variables. Controlling for seasonal, internal, and short-term factors, competitive considerations play a consistent role in the timing of advertising decisions, with 19.6% *(12.8%)* of dyads showing evidence of significant in-phase or out-of-phase behavior at the .10 *(.05)* level.

5.3. In-Phase Versus Out-of-Phase Scheduling and Relative Competitive Position

As shown in Table 3, in-phase competitive advertising timing is more common for brands than out-of-phase scheduling. However, we also find considerable heterogeneity in the *extent* to which brands advertise in-phase with competitors, depending on their own and their competitor's relative position in the competitive interaction. In our full model we find significant evidence in-phase behavior, i.e., positive coefficient for *CompPulse*, in 11.7% of cases and significant out-of-phase behavior, i.e., negative coefficient for *CompPulse*, in 8.7% of cases. Table 4 presents the phase coefficient for different types of competitive interactions, taking into account the relative position of the focal brands in the interaction.

Table 4. Weighted Phase Coefficients for Different Types of Competitive Interactions

Interaction Type	Weighted Phase Coefficient
Advertising effectiveness	
High vs High	.200***
High vs Low	.068
Low vs High	.056
Low vs Low	.291***
Price positioning	
Premium vs Premium	.228***
Premium vs Value	.156***
Value vs Premium	.164***
Value vs Value	-.059
Market power	
Leader vs Follower	.109*
Follower vs Leader	.200**
Follower vs Follower	.136***

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

Advertising effectiveness. Brands with low advertising elasticities show the strongest in-phase advertising behavior in their interactions with other low-effectiveness brands (Low vs Low $\bar{\beta}_{4LoLoEff}$= .291, p < .01). Brands with high advertising elasticities, in turn, use advertising as an effective tool to compete with other brands that also show a high advertising effectiveness (High vs High $\bar{\beta}_{4HiHiEff}$= .200, p < .01) and are thus more likely to advertise in phase. Surprisingly, brands with low advertising effectiveness do not seek to advertise out-of-phase with more effective competitors (Low vs High $\bar{\beta}_{4LoHiEff}$: p > .10), while the latter are seemingly indifferent to what the low-effectiveness advertisers decide (High vs Low $\bar{\beta}_{4HiLoEff}$: p > .10).

Price positioning. Premium brands show strong in-phase advertising behavior with other premium brands (Premium vs Premium $\bar{\beta}_{4PrPrPrice}$= .228, p < .01). Premium brands are more likely to use non-price forms of competition like advertising in order to maintain both their price image and their margins. Value brands, in turn, cater to the more price-sensitive segments, and are more likely to use their marketing budgets for price-oriented actions rather than advertising in their competitive interactions with other value brands (Value vs Value $\bar{\beta}_{4VaVaPrice}$: p > .10).

Market power. Market leaders show only a weak tendency to advertise in-phase with followers (Leader vs Follower $\bar{\beta}_{4LeFoBS}$= .109, p < .10), Followers, on the other hand, more actively react to the advertising actions by the leader, and show a stronger tendency to advertise in-phase with the latter (Follower vs Leader $\bar{\beta}_{4FoLeBS}$= .200, p < .05).

6. DISCUSSION

6.1. Summary

In contrast to the large body of literature devoted to advertising effectiveness, the competitive timing of advertising actions has 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 the timing of advertising actions. Insights are based on a unique dataset covering four years of weekly data for 370 brands in 71 CPG categories. In contrast to many previous advertising studies we utilize data for both large and small brands.

Our results first of all demonstrate that the vast majority of observed advertising patterns can be categorized as pulsing patterns, as most brands alternate multi-week advertising pulses (i.e., campaigns, combined or not with one-week spikes) with extended periods without any or just low maintenance advertising expenditures. The high coefficient of variation in ad spending for the majority of brands further supports this result.

We provide model-free evidence of managers' tendency to advertise in-phase with their competitors. Model-based results that account for the effects of competitive and internal factors, short-term deviations in performance, and time-related factors such as seasonality, are in line with the model-free findings and confirm that in-phase scheduling is more common than out-of-phase scheduling (see Freimer and Horsky [2012] for a discussion on the theory underlying in-phase advertising).

Furthermore, we find considerable heterogeneity in the extent to which brands' advertising schedules are influenced by their competitors' actions, be it in-phase or out-of-phase, and this depending on the relative position of the focal brand versus the competitor in their competitive interaction. Brands which are very effective in their advertising advertise more in-phase with other brands that are very effective, while low-effective advertisers advertise more in-phase with other low-effective advertisers. High-price premium brands compete among each other with advertising, leading to more in-phase advertising, while low-price value brands are more likely to use price-based competitive actions in their interactions with other value brands.

Finally, market followers show a strong tendency to follow the market leader in its advertising decisions, leading to stronger in-phase advertising scheduling.

6.2. Conclusion

The extent to which our empirical findings are in line with the normative literature is encouraging. While advertising has traditionally been regarded as a field where much is decided by gut-feel with little accountability and structure ("half the money I spend on advertising is wasted, however, I do not know which half") we find evidence that advertising timing decisions are, at least partially, predictable.

Notwithstanding the fact that observed patterns appear in line with guidelines from normative research, the influence of competitive factors on managers' decisions is still limited. Our analyses show that the explanatory power of internal factors (i.e., Time Since Previous Pulse and Time In Pulse) on advertising timing decisions is nearly seven times larger than the explanatory power of competitive factors. This result is in line with findings by both Steenkamp et al. (2005), who find limited evidence of competitive reactions, and 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.

The limited attention given to competitive timing is even more surprising if we consider that the effectiveness of marketing investments can be influenced by the competitors' actions. Danaher et al. (2008), for instance, show how the impact of advertising on sales can be strongly affected by the competitive timing of advertising campaigns. Their work confirms Chen's (1996) influential inference that *"the ultimate effectiveness of an action depends largely on the defenders' response*". Our findings consequently call for more empirical research to uncover the profitability implications of advertising timing decisions. Although no insights on this issue exist as yet, related work by Nijs et al. (2007) shows that inertia in pricing decisions is associated with lower retail margins. This result suggests that reliance on internal factors for advertising timing decisions (e.g., inertia) could negatively affect financial performance. If regularity in advertising timing is very high it is straightforward for competitors to anticipate these actions. For example, if Tide consistently advertises every other week competitors can time their advertising campaigns (either in- or out-of-phase) to their own advantage. These authors also show that margins are higher when pricing decisions are (partially) guided by changes in demand (i.e., demand-based pricing). If this insight extends beyond pricing it suggests that adjusting advertising schedules based on changes in market shares could bolster performance.

The scope of our dataset, including brands from a wide range of different CPG categories, allowed us to study the heterogeneity in advertising behavior among brands and the role of the relative brand position in competitive interactions. In contrast to most empirical studies, we do not impose a minimum size for brands to be included in our analysis, adding to the external validity and generalizability of our findings. By studying boundary conditions, we are able to provide in-depth insights on when in-phase advertising is more likely to occur. Our study shows that the extent of “in-phaseness” of advertising depends on the relative position of the brands in the competitive interaction. Our findings on the impact of brands’ relative position with regard to advertising effectiveness, price positioning and market power on the extent to which they advertise in-phase with their competitors are in line with expectations derived from previous normative and empirical research. These results may also have implications for the assumptions used in analytical models. Not imposing a size threshold but including both large and small brands, allowed us to establish that market (share) leaders also lead in advertising decisions, whereas market followers also follow in these decisions. At the same time, premium brands react stronger to premium brands, while interactions with value brands are much weaker. These insights suggests that theoretical models should consider additional brand level differences such as quality, pricing, etc. that influence market shares.

Previous research has extensively studied the performance consequences of advertising spending. Much less is known about (1) how managers decide when to advertise and (2) to what extent decisions are in line with normative models and guidelines. Using data for 370 brands in 71 CPG categories we provide new empirical insights in this important area. We hope our research inspires additional work on advertising decision making in competitive settings.

REFERENCES

Advertising Age (2016), *Marketing Fact Pack. 2016 edition*.

Aravindakshan, Ashwin and Prasad A. Naik (2011), "How Does Awareness Evolve When Advertising Stops? The Role of Memory," *Marketing Letters*, 22 (3), 315-26.

——— and ——— (2015), "Understanding the Memory Effects in Pulsing Advertising," *Operations Research*, 63 (1), 35-47.

Broadbent, Simon S. (1979), "One Way TV Advertisements Work", *Journal of the Market Research Society*, 21, 139-66.

——— (1984), "Modeling with Adstock", *Journal of the Market Research Society*, 26 (4), 295-312.

Chen, Ming-Jer (1996), "Competitor Analysis and Interfirm Rivalry: Toward a Theoretical Integration," *Academy of Management Review*, 21 (1), 100-34.

——— and Ian C. MacMillan (1992), "Nonresponse and Delayed Response to Competitive Moves: The Roles of Competitor Dependence and Action Irreversibility," *Academy of Management Journal*, 35 (3), 539-70.

Chevalier, Judith A., Anil K. Kashyap, and Peter Rossi (2003), "Why Don't Prices Rise During Periods of Peak Demand? Evidence from Scanner Data," *American Economic Review*, 93 (1), 15-37.

Danaher, Peter J., André Bonfrer, and Sanjay Dhar (2008), "The Effect of Competitive Advertising Interference on Sales for Packaged Goods," *Journal of Marketing Research*, 45 (April), 211-25.

Debruyne, Marion, and David J. Reibstein (2005), "Competitor See, Competitor Do: Incumbent Entry in New Market Niches," *Marketing Science*, 24 (1), 55-66.

Doganoglu, Toker and Daniel Klapper (2006), "Goodwill and Dynamic Advertising Strategies," *Quantitative Marketing and Economics*, 4 (1), 5-29.

Dubé, Jean-Paul, Günther J. Hitsch, and Puneet Manchanda (2005), "An Empirical Model of Advertising Dynamics," *Quantitative Marketing and Economics*, 3 (2), 107-44.

Feinberg, Fred M. (1992), "Pulsing Policies for Aggregate Advertising Models", *Marketing Science*, 11 (3), 221-34.

Franses, Philip H. and Gary Koop (1998), "On the Sensitivity of Unit Root Inference to Nonlinear Data Transformations," *Economics Letters*, 59 (1), 7-15.

Freimer, Marshall and Dan Horsky (2012), "Periodic Advertising Pulsing in a Competitive Market," *Marketing Science*, 31 (4), 637-48.

Gatignon, Hubert, Barton Weitz, and Pradeep Bansal (1990), "Brand Introduction Strategies and Competitive Environments," *Journal of Marketing Research*, 27 (November), 390-401.

Gijsenberg, Maarten J. (2014), "Going for Gold. Investigating the (Non)Sense of Increased Advertising around Major Sports Events," *International Journal of Research in Marketing*, 33 (1), 2-15.

Gijsenberg, Maarten J. (2017), "Riding the Waves. Revealing the Impact of Intra-Year Category Demand Cycles on Advertising and Pricing Effectiveness," *Journal of Marketing Research*, forthcoming.

Katz, William A. (1980), "A Sliding Schedule of Advertising Weight," *Journal of Advertising Research*, 20 (4), 39-44.

Keller, Kevin L. (1993), "Conceptualizing, Measuring and Managing Customer-Based Brand Equity," *Journal of Marketing*, 57 (1), 1-22.

——— (2007), "Advertising and Brand Equity," in *The SAGE Handbook of Advertising*, Gerard

J. Tellis and Tim Ambler, eds. Thousand Oaks: Sage Publications ltd.

Kent, Robert J. and Chris T. Allen (1994), "Competitive Interference Effects in Consumer Memory for Advertising: The Role of Brand Familiarity," *Journal of Marketing*, 58 (3), 97-106.

Little, John D.C. and Leonard M. Lodish (1969), "A Media Planning Calculus," *Operations Research*, 17 (1), 1-35.

Lodish, Leonard M. (1971), "CALLPLAN: An Interactive Salesman's Call Planning System," *Management Science*, 18 (4-part-ii), 25-40.

Lynch, James E. and Graham J. Hooley (1990), "Increased Sophistication in Advertising Budget Setting," *Journal of Advertising Research*, 30 (1), 67-76.

MacDonald, James M. (2000), "Demand, Information, and Competition: Why Do Food Prices Fall at Seasonal Demand Peaks?," *Journal of Industrial Economics*, 48 (1), 27-45.

Mahajan, Vijay and Eitan Muller (1986), "Advertising Pulsing Policies for Generating Awareness for New Products," *Marketing Science*, 5 (2), 89-106.

Mesak, Hani I. (1992), "An Aggregate Advertising Pulsing Model with Wearout Effects," *Marketing Science*, 11 (3), 310-26.

Metwally, Mokhtar M. (1978), "Escalation Tendencies of Advertising," *Oxford Bulletin of Economics and Statistics*, 40 (2), 153-64.

Miller, Nolan and Amit Pazgal (2007), "Advertising Budgets in Competitive Environments," *Quantitative Marketing and Economics*, 5 (2), 131-61.

Montgomery, David B., Mary Chapman Moore, and Joel E. Urbany (2005), "Reasoning About Competitive Reactions: Evidence from Executives," *Marketing Science*, 24 (1), 138-49.

Morrison, Donald G. (1969), "On the Interpretation of Discriminant Analysis," *Journal of*

Marketing Research, 6 (2), 156-63.

Naik, Prasad A., Murali K. Mantrala, and Alan G. Sawyer (1998), “Planning Media Schedules in the Presence of Dynamic Advertising Quality,” *Marketing Science*, 17 (3), 214-35.

Nijs, Vincent R., Shuba Srinivasan, and Koen Pauwels (2007), “Retail Price Drivers and Retailer Profits,” *Marketing Science*, 26 (4), 473-85.

Park, Sehoon and Minhi Hahn (1991), “Pulsing in a Discrete Model of Advertising Competition,” *Journal of Marketing Research*, 28 (4), 397-405.

Patti, Charles H. and Vincent Blasko (1981), "Budgeting Practices of Big Advertisers," *Journal of Advertising Research*, 21 (6), 23-29.

Rosenthal, Robert. (1991), *Meta-analytic Procedures for Social Research.* Newbury Park, CA: Sage Publications.

Rotemberg, Julio, Garth Saloner, and Repeated Oligopoly (1986), "A Supergame-Theoretic Model of Price Wars During Booms," *New Keynesian Economics*, 2, 387-415.

Sasieni, Maurice. W. (1971), “Optimal Advertising Expenditure”, *Management Science*, 18 (4), 64-72.

——— (1989), “Optimal Advertising Strategies”, *Marketing Science*, 8 (4), 358-70.

Sethuraman, Raj, Gerard J. Tellis, and Richard A. Briesch (2011), “How Well Does Advertising Work? Generalizations From a Meta-Analysis of Brand Advertising Elasticity,” *Journal of Marketing Research*, 48 (June), 457-71.

Shimp, Terence A. (2010), *Integrated Marketing Communications in Advertising and Promotion*. Florence, KY: South-Western/Cengage Learning.

Steenkamp, Jan-Benedict E.M., Vincent R. Nijs, Dominique M. Hanssens, and Marnik G. Dekimpe (2005), “Competitive Reactions to Advertising and Promotion Attacks,” *Marketing*

Science, 24 (1), 35-54.

Tellis, Gerard J. and Tim Ambler, eds. (2007), *The SAGE Handbook of Advertising.* Thousand Oaks CA: Sage Publications.

Van Heerde, Harald J. (1999), *Models for Sales Promotion Effects Based on Store-Level Scanner Data*. Capelle a/d Ijssel, Netherland: Labyrint Publication.

———, Maarten J. Gijsenberg, Marnik G. Dekimpe, and Jan-Benedict E.M. Steenkamp (2013), “Price and Advertising Effectiveness over the Business Cycle,” *Journal of Marketing Research,* 50 (2), 177-93.

Villas-Boas, Miguel J. (1993), “Predicting Advertising Pulsing Policies in an Oligopoly: A Model and Empirical Test”, *Marketing Science*, 12 (1), 88-102.

Zielske, Hubert. A. (1959), The Remembering and Forgetting of Advertising,” *Journal of Marketing*, 23 (3), 239-43.

APPENDIX A. PARTIAL ADJUSTMENT MODEL FOR SALES CARRY-OVER ESTIMATION

In line with Naik and Raman (2003) we formulate the following partial-adjustment model to obtain the individual brands' advertising elasticities and sales carry-over parameters:

$$\begin{aligned} lnSales_{b,t} = \ & \alpha_{b,0} + \alpha_{b,1} lnAdv_{b,t} + \alpha_{b,2} lnPrice_{b,t} \\ & + \alpha_{b,3} lnCompAdv_{b,t} + \alpha_{b,4} lnCompPrice_{b,t} \\ & + \delta_b lnSales_{b,t-1} + \varepsilon_{b,t} \end{aligned} \quad \text{(B1)}$$

In equation (B1), we relate sales of brand b in week t ($lnSales_{b,t}$) to the brand's own marketing-mix instruments, i.e., advertising ($lnAdv_{b,t}$) and price ($lnPrice_{b,t}$). In addition, we control for the effects of marketing actions by competitors in the same category by including total advertising by competitors ($lnCompAdv_{b,t}$) and average price across competitors ($lnCompPrice_{b,t}$) as explanatory variables. Finally, we include sales in the previous week ($lnSales_{b,t-1}$) in the model to account for sales carry-over effects. Parameter $\alpha_{b,1}$ represents brand b's advertising elasticity and parameter δ_b captures the brand-specific carry-over effect we are looking for.

APPENDIX B. RIVAL MODEL SPECIFICATIONS

		Expected sign	**α = .05 δ = .50 Weeks = 26**		**α = .10 δ = .50 Weeks = 13**		**α = .10 δ = .25 Weeks = 26**		**α = .10 δ = 1.00 Weeks = 26**	
Intercept	$\bar{\beta}_0$	≠ 0	-2.823	***	-2.574	***	-2.652	***	-2.654	***
Holiday	$\bar{\beta}_1$	≠ 0	-.045		-.057	*	-.075	**	-.070	**
Period1	$\bar{\beta}_{2,1}$	≠ 0	-.106		-.295	*	-.087		-.043	
Period2	$\bar{\beta}_{2,2}$	≠ 0	.790	***	.476	***	.602	***	.663	***
Period3	$\bar{\beta}_{2,3}$	≠ 0	.470	***	-.024		.347	***	.377	***
Period4	$\bar{\beta}_{2,4}$	≠ 0	.131		-.179		-.061		-.019	
Period5	$\bar{\beta}_{2,5}$	≠ 0	.769	***	.242	**	.733	***	.741	***
Period6	$\bar{\beta}_{2,6}$	≠ 0	.393	***	-.474	***	.492	***	.544	***
Period7	$\bar{\beta}_{2,7}$	≠ 0	.218	*	-.507	***	.321	***	.385	***
Period8	$\bar{\beta}_{2,8}$	≠ 0	.357	***	-.177		.402	***	.483	***
Period9	$\bar{\beta}_{2,9}$	≠ 0	.234	**	-.265	**	.128		.170	
Period10	$\bar{\beta}_{2,10}$	≠ 0	.058		-.429	***	-.012		.064	
Period11	$\bar{\beta}_{2,11}$	≠ 0	.225	**	-.068		.088		.164	
Period12	$\bar{\beta}_{2,12}$	≠ 0	.027		-.286	**	.078		.119	
Trend	$\bar{\beta}_3$	≠ 0	-.217	*	.051		-.113		-.110	
CompPulse	$\bar{\beta}_4$	> 0	.138	***	.165	***	.140	***	.139	***
CompAdPressure	$\bar{\beta}_5$	> 0	.231	***	.208	***	.214	***	.213	***
TSPP ≤ $TSPP^{exp}$	$\bar{\beta}_6$	> 0	1.892	***	1.601	***	1.816	***	1.783	***
TSPP > $TSPP^{exp}$	$\bar{\beta}_7$	≠ 0	.031	***	.091	***	.039	***	.041	***
TIP ≤ TIP^{exp}	$\bar{\beta}_8$	< 0	-4.228	***	-4.256	***	-4.229	***	-4.195	***
TIP > TIP^{exp}	$\bar{\beta}_9$	≠ 0	.042	***	.034	***	.018	*	.011	
ΔMarketShare	$\bar{\beta}_{10}$	≠ 0	2.625	***	2.822	***	3.229	***	3.680	***
Median Pseudo R^2			.660		.627		.672		.668	
Median BIC			1.048		1.123		1.064		1.064	
Median Hit Rate			.925		.923		.936		.936	
Median Hit Rate Pulses (Ones)			.837		.818		.840		.840	

* *p* < .10; ** *p* < .05; *** *p* < .01. Tests are one-sided if clear directional effects are expected (see Expected sign column), two-sided if not (Rosenthal, 1991)

List of research reports

13001-EEF: Kuper, G.H. and M. Mulder, Cross-border infrastructure constraints, regulatory measures and economic integration of the Dutch – German gas market

13002-EEF: Klein Goldewijk, G.M. and J.P.A.M. Jacobs, The relation between stature and long bone length in the Roman Empire

13003-EEF: Mulder, M. and L. Schoonbeek, Decomposing changes in competition in the Dutch electricity market through the Residual Supply Index

13004-EEF: Kuper, G.H. and M. Mulder, Cross-border constraints, institutional changes and integration of the Dutch – German gas market

13005-EEF: Wiese, R., Do political or economic factors drive healthcare financing privatisations? Empirical evidence from OECD countries

13006-EEF: Elhorst, J.P., P. Heijnen, A. Samarina and J.P.A.M. Jacobs, State transfers at different moments in time: A spatial probit approach

13007-EEF: Mierau, J.O., The activity and lethality of militant groups: Ideology, capacity, and environment

13008-EEF: Dijkstra, P.T., M.A. Haan and M. Mulder, The effect of industry structure and yardstick design on strategic behavior with yardstick competition: an experimental study

13009-GEM: Hoorn, A.A.J. van, Values of financial services professionals and the global financial crisis as a crisis of ethics

13010-EEF: Boonman, T.M., Sovereign defaults, business cycles and economic growth in Latin America, 1870-2012

13011-EEF: He, X., J.P.A.M Jacobs, G.H. Kuper and J.E. Ligthart, On the impact of the global financial crisis on the euro area

13012-GEM: Hoorn, A.A.J. van, Generational shifts in managerial values and the coming of a global business culture

13013-EEF: Samarina, A. and J.E. Sturm, Factors leading to inflation targeting – The impact of adoption

13014-EEF: Allers, M.A. and E. Merkus, Soft budget constraint but no moral hazard? The Dutch local government bailout puzzle

13015-GEM: Hoorn, A.A.J. van, Trust and management: Explaining cross-national differences in work autonomy

13016-EEF: Boonman, T.M., J.P.A.M. Jacobs and G.H. Kuper, Sovereign debt crises in Latin America: A market pressure approach

13017-GEM: Oosterhaven, J., M.C. Bouwmeester and M. Nozaki, The impact of production and infrastructure shocks: A non-linear input-output programming approach, tested on an hypothetical economy

13018-EEF: Cavapozzi, D., W. Han and R. Miniaci, Alternative weighting structures for multidimensional poverty assessment

14001-OPERA: Germs, R. and N.D. van Foreest, Optimal control of production-inventory systems with constant and compound poisson demand

14002-EEF: Bao, T. and J. Duffy, Adaptive vs. eductive learning: Theory and evidence

14003-OPERA: Syntetos, A.A. and R.H. Teunter, On the calculation of safety stocks

14004-EEF: Bouwmeester, M.C., J. Oosterhaven and J.M. Rueda-Cantuche, Measuring the EU value added embodied in EU foreign exports by consolidating 27 national supply and use tables for 2000-2007

14005-OPERA: Prak, D.R.J., R.H. Teunter and J. Riezebos, Periodic review and continuous ordering

14006-EEF: Reijnders, L.S.M., The college gender gap reversal: Insights from a life-cycle perspective

14007-EEF: Reijnders, L.S.M., Child care subsidies with endogenous education and fertility

14008-EEF: Otter, P.W., J.P.A.M. Jacobs and A.H.J. den Reijer, A criterion for the number of factors in a data-rich environment

14009-EEF: Mierau, J.O. and E. Suari Andreu, Fiscal rules and government size in the European Union

14010-EEF: Dijkstra, P.T., M.A. Haan and M. Mulder, Industry structure and collusion with uniform yardstick competition: theory and experiments

14011-EEF: Huizingh, E. and M. Mulder, Effectiveness of regulatory interventions on firm behavior: a randomized field experiment with e-commerce firms

14012-GEM: Bressand, A., Proving the old spell wrong: New African hydrocarbon producers and the ‘resource curse’

14013-EEF: Dijkstra P.T., Price leadership and unequal market sharing: Collusion in experimental markets

14014-EEF: Angelini, V., M. Bertoni, and L. Corazzini, Unpacking the determinants of life satisfaction: A survey experiment

14015-EEF: Heijdra, B.J., J.O. Mierau, and T. Trimborn, Stimulating annuity markets

14016-GEM: Bezemer, D., M. Grydaki, and L. Zhang, Is financial development bad for growth?

14017-EEF: De Cao, E. and C. Lutz, Sensitive survey questions: measuring attitudes regarding female circumcision through a list experiment

14018-EEF: De Cao, E., The height production function from birth to maturity

14019-EEF: Allers, M.A. and J.B. Geertsema, The effects of local government amalgamation on public spending and service levels. Evidence from 15 years of municipal boundary reform

14020-EEF: Kuper, G.H. and J.H. Veurink, Central bank independence and political pressure in the Greenspan era

14021-GEM: Samarina, A. and D. Bezemer, Do Capital Flows Change Domestic Credit Allocation?

14022-EEF: Soetevent, A.R. and L. Zhou, Loss Modification Incentives for Insurers Under ExpectedUtility and Loss Aversion
14023-EEF: Allers, M.A. and W. Vermeulen, Fiscal Equalization, Capitalization and the Flypaper Effect.

14024-GEM: Hoorn, A.A.J. van, Trust, Workplace Organization, and Comparative Economic Development.

14025-GEM: Bezemer, D., and L. Zhang, From Boom to Bust in de Credit Cycle: The Role of Mortgage Credit.

14026-GEM: Zhang, L., and D. Bezemer, How the Credit Cycle Affects Growth: The Role of Bank Balance Sheets.

14027-EEF: Bružikas, T., and A.R. Soetevent, Detailed Data and Changes in Market Structure: The Move to Unmanned Gasoline Service Stations.

14028-EEF: Bouwmeester, M.C., and B. Scholtens, Cross-border Spillovers from European Gas Infrastructure Investments.

14029-EEF: Lestano, and G.H. Kuper, Correlation Dynamics in East Asian Financial Markets.

14030-GEM: Bezemer, D.J., and M. Grydaki, Nonfinancial Sectors Debt and the U.S. Great Moderation.

14031-EEF: Hermes, N., and R. Lensink, Financial Liberalization and Capital Flight: Evidence from the African Continent.

14032-OPERA: Blok, C. de, A. Seepma, I. Roukema, D.P. van Donk, B. Keulen, and R. Otte, Digitalisering in Strafrechtketens: Ervaringen in Denemarken, Engeland, Oostenrijk en Estland vanuit een Supply Chain Perspectief.

14033-OPERA: Olde Keizer, M.C.A., and R.H. Teunter, Opportunistic condition-based maintenance and aperiodic inspections for a two-unit series system.

14034-EEF: Kuper, G.H., G. Sierksma, and F.C.R. Spieksma, Using Tennis Rankings to Predict Performance in Upcoming Tournaments

15001-EEF: Bao, T., X. Tian, X. Yu, Dictator Game with Indivisibility of Money

15002-GEM: Chen, Q., E. Dietzenbacher, and B. Los, The Effects of Ageing and Urbanization on China's Future Population and Labor Force

15003-EEF: Allers, M., B. van Ommeren, and B. Geertsema, Does intermunicipal cooperation create inefficiency? A comparison of interest rates paid by intermunicipal organizations, amalgamated municipalities and not recently amalgamated municipalities

15004-EEF: Dijkstra, P.T., M.A. Haan, and M. Mulder, Design of Yardstick Competition and Consumer Prices: Experimental Evidence

15005-EEF: Dijkstra, P.T., Price Leadership and Unequal Market Sharing: Collusion in Experimental Markets

15006-EEF: Anufriev, M., T. Bao, A. Sutin, and J. Tuinstra, Fee Structure, Return Chasing and Mutual Fund Choice: An Experiment

15007-EEF: Lamers, M., Depositor Discipline and Bank Failures in Local Markets During the Financial Crisis

15008-EEF: Oosterhaven, J., On de Doubtful Usability of the Inoperability IO Model

15009-GEM: Zhang, L. and D. Bezemer, A Global House of Debt Effect? Mortgages and Post-Crisis Recessions in Fifty Economies

15010-I&O: Hooghiemstra, R., N. Hermes, L. Oxelheim, and T. Randøy, The Impact of Board Internationalization on Earnings Management

15011-EEF: Haan, M.A., and W.H. Siekman, Winning Back the Unfaithful while Exploiting the Loyal: Retention Offers and Heterogeneous Switching Costs

15012-EEF: Haan, M.A., J.L. Moraga-González, and V. Petrikaite, Price and Match-Value Advertising with Directed Consumer Search

15013-EEF: Wiese, R., and S. Eriksen, Do Healthcare Financing Privatisations Curb Total Healthcare Expenditures? Evidence from OECD Countries

15014-EEF: Siekman, W.H., Directed Consumer Search

15015-GEM: Hoorn, A.A.J. van, Organizational Culture in the Financial Sector: Evidence from a Cross-Industry Analysis of Employee Personal Values and Career Success

15016-EEF: Te Bao, and C. Hommes, When Speculators Meet Constructors: Positive and Negative Feedback in Experimental Housing Markets

15017-EEF: Te Bao, and Xiaohua Yu, Memory and Discounting: Theory and Evidence

15018-EEF: Suari-Andreu, E., The Effect of House Price Changes on Household Saving Behaviour: A Theoretical and Empirical Study of the Dutch Case

15019-EEF: Bijlsma, M., J. Boone, and G. Zwart, Community Rating in Health Insurance: Trade-off between Coverage and Selection

15020-EEF: Mulder, M., and B. Scholtens, A Plant-level Analysis of the Spill-over Effects of the German *Energiewende*

15021-GEM: Samarina, A., L. Zhang, and D. Bezemer, Mortgages and Credit Cycle Divergence in Eurozone Economies

16001-GEM: Hoorn, A. van, How Are Migrant Employees Manages? An Integrated Analysis

16002-EEF: Soetevent, A.R., Te Bao, A.L. Schippers, A Commercial Gift for Charity

16003-GEM: Bouwmeerster, M.C., and J. Oosterhaven, Economic Impacts of Natural Gas Flow Disruptions

16004-MARK: Holtrop, N., J.E. Wieringa, M.J. Gijsenberg, and P. Stern, Competitive Reactions to Personal Selling: The Difference between Strategic and Tactical Actions

16005-EEF: Plantinga, A. and B. Scholtens, The Financial Impact of Divestment from Fossil Fuels

16006-GEM: Hoorn, A. van, Trust and Signals in Workplace Organization: Evidence from Job Autonomy Differentials between Immigrant Groups

16007-EEF: Willems, B. and G. Zwart, Regulatory Holidays and Optimal Network Expansion

16008-GEF: Hoorn, A. van, Reliability and Validity of the Happiness Approach to Measuring Preferences

16009-EEF: Hinloopen, J., and A.R. Soetevent, (Non-)Insurance Markets, Loss Size Manipulation and Competition: Experimental Evidence

16010-EEF: Bekker, P.A., A Generalized Dynamic Arbitrage Free Yield Model

16011-EEF: Mierau, J.A., and M. Mink, A Descriptive Model of Banking and Aggregate Demand

16012-EEF: Mulder, M. and B. Willems, Competition in Retail Electricity Markets: An Assessment of Ten Year Dutch Experience

16013-GEM: Rozite, K., D.J. Bezemer, and J.P.A.M. Jacobs, Towards a Financial Cycle for the US, 1873-2014

16014-EEF: Neuteleers, S., M. Mulder, and F. Hindriks, Assessing Fairness of Dynamic Grid Tariffs

16015-EEF: Soetevent, A.R., and T. Bružikas, Risk and Loss Aversion, Price Uncertainty and the Implications for Consumer Search

16016-HRM&OB: Meer, P.H. van der, and R. Wielers, Happiness, Unemployment and Self-esteem

16017-EEF: Mulder, M., and M. Pangan, Influence of Environmental Policy and Market Forces on Coal-fired Power Plants: Evidence on the Dutch Market over 2006-2014

16018-EEF: Zeng,Y., and M. Mulder, Exploring Interaction Effects of Climate Policies: A Model Analysis of the Power Market

16019-EEF: Ma, Yiqun, Demand Response Potential of Electricity End-users Facing Real Time Pricing

16020-GEM: Bezemer, D., and A. Samarina, Debt Shift, Financial Development and Income Inequality in Europe

16021-EEF: Elkhuizen, L, N. Hermes, and J. Jacobs, Financial Development, Financial Liberalization and Social Capital

16022-GEM: Gerritse, M., Does Trade Cause Institutional Change? Evidence from Countries South of the Suez Canal

16023-EEF: Rook, M., and M. Mulder, Implicit Premiums in Renewable-Energy Support Schemes

17001-EEF: Trinks, A., B. Scholtens, M. Mulder, and L. Dam, Divesting Fossil Fuels: The Implications for Investment Portfolios

17002-EEF: Angelini, V., and J.O. Mierau, Late-life Health Effects of Teenage Motherhood

17003-EEF: Jong-A-Pin, R., M. Laméris, and H. Garretsen, Political Preferences of (Un)happy Voters: Evidence Based on New Ideological Measures

17004-EEF: Jiang, X., N. Hermes, and A. Meesters, Financial Liberalization, the Institutional Environment and Bank Efficiency

17005-EEF: Kwaak, C. van der, Financial Fragility and Unconventional Central Bank Lending Operations

17006-EEF: Postelnicu, L. and N. Hermes, The Economic Value of Social Capital

17007-EEF: Ommeren, B.J.F. van, M.A. Allers, and M.H. Vellekoop, Choosing the Optimal Moment to Arrange a Loan

17008-EEF: Bekker, P.A., and K.E. Bouwman, A Unified Approach to Dynamic Mean-Variance Analysis in Discrete and Continuous Time

17009-EEF: Bekker, P.A., Interpretable Parsimonious Arbitrage-free Modeling of the Yield Curve

17010-GEM: Schasfoort, J., A. Godin, D. Bezemer, A. Caiani, and S. Kinsella, Monetary Policy Transmission in a Macroeconomic Agent-Based Model

17011-I&O: Bogt, H. ter, Accountability, Transparency and Control of Outsourced Public Sector Activities

17012-GEM: Bezemer, D., A. Samarina, and L. Zhang, The Shift in Bank Credit Allocation: New Data and New Findings

17013-EEF: Boer, W.I.J. de, R.H. Koning, and J.O. Mierau, Ex-ante and Ex-post Willingness-to-pay for Hosting a Major Cycling Event

17014-OPERA: Laan, N. van der, W. Romeijnders, and M.H. van der Vlerk, Higher-order Total Variation Bounds for Expectations of Periodic Functions and Simple Integer Recourse Approximations

17015-GEM: Oosterhaven, J., Key Sector Analysis: A Note on the Other Side of the Coin

17016-EEF: Romensen, G.J., A.R. Soetevent: Tailored Feedback and Worker Green Behavior: Field Evidence from Bus Drivers

17017-EEF: Trinks, A., G. Ibikunle, M. Mulder, and B. Scholtens, Greenhouse Gas Emissions Intensity and the Cost of Capital

17018-GEM: Qian, X. and A. Steiner, The Reinforcement Effect of International Reserves for Financial Stability

17019-GEM/EEF: Klasing, M.J. and P. Milionis, The International Epidemiological Transition and the Education Gender Gap

2018001-EEF: Keller, J.T., G.H. Kuper, and M. Mulder, Mergers of Gas Markets Areas and Competition amongst Transmission System Operators: Evidence on Booking Behaviour in the German Markets

2018002-EEF: Soetevent, A.R. and S. Adikyan, The Impact of Short-Term Goals on Long-Term Objectives: Evidence from Running Data

2018003-MARK: Gijsenberg, M.J. and P.C. Verhoef, Moving Forward: The Role of Marketing in Fostering Public Transport Usage

2018004-MARK: Gijsenberg, M.J. and V.R. Nijs, Advertising Timing: In-Phase or Out-of-Phase with Competitors?

www.rug.nl/feb