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Maarten J. Gijsenberg

Harald J. van Heerde

Marnik G. Dekimpe

Vincent R. Nijs

Maarten J. Gijsenberg is Assistant Professor of Marketing at the Faculty of Economics and Business, University of Groningen, The Netherlands, Email: m.j.gijsenberg@rug.nl. Harald J. van Heerde is Professor of Marketing at the Waikato Management School, University of Waikato, New Zealand, Email: heerde@waikato.ac.nz, and Extramural Fellow at CentER, Tilburg University, The Netherlands. Marnik G. Dekimpe is Research Professor of Marketing & CentER Fellow, Tilburg University, The Netherlands & Professor of Marketing, Catholic University Leuven, Belgium, Email: m.g.dekimpe@uvt.nl. Vincent R. Nijs is Assistant Professor of Marketing at the Rady School of Management, UC San Diego, USA, Email: vnijs@rady.ucsd.edu.

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Understanding the Role of Adstock in Advertising Decisions

Abstract

Adstock plays a central role in advertising research. Adstock, or goodwill, is the cumulative value of a brand's advertising at a given point in time. A critical assumption in many advertising models is that managers take Adstock into account when making their advertising decisions. However, there is little empirical evidence to support this basic premise. Therefore, we develop a multivariate heterogeneous Tobit-II model to determine whether the *level* and rate of *change* in a brand's Adstock influence the *timing* and/or *magnitude* of advertising investments. We calibrate the model on a comprehensive data set covering the weekly advertising expenditures of close to 750 brands in 129 CPG categories. We find that advertising timing and magnitude decisions do rely on Adstock levels and changes. The reliance is stronger for larger brands and more frequently advertising brands. We also find that responding to *changes* in Adstock is associated with a higher advertising elasticity. On the other hand, inertia in advertising decision-making, reflected in a strong reliance on past Adstock *levels*, is linked with a lower advertising elasticity.

1. INTRODUCTION

Advertising remains one of the most visible and frequently-used marketing instruments. In 2009, the world's 100 largest advertisers collectively spent $125.3 billion (Advertising Age 2009). The largest advertiser was Procter & Gamble, with $8.7 billion. Other heavy spenders in the FCPG sector included Unilever ($6.03 billion), L'Oréal ($4.56 billion), and Kraft Foods ($2.12billion). In the car industry, General Motors and Ford Motor Company spent $3.3 billion and $2.1 billion each, while Visa and Mastercard spent $403.7 and 299.8 million, 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 considerably 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, 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 recent review). Two important research streams can be distinguished. First, an extensive *empirical* (econometric) 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 0.12 (0.24). Second, there is also a more *normative* literature that has studied under what conditions pulsing (as opposed to even spending) is an optimal strategy (see e.g., Sasieni 1971, Feinberg 1992, Villas-Boas 1993).

A central role in both research traditions is played by the Adstock concept. Adstock is the cumulative value of a brand's advertising at a given point in time. Simon Broadbent's Adstock theory (Broadbent 1979, 1984) posits that with each exposure advertising builds awareness, while in the absence of advertising Adstock eventually decays. Ephron and Mcdonald (2002) call the

Adstock concept "central to the econometric modeling of advertising effects over time" (p. 66). Similarly, Doganoglu and Klapper (2006) start from the basic axiom that advertising is used to increase brand value, and "as standard in the literature" (p. 6) assume that this effect is induced by a goodwill stock (an alternative term for Adstock). Dubé, Hitsch, and Manchanda (2005), in turn, investigate how brands should optimally schedule their advertising over time. They formulate the problem as a dynamic game, and solve for the set of Markov Perfect Equilibrium (MPE) spending strategies. They discuss how such strategies depend only on the payoff-relevant information captured by goodwill (or Adstock).

A critical assumption underlying the aforementioned studies is that managers use measures of Adstock to make their advertising decisions. Doganoglu and Klapper (2006, p. 6), e.g., argue that "it is presumable that firms base their advertising policies on their goodwill levels", while Dubé et al. (2005, p. 116) require "that managers understand how to convert own and competitive advertising levels into goodwill stocks." However, in spite of the pervasiveness of the Adstock (goodwill) concept in both econometric and normative advertising studies, little empirical evidence is available to support this basic premise.

The literature lacks generalizable insights into how managers make advertising decisions, and to what extent these are driven by Adstock considerations. As argued by Wierenga (2011), it is crucial to understand how marketing managers come to their decisions to (1) improve the quality of their decision-making process, and (2) design effective decision support systems. Therefore, we aim to address the following research questions:

- *Do Adstock considerations affect managers' advertising decisions*? Specifically, we consider whether the level and rate of change in a brand's Adstock influence the timing and magnitude of its advertising investments. By focusing on different Adstock components (level and change) and two key decisions (timing and size), we obtain detailed insights into the use (or neglect) of the Adstock concept.

- *Do brands differ in the extent to which they take Adstock considerations into account*? Marketing research has a tendency to focus on the largest and/or most frequently advertising brands (see e.g., Steenkamp et al. 2005). However, these may not be representative, and therefore bias any inferences on the usage and usefulness of the Adstock concept in practice. Following Zanutto and Bradlow (2006) and Slotegraaf and Pauwels (2008), we make no such a-priori selection. We use a comprehensive data set covering the weekly advertising expenditures of close to 750 brands in 129 CPG categories. This allows us to investigate to what extent larger brands (which may have more advertising resources) and/or more frequently advertising brands (which may have more advertising expertise) rely more or less on Adstock when making advertising decisions.
- *If brands indeed rely on Adstock to make advertising decisions, does this influence the effectiveness of their advertising?* If a brand's advertising timing and magnitude decisions are based on (level of or change in) Adstock, is that associated with a larger or smaller advertising elasticity?

To address these issues, we develop a parsimonious, yet flexible, hierarchical Bayesian model of a brand's advertising decisions (timing and magnitude) as a function of past levels and changes in a brand's Adstock (both own and competitive). The model is a heterogeneous multivariate Tobit-II model, with a probit model for the timing decision, and a regression model for the magnitude decision. It allows for a full error-covariance matrix not only between the timing and the magnitude decisions, but also between all brands in the category. In addition, it accommodates full between-brand heterogeneity in intercept and slope parameters, which are modeled in turn as a function of observable brand characteristics.

The paper is organized as follows. In the next section, we describe the conceptual background and introduce the core concepts used in our study. Subsequently, we provide a description of our econometric model (Section 3) and the data (Section 4). We then present the results of the model for advertising decisions (Section 5), and of the relationship between reliance on Adstock and advertising effectiveness (Section 6). We conclude with a discussion of key insights and suggestions for future research (Section 7).

2. CONCEPTUAL BACKGROUND

In the following sections, we distinguish between two advertising decisions, timing and magnitude (Section 2.1), introduce the Adstock concept, and motivate why we look at both the level and change in Adstock (Section 2.2). Next, we motivate why we consider both large and small brands, as well as frequent and infrequent advertisers (Section 2.3). Finally, we discuss a set of other factors that are likely to affect advertising decisions (Section 2.4).

2.1 Advertising Investment Decisions

In many industries, brands systematically switch advertising on and off at a fairly high frequency (Dubé et al. 2005). This phenomenon is often referred to as pulsing. Moreover, in periods when brands do advertise, considerable variability exists in the amount that is spent. Such patterns are also present in our data, as illustrated in Figure 1.

-- Insert Figure 1 about here—

The three left panels show the weekly expenditures for three soft-drink brands in the UK. Brand A is a frequent and heavy advertiser (100% of the time, average spending of £347,348 per week), while brand C is situated at the other end of the spectrum. It advertises 42% of the time and spends only £44,784 per week on average. Brand B takes an intermediate position: it advertises less often than brand A (59% of the time), but spends a larger amount on these actions than C (£134,481 per week on average). The right-hand side panels of Figure 1 show three brands in the UK cleanser market. Again, we observe considerable variability in both timing and expenditures. Moreover, the absolute spending level is considerably lower than in the soft-drinks market.

To describe the different patterns observed across brands and categories we need a flexible model that can accommodate extensive cross-sectional and longitudinal variability. Given the extensive number of categories (100+) and brands (700+), we refrain from making specific assumptions on the nature of the competitor game being played, as it is unlikely that a single game applies in all settings.[1] Instead, we adopt a specification that is flexible enough to adequately capture the wide variety of spending patterns identified in prior research (pulsing, even spending, etc.), and observed in our empirical data (see Section 3).

The advertising patterns also illustrate that advertisers must make two decisions: (i) *when* to advertise, and (ii) once the decision to advertise has been made, *how much* to spend (Tellis 2004, Danaher 2007). As pointed out by Bar-Ilan and Strange (1999), many investment decisions involve a similar duality of (i) yes or no and (ii) if yes, how much.[2]

2.2. The Role of Adstock in Advertising Decisions and Advertising Effectiveness

Adstock Concept. An important empirical generalization states that advertising actions impact brand performance (e.g., sales, market share,…) not only in the current period, but also in future periods (Hanssens 2009). The Adstock concept can be used to capture these dynamics in a

[1] For example, Doganoglu and Klapper (2006) assume a manufacturer Stackelberg game, while Dubé et al. (2005) specify a dynamic game and subsequently solve for the set of Markov Perfect Equilibrium advertising strategies.
[2] Bowman, Farley, and Schmittlein (2000) look at the selection of international service providers, where a distinction is made between the selection decision, and the subsequent intensity of usage. Similarly, in the context of international expansion of retail firms, Gielens and Dekimpe (2007) separate the entry-timing from the entry-size decision.

parsimonious fashion. The underlying intuition is simple: Over time, advertising builds a stock of consumer goodwill (Broadbent 1984), which subsequently decays with the time since the previous exposure. The Adstock concept is not only well established among practitioners using EFP (Effective Frequency Planning) in their advertising planning (Ephron and McDonald 2002, Dubé et al. 2005), it has also gained widespread acceptance in the academic marketing literature (see e.g., Broadbent et al. 1997, Cleeren et al. 2008, Danaher et al. 2008, and Steenkamp and Gielens 2003 for recent applications).

A frequently-used operationalization (see e.g., Luan and Sudhir 2010) of Adstock defines the concept for brand *b* and period *t* as:

$$(1) \qquad Adstock_{b,t} = (1-\lambda_b) * ln(Advertising_{b,t}) + \lambda_b Adstock_{b,t-1} .$$

where λ_b is the carry-over from the previous Adstock level. We now discuss how Adstock levels and changes are linked to advertising decision making, and how reliance on Adstock can impact advertising effectiveness. Table 1 summarizes our discussion.

-- Insert Table 1 about here --

Effect of Adstock <u>*Level*</u> *on Advertising Decisions.* In line with theories of inventory management, brands may engage in new advertising actions to replenish Adstock when it is low, and stop advertising when it has reached a sufficiently high level (Zufryden 1973). This corresponds to an (s,S) inventory strategy (as also pointed out by Doganoglu and Klapper 2006), aimed at keeping Adstock level between a lower and upper bound. Not only are brands more likely to replenish (i.e., advertise) when Adstock levels are low, they may also aim to restore that level quickly, and therefore spend more. Similarly, when Adstock levels are high there is less need to continue advertising or spend heavily. If advertising decisions are made according to such an active inventory management strategy, the effect of Adstock level on the timing and magnitude decisions should be negative (see first line in Table 1).

Alternatively, brand managers may be inclined to do the same thing as in the previous period, i.e., show a tendency towards inertia (e.g., Nijs et al. 2007). Similarly, decision-making processes are often characterized by a strong preference for the status quo (e.g., Samuelson and Zeckhauser 1988). Indeed, an often-used decision rule is to simply maintain advertising budgets from the previous period (Dekimpe and Hanssens 1995). Such state dependence results in a positive effect of Adstock level on the timing and magnitude decisions (see line 2 in Table 1). It is not clear, a priori, which of these approaches (i.e., inventory management of Adstock levels or state dependence) will prevail in practice.

Effect of Adstock Change on Advertising Decisions. Hanssens and Dekimpe (2008) and Leeflang et al. (2009) distinguish between stock and flow variables, and argue that managers should not only look at the level of a stock variable, but also at its rate of change (i.e., its first difference or flow). Again, there is an analogy with the inventory-management literature. Inventory models with inventory-level-dependent demand (see e.g., Urban 2005 for a review) recognize there is an incentive to re-order faster when the inventory depletion rate is higher. In our setting, the more quickly Adstock drops, the more managers may be inclined to spend on advertising to maintain (restore) the original level. This would imply a negative effect of Adstock Change on advertising timing and magnitude decisions (see line 3 in Table 1).

Conversely, one could also argue for a positive effect. Naik et al. (1998) offer a theoretical argument why brands may pulse their advertising as opposed to even spending. They argue that once an advertising campaign (which consists of several consecutive periods of non-zero spending) has started, exposures become less effective due to wear-out. This may be associated with a decline in advertising quality, and can provide a signal to stop the campaign to avoid ineffective advertising spending. They further argue that consumer forgetting effects after a period of no advertising help to restore advertising quality, after which the next campaign can begin.

Figure 2 offers a stylized example (using a value for λ_b of .6) with two 6-week campaigns. The Figure shows how advertising expenditures convert into, respectively, Adstock Levels and Adstock Changes. In the beginning of the campaign (when advertising quality is still high), Adstock Change is positive, creating pressure to keep on advertising. However, some time after the start of a campaign, when advertising quality tapers off, the change in Adstock becomes smaller (as of week 7) and even negative (as of week 12), providing less and less incentive to continue. After the campaign, as consumers forget and Adstock converges to its lower bound, Adstock change starts to grow again (as of week 13). In line with Naik et al. (1998), this may suggest that advertising quality has been restored sufficiently, providing an incentive to start a new campaign. This argument for advertising in campaigns implies a positive effect of Adstock Change on advertising timing and magnitude decisions (see line 4 in Table 1).

-- Insert Figure 2 about here –

How does the adopted Adstock management process influence the effectiveness of advertising decisions? As before, we distinguish between a reliance on Adstock level and Adstock change.

Link between Reliance on Adstock <u>Level</u> and Advertising Effectiveness. Active inventory management can help avoid demand losses due to out-of-stock (e.g., Campo et al. 2003) as well as the high costs of excess inventory. Similarly, Active adstock management helps to keep Adstock between lower and upper bounds. This implies increasing advertising when the Adstock level is low and decreasing it when Adstock is already high. This type of (contra or negative) reliance on Adstock *levels* should foster a productive use of this scarce resource, i.e., a stronger advertising elasticity, as indicated in line 1 of Table 1. Assumptions on managers' ability to develop optimal advertising plans using Adstock/Goodwill as input imply a similar relationship (e.g., Dubé et al. 2005).

In contrast, previous research has shown detrimental performance implications of inertia and state dependence in pricing (e.g., Nijs et al. 2007, Srinivasan et al. 2008). This relationship may plausibly extend to advertising as well, implying that inert (i.e., positive) reliance on Adstock *level* inhibits advertising elasticity. However, no empirical tests for the existence of such an inertia trap (line 2 in Table 1) in the advertising domain exist to date.

Link between Reliance on Adstock Change and Advertising Effectiveness. Monitoring Adstock *change* as part of advertising planning can help managers to avoid advertising when quality is too low, and allow for adequate restoration when this is called for (Naik et al. 1998). As such, we expect that when Adstock change has a positive effect on advertising decision-making, advertising effectiveness is enhanced. To exploit the momentum, advertising is done when it is most influential (line 4 in Table 1).

In contrast, when Adstock is on a downward trajectory (1) wear-out effects are setting in or (2) restoration is not yet complete (Naik et al. 1998). This makes additional exposures less effective, and it may be a waste of resources and an uphill battle to fight against the flow (line 3 in Table 1).

2.3 Large versus Small Brands and Frequent versus Infrequent Advertisers

Many studies have restricted attention to large and frequent advertisers. Steenkamp et al. (2005), for example, looked at the top three brands in each category provided they had an average share of 5% over the sampling period, and (to compute the advertising reaction elasticity) excluded brands that advertised in fewer than 25 weeks in 4 years. Brands typically included in previous studies on the basis of similar selection rules, however, are not representative for the market as a whole (Slotegraaf and Pauwels 2008), and insights based on these subsets are likely to be incomplete and/or biased (Zanutto and Bradlow 2006). In our setting, these two decision rules would have resulted in the exclusion of 595 out of 745 brands. As we include all types of brands, we are able to provide a more comprehensive picture of advertising decision making across time, brands, and categories.

We argue that smaller and/or less frequent advertisers may rely in different ways on Adstock level and Adstock change when making advertising decisions. Larger brands generally have more extensive marketing budgets, as these are often determined on a percentage of sales basis (Allenby and Hanssens 2005), offering enhanced opportunities to track fluctuations in Adstock (change) over time, for instance, through investments in marketing research. However, larger brands (firms) are also known to be more susceptible to inertia in their decision-making processes (Lieberman and Montgomery 1988). Consequently, we expect the influence of Adstock level and change on both decisions to be stronger for larger-share brands.

Frequent use of advertising may create learning effects, allowing experienced brands to become more efficient and establish effective advertising decision processes. We therefore expect closer monitoring of Adstock (change). However, frequent advertisers are also more likely to routinize decisions. Processes tend to remain in place over extended periods of time (Frederickson and Iaquinto, 1989) as organizations are required to be reliable, accountable, and reproducible (Boeker, 1988) making firms prone to inertia (Gilbert 2005). Hence, we posit that (Prior) *Advertising Frequency* will increase the influence of Adstock level and change on advertising decisions.

2.4 Covariates

To allow for the influence on advertising decisions beyond a brands' own internal Adstock monitoring, we include three sets of covariates: (i) Company factors, (ii) Competitor factors, and (iii) Category factors (see e.g. Montgomery et al. 2005). While these covariates are not the focus of our study, controlling for their influence provides a stronger test for the influence of our focal constructs (Adstock level and Adstock change). The resulting conceptual model for advertising decisions is summarized in Figure 3.

-- Insert Figure 3 about here --

Company Factors. Advertising decisions may be affected by company-specific factors such as new product introductions, performance evolution, and end-of-year budget depletion. Advertising theory tells us that *New Product Introductions* should be advertised more intensively to inform customers about the new product (e.g., Rossiter and Percy 1997). Advertising is known to be more effective for new products (Lodish et al. 1995), which offers an economic rationale for higher spending levels and frequencies. *Performance Evolution* may enhance current-period advertising as budgets are often set as a percentage of past sales (see e.g., Allenby and Hanssens 2005). Whereas tactical advertising decisions are usually at the weekly level (e.g., Danaher, 2007, Vakratsas and Ambler 2007), total budgets are often set on an annual basis (e.g., Farris and West 2007, Low and Mohr 1992), often involving different decision makers.[3] As these are gradually depleted over time (e.g. Montgomery et al. 2005), brands may be faced with relative shortages by the end of the year, in which case one can expect fewer and smaller advertising actions near the *End-Of-Year*. Alternatively, managers may notice that they could end up with a surplus. As this could affect their budget for the coming year, they may increase their spending frequency and/or level to avoid ending up with un-spent budgets.

[3] The determination of this total budget is beyond the scope of the current manuscript.

Competitor Factors. We not only look at the impact of the brand's own Adstock, but also at *Competitor Adstock Level* and *Competitor Adstock Change*. 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 current advertising spending (see also Montgomery et al. 2005). To test this assertion, we investigate whether competitors' Adstock level and change influence the timing and/or magnitude of a brand's advertising decision. The direction of these effects is not clear a priori, as arguments in both directions can be found with brands trying to trump each other (e.g., Metwally 1978; Chen and MacMillan 1992), trying to avoid competitive clutter (Danaher et al. 2008), or not responding at all (Steenkamp et al. 2005).

Category Factors. To control for market characteristics, we include category growth and concentration. Markets characterized by high *Category Growth* are often younger product categories, requiring more advertising to inform and convince new customers (Narayanan et al. 2005). Higher growth, in addition, can be regarded as an indicator of potential future profits, causing brands to claim/defend their positions in such categories more aggressively (Gatignon et al. 1990). Therefore, we expect a positive effect of category growth on advertising incidence and magnitude decisions. Markets with high *Category Concentration* tend to show higher profits, as such markets are often characterized by entry barriers (e.g., Karakaya and Stahl 1989). Using a similar logic as before, companies can be expected to more severely defend their positions, and engage in more intense advertising spending. The easy monitoring of competitors' actions in such markets, on the other hand, may lead to collusive behavior in order to preserve these higher margins, resulting in lower competitiveness (e.g., Steenkamp et al. 2005) and lower overall advertising spending. The resulting net effect is not clear a priori.

3. MODEL DEVELOPMENT

The advertising-decision framework discussed above implies four modeling requirements. First, we need to model, for each period, both the timing (yes/no) and spending decision (monetary value), while allowing for different response parameters for both decisions. Second, these response parameters are allowed to vary across brands (between-brand heterogeneity). Third, we need to accommodate the effects of the moderating variables in a simultaneous estimation procedure for maximal statistical efficiency. Fourth, the decisions of when and how much to spend may be interrelated between brands within a category, and hence we need to specify a full error covariance structure.

To meet these requirements, we link the drivers to the two decision variables (i.e., timing and magnitude) through a new multivariate Hierarchical Tobit-II model, which extends the models of Bucklin and Sismeiro (2003), Fox et al. (2004), Van Heerde et al. (2008) and Van Nierop et al. (2011). These models, as shown in Table 2, do not comply with all four requirements.

-- Insert Table 2 about here --

3.1 Timing

An advertising decision in category c ($c = 1,\ldots,C$) by brand b ($b = 1,\ldots,B_c$) in week t (z_{cbt}) is described by a multivariate probit model:

$$(4) \qquad z_{cbt} = \begin{cases} 1 \ \mathit{if} \ z^{*}_{cbt} > 0 \\ 0 \ \mathit{otherwise} \end{cases}$$

Consistent with previous research, we analyze decisions at a weekly level to avoid unnecessary data aggregation and provide more accurate results (Tellis and Franses 2006). In addition, the managerial survey reported by Steenkamp et al. (2005) indicated that brands can react to events as fast as within one week, but generally not faster. Moreover, weekly data are needed to capture the kind of pulsing observed in Figure 1 (see Dubé et al. 2005 for a similar reasoning).

The latent variable z^*_{cbt}, describing the timing decision process of the brand, is modeled as:

$$
\begin{aligned}
z^*_{cbt} = \zeta^{cb}_{1,0} &+ \zeta^{cb}_{1,1} Adstock_{cb,t-1} + \zeta^{cb}_{1,2} \Delta Adstock_{cb,t-1} + \zeta^{cb}_{1,3} NewProductIntroduction_{cb,t} \\
&+ \zeta^{cb}_{1,4} PerformanceEvolution_{cb,t-1} + \zeta^{cb}_{1,5} EndOfYear_{cb,t} \\
&+ \zeta^{cb}_{1,6} CompetitorAdstock_{cb,t-1} + \zeta^{cb}_{1,7} \Delta CompetitorAdstock_{cb,t-1} \\
&+ \zeta^{cb}_{1,8} CategoryGrowth_{c,t-1} + \zeta^{cb}_{1,9} CategoryConcentration_{c,t-1} \\
&+ \zeta^{cb}_{2,1} Holiday_t + \zeta^{cb}_{2,2} Qrtr1_t + \zeta^{cb}_{2,3} Qrtr2_t + \zeta^{cb}_{2,4} Qrtr3_t + \zeta^{cb}_{2,5} Trend_t + \mu_{cbt}
\end{aligned} \tag{5}
$$

In equation (5), we include the two central variables Adstock level and Adstock change (=Δ), along with the covariates New Product Introduction, Performance Evolution, End-Of-Year indicator, Competitor Adstock Level, Competitor Adstock Change, Category Growth, and Category Concentration. In addition, we control for holidays[4], quarterly seasonality (to account for the fact that some products may be more likely to be sold and advertised in some quarters/seasons than others), and add a trend variable to account for gradual changes in a myriad of factors not formally included in our model (see Dekimpe and Hanssens 1995 for a similar practice). As advertising decisions for time *t* are based on information available up to time *t*-1, we include one-period lagged versions of the pertinent time-varying explanatory variables.

3.2 Magnitude

Conditional on the decision to advertise (z_{cbt} = 1), we model $y_{cb,t}$, the natural logarithm of the amount spent on advertising by brand *b* in category *c* during week *t* as:

---

[4] We define a dummy variable which receives a value of one for weeks with one of the following bank holidays, a value of zero otherwise: New Year's Day, Good Friday, Easter Monday, Early May Bank Holiday, Spring Bank Holiday, Summer Bank Holiday, Christmas Day, Boxing Day.

(6) $$\begin{aligned} y_{cb,t} = {} & \omega_{1,0}^{cb} + \omega_{1,1}^{cb} Adstock_{cb,t-1} + \omega_{1,2}^{cb} \Delta Adstock_{cb,t-1} + \omega_{1,3}^{cb} NewProductIntroduction_{cb,t} \\ & + \omega_{1,4}^{cb} PerformanceEvolution_{cb,t-1} + \omega_{1,5}^{cb} EndOfYear_{cb,t} \\ & + \omega_{1,6}^{cb} CompetitorAdstock_{cb,t-1} + \omega_{1,7}^{cb} \Delta CompetitorAdstock_{cb,t-1} \\ & + \omega_{1,8}^{cb} CategoryGrowth_{c,t-1} + \omega_{1,9}^{cb} CategoryConcentration_{c,t-1} \\ & + \omega_{2,1}^{cb} Holiday_t + \omega_{2,2}^{cb} Qrtr1_t + \omega_{2,3}^{cb} Qrtr2_t + \omega_{2,4}^{cb} Qrtr3_t + \omega_{2,5}^{cb} Trend_t + \varepsilon_{cbt} \end{aligned}$$

We include the same explanatory variables in both the magnitude and timing equation. Although there is no requirement to have the same set in both equations, we include them in an exploratory way to investigate to what extent differential effects can be found in both decisions.

3.3 Moderating Factors

Consistent with our conceptual framework, we relate a subset of the response parameters $\boldsymbol{\zeta}_1^{cb}$ and $\boldsymbol{\omega}_1^{cb}$ to a set of moderator variables:

(7) $$\begin{aligned} \zeta_{1,0}^{cb} = {} & \overline{\zeta}_{1,0,0} + \overline{\zeta}_{1,0,1} BrandMarketShare_{cb} + \overline{\zeta}_{1,0,2} AdvertisingFrequency_{cb} \\ & + \overline{\zeta}_{1,0,3} Food_c + \overline{\zeta}_{1,0,4} Drinks_c + \overline{\zeta}_{1,0,5} Cosmetics_c + u_{1,0}^{cb} \end{aligned}$$

(8) $$\begin{aligned} \zeta_{1,i}^{cb} = {} & \overline{\zeta}_{1,i,0} + \overline{\zeta}_{1,i,1} BrandMarketShare_{cb} + \overline{\zeta}_{1,i,2} AdvertisingFrequency_{cb} + u_{1,i}^{cb}, \\ & for\ i = 1,2. \end{aligned}$$

(9) $$\begin{aligned} \omega_{1,0}^{cb} = {} & \overline{\omega}_{1,0,0} + \overline{\omega}_{1,0,1} BrandMarketShare_{cb} + \overline{\omega}_{1,0,2} AdvertisingFrequency_{cb} \\ & + \overline{\omega}_{1,0,3} Food_c + \overline{\omega}_{1,0,4} Drinks_c + \overline{\omega}_{1,0,5} Cosmetics_c + e_{1,0}^{cb} \end{aligned}$$

(10) $$\begin{aligned} \omega_{1,i}^{cb} = {} & \overline{\omega}_{1,i,0} + \overline{\omega}_{1,i,1} BrandMarketShare_{cb} + \overline{\omega}_{1,i,2} AdvertisingFrequency_{cb} + e_{1,i}^{cb}, \\ & for\ i = 1,2. \end{aligned}$$

For the intercepts of Equations (5) and (6), we include dummy variables for the four main CPG product classes in our sample[5], i.e., Household Products (base category), Food, Drinks, and Cosmetics, as well as Brand market share and Advertising frequency as moderators, as detailed in Equations (7) and (9). The responses to Adstock level and Adstock change on the advertising decisions are moderated by Brand market share and Advertising frequency, as specified in

[5] We thus control for category-specific main effects.

Equations (8) and (10). Mean-centering of both moderators allows us to examine the effects of deviations relative to an average brand.

The effects of the covariates, captured by $\zeta_{1,i}^{cb}$ and $\omega_{1,i}^{cb}$ (for i = 3,…,9) in Equations (5) and (6), are related to the hyperparameters $\overline{\zeta}_{1,i,0}$ and $\overline{\omega}_{1,i,0}$, and the brand-specific error terms $u_{1,i}^{cb}$ and $e_{1,i}^{cb}$ as follows: $\zeta_{1,i}^{cb} = \overline{\zeta}_{1,i,0} + u_{1,i}^{cb}$ and $\omega_{1,i}^{cb} = \overline{\omega}_{1,i,0} + e_{1,i}^{cb}$. No moderating effects are considered on those parameters (which are not our focal interest) to avoid over-parameterization.

To allow decisions by one brand on when and how much to advertise to be influenced by the decisions made for other brands, we specify that the error vectors $\boldsymbol{\mu}_{ct} = (\mu_{c1t}, \ldots, \mu_{cB_c t})'$ and $\boldsymbol{\varepsilon}_{ct} = (\varepsilon_{c1t}, \ldots, \varepsilon_{cB_c t})'$ follow a joint multivariate normal distribution with a full variance-covariance matrix: $(\boldsymbol{\varepsilon}_{ct}^{'}, \boldsymbol{\mu}_{ct}^{'})' \sim MVN(0, \boldsymbol{\Sigma}_c)$. Finally, unobserved drivers of model parameters may cause the error terms in (7)-(10) to be correlated as well: $(\mathbf{e}_{cb}^{'}, \mathbf{u}_{cb}^{'})' \sim MVN(0, \boldsymbol{\Omega})$.

We estimate model (5)-(10) with Gibbs sampling. The benefit of this approach over classical approaches is that it (i) accommodates the multivariate nature of our dependent variable, (ii) allows for full variance-covariance between all decisions within the same category, and (iii) estimates the moderator effects simultaneously with the other parameters, rather than in a two-step approach. An overview of the estimation approach is given in the Online Appendix.

In line with Naik and Raman (2003), we obtain the carry-over parameter λ_{cb} for brand *b* from category *c* from the following partial-adjustment model

$$
\begin{aligned}
lnSales_{cb,t} = \alpha_0^{cb} &+ \alpha_1^{cb} lnPrice_{cb,t} + \alpha_2^{cb} lnAdvertising_{cb,t} + \alpha_3^{cb} lnCompetitorPrice_{cb,t} \\
&+ \alpha_4^{cb} lnCompetitorAdvertising_{cb,t} + \alpha_5^{cb} EndOfYear_{cb,t} \\
&+ \alpha_6^{cb} Holiday_t + \alpha_7^{cb} Qrtr1_t + \alpha_8^{cb} Qrtr2_t + \alpha_9^{cb} Qrtr3_t \\
&+ \alpha_{10}^{cb} NoAdvertising_{cb,t} + \alpha_{11}^{cb} NoSales_{cb,t-1} + \lambda_{cb} lnSales_{cb,t-1} + \varepsilon_{cb,t}^{\lambda}
\end{aligned} \tag{11}
$$

In equation (11), we relate sales to own and competitors' marketing-mix instruments, i.e. price and advertising, and control for end-of-year spending by customers. As in equations (5) and (6), we control for holidays and seasonality. The lagged dependent variable captures the brand-specific carry-over effect we are looking for. To mitigate the effect of zero-advertising observations, we follow the recommendation of Battese (1997), and (i) add a $\text{NoAdvertising}_{cb,t}$ dummy that takes the value 1 when advertising is zero, and 0 otherwise, and (ii) set $\ln\text{Advertising}_{cb,t}$ equal to zero when advertising is zero. The same methodology applies to the lagged dependent variable. Finally, we allow for a full error variance-covariance structure between brands within the same category: $\boldsymbol{\varepsilon}_{ct}^{\lambda} \sim MVN(0, \boldsymbol{\Sigma}_{c}^{\lambda})$.

We use Gibbs sampling to obtain draws for λ_{cb} and the other parameters. We account for the uncertainty in λ_{cb} by using the individual draws of λ_{cb} to calculate Adstock for each individual draw of the main model (5) and (6). Please see the Online Appendix for more details on model estimation.

4. DATA DESCRIPTION

We estimate our model on 129 CPG categories in the UK that virtually cover the complete assortment offered in a typical supermarket. An overview of the included product categories, along with the number of included brands is given in Table 3.

-- Insert Table 3 about here --

We obtained four years (2001-2005) of weekly advertising spending data from NielsenMedia, and use 52 weeks as initialization and the remaining 156 weeks for estimation of both the carry-over parameters and the focal model. Brands included in the analysis advertised at least once, and were present in the market during the entire estimation period. In contrast to previous studies, we include both small and large brands resulting in an average market share of

6.4% (standard deviation: 10.9%). We focused on national brands, as private labels are typically not advertised individually (Lamey et al 2011).[6] Our sample includes 745 brands.

As a second main data source, we obtained (through Kantar Worldpanel) sales and price data aggregated across its consumer panel of 17,000+ households. We used these data to estimate the partial-adjustment model (11), and to calculate the moderators and covariates used in equations (5)-(10). Finally, data on new product introductions, needed to operationalize $\text{NewProductIntroduction}_{cb,t}$, were obtained through ProductScan (see e.g., Sorescu and Spanjol 2008).

Among the 745 brands that advertised at least once, considerable variability exists in their advertising behavior. Approximately 10% advertised only once, six brands advertised every week, while nearly half the brands advertised less than 10% of the time (see Figure 4 for a full distribution of the advertising frequency). On average, brands advertised 37 out of 156 weeks (24% of the time) with a standard deviation of 42. Average spending per advertising week was equal to £56,558, with a standard deviation of £71,972.

-- Insert Figure 4 about here --

If we would only include those brands in our empirical dataset that pass the selection rules used in Steenkamp et al. (2005), we would end up with only 150 (or 20%) of the 745 brands. They would cover 63.9% of all advertising expenditures, and advertise on average 82 out of 156 weeks. However, these brands, combined, account for only 29.3% of the total category sales. Instead, we use all 745 brands in the analyses.

We now turn to the measurement of the different constructs. In Section 4, we already provided an in-depth discussion of the *Adstock Level* and *Adstock Change* concepts. *Advertising Frequency* is the percentage of time the brand was advertised during the initialization period, thus

[6] Private label brands were considered in the derivation of covariates such as concentration level and market share.

avoiding a confound with the dependent variable during the estimation period, whereas *Brand Market Share* is defined as the average market share over the estimation period. *New Product Introduction* and *End-Of-Year budget depletion* are operationalized as dummy variables and *Performance Evolution* is expressed by the first difference of the logarithm of the brand volume shares over a 26 weeks moving window. *Competitor Adstock Level* is defined as the weighted average of the competitors' Adstock values, and *Competitor Adstock Change* as the week-to-week change in that level. *Category Growth* is measured as the first difference of the log-transformed category volume sales (cfr. Franses and Koop 1998). The Herfindahl index of volume shares is used to quantify *Category Concentration*. Both variables are defined over a 26 weeks moving window. All operationalizations are summarized in the Appendix.

5. EMPIRICAL RESULTS

In a first step, we assess to what extent the model is capable of predicting the weekly timing and magnitude of advertising actions. The in-sample hit rate (based on the first 2 ½ years of data) for the timing decision is a high 0.90, while the correlation between observed and predicted spending levels is 0.78. Theil's U is 0.55, which is considerably lower than 1, the first-order autoregressive benchmark model. Based on these numbers, we conclude that our model provides a good fit to the actual spending patterns in the marketplace.

In a holdout sample exercise (last ½ year of data), we contrast our model to a benchmark model which does not allow for multivariate errors in equations (5) and (6). On two of the three criteria (correlation and Theil's U), the focal model outperforms the benchmark. The benchmark only has a slight edge in terms of out-of-sample hit rate: 0.87 versus 0.85.

Next, we present parameter estimates for the full sample of 3 years. Section 5.1 reports to what extent advertising timing and magnitude decisions rely on Adstock level and Adstock change. Next, Section 5.2 presents the moderating effects of Brand Market Share and Advertising

Frequency. Finally, Section 5.3 discusses the role of the covariates. Coefficient estimates and their 95% posterior density intervals are shown in Table 4, with medians printed in bold if zero is not included in the interval.

-- Insert Tables 4 and 5 about here --

5.1 Reliance on Adstock Level and Adstock Change in Advertising Decisions

Table 4 shows the results for the hyper-parameters, which represent the effects for an average brand. They show a positive relationship between the Adstock level and the timing ($\overline{\zeta}_{1,1,0}$ = .25) and magnitude ($\overline{\omega}_{1,1,0}$ = .02) of advertising actions. As argued in Section 2.2, this provides evidence of state-dependence or stickiness in advertising decisions.

However, despite the significant hyper-parameters, considerable variability exists in the nature of this relationship across brands. Table 5 shows the result for the brand-specific parameters $\zeta_{1,i}^{cb}$ and $\omega_{1,i}^{cb}$. We observe that many brands (41.21%) do *not* take Adstock level into account when deciding whether or not to advertise. Even more (71.68%) do not rely on Adstock levels when deciding on the magnitude of their spending. This calls into question a fundamental premise of many (normative and econometric) advertising response models. For those brands that do react to Adstock levels, we find much evidence of a positive relationship both in the timing (state dependence; 55.7%) and magnitude (27.5%) decision. There is hardly any support for the negative relationship that one would expect if brands try to advertise more when Adstock is low and vice versa, as would be suggested when brands follow an (s,S) inventory strategy. Indeed, the number of significant negative effects (3.1%) hardly exceeds the number that is expected by chance (2.5%).

In terms of the impact of Adstock changes, we find that the number of positive effects is much larger than the number of negative effects (even though the absence of any relationship is the dominant pattern), resulting in significantly positive hyper-parameters in both the advertising timing ($\bar{\zeta}_{1,2,0}$ = .12) and magnitude ($\bar{\varpi}_{1,2,0}$ = .01) decision.

5.2 The Moderating Effects of Brand Market Share and Advertising Frequency

Looking at the moderating effects of *Brand Market Share* and *Advertising Frequency,* we observe that the significant main effect of Adstock level in the timing decision is amplified as brands become larger ($\bar{\zeta}_{1,1,1}$ = .08). This confirms the arguments in Lieberman and Montgomery (1988) and Hill and Rothaermel (2003) that larger firms are more susceptible to inertia in their decision-making processes. In line with Gilbert (2005), we find this also to be the case for more frequent advertisers, and this in both decisions ($\bar{\zeta}_{1,1,2}$ = .09 and $\bar{\varpi}_{1,1,2}$ = .01).[7] Similar patterns are observed for the moderation of Adstock change, where its positive hyper-mean effect in the timing equation is amplified for both large brands ($\bar{\zeta}_{1,2,1}$ = .03) and frequent ($\bar{\zeta}_{1,2,2}$ = .05) advertisers, and in the magnitude equation for frequent advertisers ($\bar{\varpi}_{1,2,2}$ = .01). These findings underscore the importance of including a wide variety of brands (size and frequency) in the analysis of advertising decision processes.

Apart from these Adstock-related effects, we find that both large brands and frequent advertisers spend more when they do advertise ($\bar{\varpi}_{1,0,1}$ = .03 and $\bar{\varpi}_{1,0,2}$ =.13). As expected, brands that spent more frequently in the initialization period, continued to do so in the estimation period ($\bar{\zeta}_{1,0,2}$ = 1.63).

5.3 Covariates

[7] Please note that the Advertising Frequency variable was defined on the initialization period to preclude the tautological reasoning that would occur when modeling the impact of frequency on advertising probability with both constructs defined on the same time span.

Table 4 also contains parameter estimates for the covariates. As expected, we find that *New Product Introduction* increases the incidence of advertising actions ($\overline{\zeta}_{1,3,0}$ = .65). The effect on magnitude is positive but not significant. *Performance Evolution* does not have a significant effect on the decisions. Our results further indicate that managers are less inclined to advertise at the end of the year ($\overline{\zeta}_{1,5,0}$ = -.17), consistent with the idea that resources have become depleted.

Brand advertising actions (timing or size) do not seem to be guided by fluctuations in *Competitor Adstock level* nor *Competitor Adstock change*. In high *Category Growth* environments, brands tend to advertise more often ($\overline{\zeta}_{1,8,0}$ = 3.39) and spend more as well ($\overline{\varpi}_{1,8,0}$ = .47), while they appear less inclined to advertise when *Category Concentration* is high ($\overline{\zeta}_{1,9,0}$ = -2.48), which supports the potential-for-collusion idea discussed in Steenkamp et al. (2005).

Comparing Effects across Timing vs Magnitude. Allowing for differential processes guiding the timing and magnitude decisions appears warranted. We find that the timing decision is partially driven by different factors (New Product Introduction, Category Concentration, End of Year) than the magnitude decision (Brand Market Share). Moreover, the moderating effects are also different, with Brand Market Share only having a significant moderating effect on Adstock level and change in the timing decision, and not in the magnitude decision.

6. RELIANCE ON ADSTOCK AND ADVERTISING EFFECTIVENESS

As discussed in Section 2.2, the reliance on Adstock level and Adstock change in advertising decisions is likely to correlate with the effectiveness of advertising actions. To validate this expectation, we compare the average advertising effectiveness of brands with a significant positive effect of Adstock level and/or change to those that do not rely on Adstock level and/or change (= base case). For this analysis, we use both the short-term (α_2^{cb} in Equation 11) and long-term elasticities [i.e., $\alpha_2^{cb}/(1-\lambda_{cb})$].

Figure 5 shows that, compared to brands that do not pay attention to Adstock variables, brands that only rely on Adstock *level* in the timing of their advertising investments, have a 9.86% lower short-run advertising elasticity ($p < .001$) and a 32.11% lower long-run advertising elasticity ($p < .001$).[8] In contrast, those brands that exclusively rely on Adstock *change* advertise more effectively in both the short and the long run (+7.62%, $p < .001$; and +10.44%, $p < .01$, respectively). When brands rely on both Adstock *level* and *change,* the short-run elasticity is similar to the base case (-1.6%, $p > .10$), but the long-run elasticity is lower (-12.98%, $p < .001$).

-- Insert Figures 5 and 6 about here --

Having decided to advertise, brands still have to determine the magnitude of their investment. We find that when the magnitude decision is solely based on Adstock levels, brands advertise less effectively in both the short and the long run (-6.76%, $p < .001$; and -22.84%, $p < .001$, respectively) compared to brands that do not pay attention to Adstock variables (see Figure 6). In contrast, reliance on Adstock change is again associated with a higher advertising elasticity (short run: +5.01%, $p < .001$; long run: +17.13%, $p < .001$). When magnitude decisions are influenced by both Adstock level and Adstock change, the positive and negative effects cancel out in both the short and the long run (+1.98%, $p > .10$; and +.61%, $p > .10$, respectively).

Overall, the influence of state dependence on advertising effectiveness (positive reliance on Adstock level) in advertising decision processes is clearly negative. This is consistent with previous research in the pricing domain (see e.g. Nijs et al., 2007; Srinivasan et al. 2008)

[8] All *p*-values reported in this section are two-sided.

suggesting that inertia, while perhaps operationally convenient, can be damaging to firm performance and efficiency. Our results point out that active monitoring of the dynamics, accounted for by the change in Adstock, is a much more rewarding strategy.

7. DISCUSSION

While advertising stock (Adstock) is a central construct in both descriptive and normative advertising research, little is known about whether (and how it) influences advertising decisions. Therefore, our first research question is *Do Adstock considerations affect managers' advertising decisions*? To answer this question, we developed a model to determine whether the level and rate of change in a brand's Adstock influence the timing and/or magnitude of its advertising investments. We calibrated a heterogeneous multivariate Tobit-II model on a comprehensive data set covering the weekly advertising expenditures of close to 750 brands in 129 CPG categories. We find that Adstock level and change exert a positive influence on the timing and magnitude of advertising actions.

Although it has often been argued that advertising is driven by competitive reasoning and reaction (e.g., Metwally, 1978; Armstrong and Collopy, 1996; Allenby and Hanssens 2005), we find no empirical evidence to support such claims. This is consistent with Steenkamp et al. (2005) who also find little evidence of reactions to competitor's advertising actions. Hence, brand managers tend to rely mostly on their own internal utility calculi when making advertising decisions rather than focusing on what competitors are doing.

We find considerable heterogeneity across brands in the extent to which they rely on their own Adstock. In the magnitude decision, there are relatively many brands (around 75%) that do not pay attention to Adstock levels or changes. Also for the timing decision, nearly half of the brands do not pay attention to their Adstock level (41%) or change (51%). These findings suggest that a basic and broadly accepted premise of the advertising literature – reliance on Adstock – should be questioned.

These findings also answer our second research question, as *brands clearly differ in the extent to which they take Adstock considerations into account*. To shed further light on this issue, we used the fact that our data set comprises not only large and frequently advertising brands but also smaller and less frequently advertising brands. We find that advertising timing decisions are more strongly driven by Adstock level and change for larger and more frequently advertising brands. Brands that advertise more frequently also show a stronger reliance on Adstock level and change when they decide on the magnitude of advertising investments. The findings illustrate that incomplete and biased results may be obtained when restricting the analyses to the more popular brands.

Our final research question is *If brands do indeed rely on Adstock to make advertising decisions, does this influence the effectiveness of their advertising?* We find a significant link between Adstock's influence on advertising actions and the resulting effectiveness of those actions. Monitoring of and relying on the dynamics of advertising efforts, as expressed by the change in Adstock, shows a positive association with advertising effectiveness, consistent with the concept of campaigning (Naik et al. 1998). It thus pays for a brand to exploit the momentum in its campaign and to advertise when Adstock change is positive. On the other hand, state dependence in advertising decision-making, reflected in a strong positive reliance on Adstock level (inertia trap), harms the power of advertising to enhance brand performance. Hence, *many brands either ignore a relevant metric (Adstock change) or habitually follow a less relevant one (Adstock level).* Our study suggests that monitoring and flagging Adstock change should become a key component of marketing dashboards (Pauwels et al. 2009) and/or decision support systems (Wierenga and Van Bruggen 2000).

Conclusion. This paper provides new insights on how brands manage their advertising decision processes. While previous research has extensively studied the performance consequences of advertising spending, much less is know about how managers make their decisions on when and how much to advertise, in spite of the large amounts of money involved, and in spite of the often-heard calls to make marketing (managers) more accountable. This not only applies to the advertising field but is a more broadly observed phenomenon in the marketing discipline (see e.g., Wierenga 2011, Figure 1). Our results suggest that (i) basic, but untested, premises on how managers make decisions may have to be questioned, (ii) the extent to which they adhere to these premises correlates with the effectiveness of their actions. Consistent with previous research, we find that inertia can be damaging to firm performance and efficiency, while active monitoring of changes in Adstock is a much more rewarding strategy. We hope this research inspires additional work on the antecedents and consequences of advertising decision making.

REFERENCES

Advertising Age (2009), *100 Leading National Advertisers*.

Allenby, Greg M. and Dominique M. Hanssens (2005), "Advertising Response," MSI Special Report 05-200a, Marketing Science Institute, Cambridge MA.

Armstrong, J. Scott and Fred Collopy (1996), "Competitor Orientation: Effects of Objectives and Information on Managerial Decisions and Profitability," *Journal of Marketing Research*, 33 (May), 188-199.

Bar-Ilan, Avner and William C. Strange (1999), "The Timing and Intensity of Investment," Journal of Macroeconomics, 21 (1), 57-77.

Battese, George E. (1997), "A Note on the Estimation of Cobb-Douglas Production Functions When Some Explanatory Variables Have Zero Values," *Journal of Agricultural Economics*, 48 (January), 250-52.

Boeker, Warren (1988), "Strategic Change: the Effects of Founding and History," *The Academy of Management Journal*, 32 (3), 489-515.

Bowman, Douglas, John U. Farley, and David C. Schmittlein (2000), "Cross-National Empirical Generalization in Business Services Buying Behavior," *Journal of International Business Studies*, 31 (4), 667-685.

Broadbent, Simon S. (1979), "One Way TV Advertisements Work", *Journal of the Market Research Society*, 21, 139-166.

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

———, Jayne Z. Spittler, and Kate Lynch (1997), "Building Better TV Schedules: New Light From the Single Source," *Journal of Advertising Research*, 37 (4), 27-31.

Bucklin, Randolph E. and Catarina Sismeiro (2003), "A Model of Web Site Browsing Behavior Estimated on Clickstream Data," *Journal of Marketing Research*, 40 (August), 249-267.

Campo, Katia, Els Gijsbrechts, and Patricia Nisol (2003), "The Impact of Retailer Stockouts on Whether, What and How Much to Buy," *International Journal of Research in Marketing*, 20 (3), 273-286.

Chen, Ming-Jer 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), 539-560.

Cleeren, Kathleen, Marnik G. Dekimpe, and Kristiaan Helsen (2008), "Weathering Product-Harm Crises,"*Journal of the Academy of Marketing Science*, 36 (2), 262-270.

Danaher, Peter J. (2007), "Media Planning," in *The SAGE Handbook of Advertising,* Gerard J. Tellis and Tim Ambler, eds. Thousand Oaks: Sage Publications ltd.

———, 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.

Dekimpe, Marnik G. and Dominique M. Hanssens (1995), "The Persistence of Marketing Effects on Sales," *Marketing Science*, 14 (1), 1-21.

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), 107-144.

Ephron, Erwin and Colin McDonald (2002), "Media Scheduling and Carry-Over Effects: Is Adstock a Useful TV Planning Tool?," *Journal of Advertising Research,* 42 (4), 66-71.

Farris, Paul W. and Douglas C. West (2007), "A Fresh View of the Advertising Budget," in *The SAGE Handbook of Advertising,* Gerard J. Tellis and Tim Ambler, eds. Thousand Oaks: Sage Publications ltd.

Feinberg, Fred M. (1992), "Pulsing Policies for Aggregate Advertising Models", *Marketing Science*, 11 (3), 221-234.

Fox, Edward J., Alan L. Montgomery, and Leonard M. Lodish (2004), "Consumer Shopping and Spending Across Retail Formats," *Journal of Business*, 77 (2), 25-60.

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

Frederickson, James W. and Anthony L. Iaquinto (1989), "Inertia and Creeping Rationality in Strategic Decision Processes," *The Academy of Management Journal,* 32 (3), 516-542.

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

Gielens, Katrijn and Marnik G. Dekimpe (2007), "The Entry Strategy of Retail Firms into Transition Economies," *Journal of Marketing,* 71 (2), 196-212.

Gilbert, Clark G. (2005), "Unbundling the Structure of Inertia: Resource vs Routine Rigidity," *The Academy of Management Journal*, 48 (5),741-763.

Hanssens, Dominique M., editor (2009), *Empirical Generalizations about Marketing Impact*. Cambridge MA: Marketing Science Institute, Relevant Knowledge Series.

——— and Marnik G. Dekimpe (2008), "Models for the Financial-Performance Effects of Marketing," in *Handbook of Marketing Decision Models*, Berend Wierenga, editor. New York: Springer.

Hill, Charles W.L. nd Frank T. Rothaermel (2003), "The Performance of Incumbent Firms in the Face of Radical Technological Innovation," *Academy of Management Review*, 28 (2), 257-274.

Karakaya, Fahri and Michael J. Stahl (1989), "Barriers to Entry and Market Entry Decisions in Consumer and Industrial Goods Markets," *Journal of Marketing,* 53 (2), 80-91.

Lamey, Lien, Barbara Deleersnyder, Jan-Benedict E.M. Steenkamp and Marnik G. Dekimpe (2011), "The Effect of Business Cycle Fluctuations on Private-Label Share: What Has Marketing Conduct Got to Do with it?" *Journal of Marketing*, forthcoming.

Leeflang, Peter S.H., Tammo H.A. Bijmolt, Jenny van Doorn, Dominique M. Hanssens, Harald J.van Heerde, Peter C. Verhoef, and Jaap E. Wieringa (2009), "Creating Lift Versus Building the Base: Current Trends in Marketing Dynamics," *International Journal of Research in Marketing,* 26, 13-20.

Lieberman, Marvin B. and David B. Montgomery (1988), "First-Mover Advantages," *Strategic Management Journal*, 9 (1), 41-58.

Lodish, Leonard M., Magid Abraham, Stuart Kalmenson, Jeanne Livelsberger, Beth Lubetkin, Bruce Richardson, and Mary E. Stevens (1995), "How T.V. advertising works: A meta-analysis of 389 real world split cable T.V. advertising experiments,"*Journal of Marketing Research*, 32 (May), 125-139.

Low, George S. and Jakki J. Mohr (1999), "Setting Advertising Budgets in Multi-Brand Companies," *Journal of Advertising Research*, 39 (1), 67-79.

Luan, Y. Jackie and K. Sudhir (2010), "Forecasting Marketing-Mix Responsiveness for New Products," *Journal of Marketing Research*, Vol 47 (June), 444-456.

Metwally, Mokhtar M. (1978), "Escalation Tendencies of Advertising," *Oxford Bulletin of Economics and Statistics,* 40 (2), 153-164.

Montgomery, David B., Mary Chapman Moore, and Joel E. Urbany (2005), "Reasoning About Competitive Reactions: Evidence from Executives," *Marketing Science*, 24 (1), 138-149.
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), 214-235.
Naik Prasad A. and Kalyan Raman (2003), "Understanding the Impact of Synergy in Multimedia Communications," *Journal of Marketing Research*, 40 (November), 375-388.
Narayanan, Sridhar, Puneet Manchanda, and Pradeep K. Chintagunta (2005), "Temporal Differences in the Role of Marketing Communication in New Product Categories," *Journal of Marketing Research,* 42 (August).278-290.
Nijs, Vincent R., Shuba Srinivasan, and Koen Pauwels (2007), "Retail Price Drivers and Retailer Profits," *Marketing Science,* 26 (4), 473-485.
Pauwels, Koen, Tim Ambler, Bruce Clark, Pat LaPointe, David Reibstein, Bernd Skiera, Berend Wierenga and Thorsten Wiesel (2009), "Dashboards as a Service: Why, What, How and What Research is Needed?" *Journal of Services* Research, 12 92), 175-189.
Rossiter, John R. and Larry Percy (1997), *Advertising Communications & Promotion Management. Second Edition*. New York, NY: McGraw-Hill.
Samuelson, William and Richard Zeckhauser (1988), "Status Quo Bias in Decision Making," *Journal of Risk and Uncertainty*, 1 (1), 7-59.
Sasieni, Maurice. W. (1971), "Optimal Advertising Expenditure", *Management Science*, 18 (4), 64-72.
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), 457-471.
Shimp, Terence A. (2010), *Integrated Marketing Communications in Advertising and Promotion*. Florence, KY: South-Western/Cengage Learning.
Slotegraaf, Rebecca J. and Koen Pauwels (2008), "The Impact of Brand Equity and Innovation on the Long-Term Effectiveness of Promotions," *Journal of Marketing Research*, 45 (June), 293-306.
Sorescu, Alina B. and Jelena Spanjol (2008), "Innovation's Effect on Firm Value and Risk: Insights from Consumer Packaged Goods," *Journal of Marketing*, 72 (2), 114-132.
Srinivasan, Shuba, Koen Pauwels, and Vincent R. Nijs (2008), "Demand-Based Pricing Versus Past-Price Dependence: A Cost-Benefit Analysis," *Journal of Marketing*, 72 (2), 15-27.
Steenkamp, Jan-Benedict E.M. and Katrijn Gielens (2003), "Consumer and Market Drivers of the Trial Probability of New Consumer Packaged Goods," *Journal of Consumer Research*, 30 (4), 368-384.
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. (2004), *Effective Advertising: Understanding When, How and Why Advertising Works.* Thousand Oaks CA: Sage Publications.
——— and Philip H. Franses (2006), "Optimal Data Interval for Estimating Advertising Response," *Marketing Science,* 25 (3), 217-229.
——— and Tim Ambler, eds. (2007), *The SAGE Handbook of Advertising.* Thousand Oaks CA: Sage Publications.

Urban, Timothy L. (2005), “Inventory Models with Inventory-Level-Dependent Demand: A Comprehensive Review and Unifying Theory,” *European Journal of Operational Research,* 162 (2005), 792-804.

Vakratsas, Demetrios and Tim Ambler (2007), “Essentials of Media Planning,” in *The SAGE Handbook of Advertising,* Gerard J. Tellis and Tim Ambler, eds. Thousand Oaks: Sage Publications ltd.

Van Heerde, Harald J., Els Gijsbrechts, and Koen Pauwels (2008), “Winners and Losers in a Major Price War,” *Journal of Marketing Research*, 45 (October), 499-518.

Van Nierop, J. Erjen M., Peter S.H. Leeflang, Marije L. Teerling, and K.R.E. Huizingh (2011), “The Impact of the Introduction and Use of an Informational Website on offline Customer Buying Behavior,” *International Journal of Research in Marketing*, 28 (2), 155-165.

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

Wierenga, Berend (2011), “Managerial Decision Making in Marketing: The Next Research Frontier,” *International Journal of Research in Marketing*, 28 (2), 89-101.

——— and Gerrit H. Van Bruggen (2000), *Marketing Management Support Systems: Principles, Tools and Implementation*, Kluwer Academic Publishers.

Zanutto, Elaine L. and Eric T. Bradlow (2006), “Data Pruning in Consumer Choice Models,” *Quantitative Marketing and Economics*, 4 (3), 267-287.

Zufryden, Fred S. (1973), “Media Scheduling: A Stochastic Dynamic Model Approach,” *Management Science*, 19 (12), 1395-1406.

Table 1. Conceptual background

Reliance on	Effect on advertising timing / magnitude	Interpretation	Advertising effectiveness prediction[1]
Adstock level	Negative	Active inventory management: advertise when adstock needs replenishment.	Increased
	Positive	Inertia trap: advertise when adstock is high.	Reduced
Adstock change	Negative	Fight the flow: advertise when adstock is declining.	Reduced
	Positive	Exploit the momentum: advertise when adstock is growing.	Increased

[1] Compared to a base case where adstock is ignored.

Table 2. Model specification comparison with previous studies

Model requirement	Bucklin & Sismeiro 2003	Fox et al. 2004	Van Heerde et al. 2008	Van Nierop et al. 2011	Our work
Two decisions with different response parameters	✓	✓	✓	✓	✓
Between-subject heterogeneity	✓	✓	✓	✓	✓
Moderation of response parameters					✓
Full error covariance structure across both equations			✓		✓

Table 3. Overview of product categories

Product Fields	Examples	No. of Categories	No. of Brands
Assorted Foods	Breakfast cereals, dry pasta, flour	27	94
Beverages	Brandy, mineral waters, softdrinks	20	169
Cakes	Oatcakes, crumpets pickelets and muffins	4	14
Candy	Cereal bars, countline chocolate, fruit bars	8	42
Canned/bottled foods	Canned fish, canned fruit	5	13
Care products	Deodorants, shampoo, toilet tissue	22	194
Cleaning products	Descalers, scouring powders, drain care	15	56
Dairy products	Butter, cream, yoghurt	6	29
Frozen foods	Frozen fish, frozen vegetables	5	17
Household supplies	Batteries, car freshener	2	11
Pet products	Dog food, cat litter	3	38
Taste enhancers	Mustard, vinegar, Worcester sauce	12	68
Total		*129*	*745*

Table 4. Advertising decision parameter estimates

	Timing				Magnitude			
		2.5th percentile	Median	97.5th percentile		2.5th percentile	Median	97.5th percentile
Brand Market Share	$\bar{\zeta}_{1,0,1}$	-.08	.08	.21	$\bar{\omega}_{1,0,1}$	.01	**.03**	.05
Advertising Frequency	$\bar{\zeta}_{1,0,2}$	1.48	**1.63**	1.77	$\bar{\omega}_{1,0,2}$	.11	**.13**	.19
Adstock Level	$\bar{\zeta}_{1,1,0}$	.23	**.25**	.28	$\bar{\omega}_{1,1,0}$	.01	**.02**	.02
x Brand Market Share	$\bar{\zeta}_{1,1,1}$	.03	**.08**	.11	$\bar{\omega}_{1,1,1}$	-.00	.00	.00
x Advertising Frequency	$\bar{\zeta}_{1,1,2}$	.07	**.09**	.12	$\bar{\omega}_{1,1,2}$	.01	**.01**	.02
Adstock Change	$\bar{\zeta}_{1,2,0}$	.10	**.12**	.13	$\bar{\omega}_{1,2,0}$	.01	**.01**	.01
x Brand Market Share	$\bar{\zeta}_{1,2,1}$	.02	**.03**	.05	$\bar{\omega}_{1,2,1}$	-.00	.00	.00
x Advertising Frequency	$\bar{\zeta}_{1,2,2}$	.04	**.05**	.07	$\bar{\omega}_{1,2,2}$	.01	**.01**	.01
New Product Introduction	$\bar{\zeta}_{1,3,0}$	.06	**.65**	1.02	$\bar{\omega}_{1,3,0}$	-.01	.04	.09
Performance Evolution	$\bar{\zeta}_{1,4,0}$	-.20	-.04	.15	$\bar{\omega}_{1,4,0}$	-.00	.03	.05
End-Of-Year remaining budget	$\bar{\zeta}_{1,5,0}$	-.25	**-.17**	-.08	$\bar{\omega}_{1,5,0}$	-.03	-.01	.00
Competitor Adstock Level	$\bar{\zeta}_{1,6,0}$	-.01	-.00	.01	$\bar{\omega}_{1,6,0}$	-.00	-.00	.00
Competitor Adstock Change	$\bar{\zeta}_{1,7,0}$	-.01	-.00	.00	$\bar{\omega}_{1,7,0}$	-.00	-.00	.00
Category Growth	$\bar{\zeta}_{1,8,0}$	.84	**3.39**	3.74	$\bar{\omega}_{1,8,0}$	.19	**.47**	.59
Category Concentration	$\bar{\zeta}_{1,9,0}$	-3.12	**-2.48**	-.88	$\bar{\omega}_{1,9,0}$	-.26	-.18	.01

* Medians are printed in bold if zero is not included in the 95% posterior density interval.

Table 5. Distribution of significant effects (95% confidence)

	Significant negative	Insignificant	Significant positive
Dep. Var: Timing decision			
Indep. Var.: Adstock level	3.09%	41.21%	55.70%
Indep. Var.: Adstock change	2.55%	50.87%	46.58%
Dep. Var: Magnitude decision			
Indep. Var.: Adstock level	.81%	71.68%	27.52%
Indep. Var.: Adstock change	.13%	78.79%	21.07%

Figure 1. Weekly advertising expenditures for three brands in the UK soft drink and cleanser markets

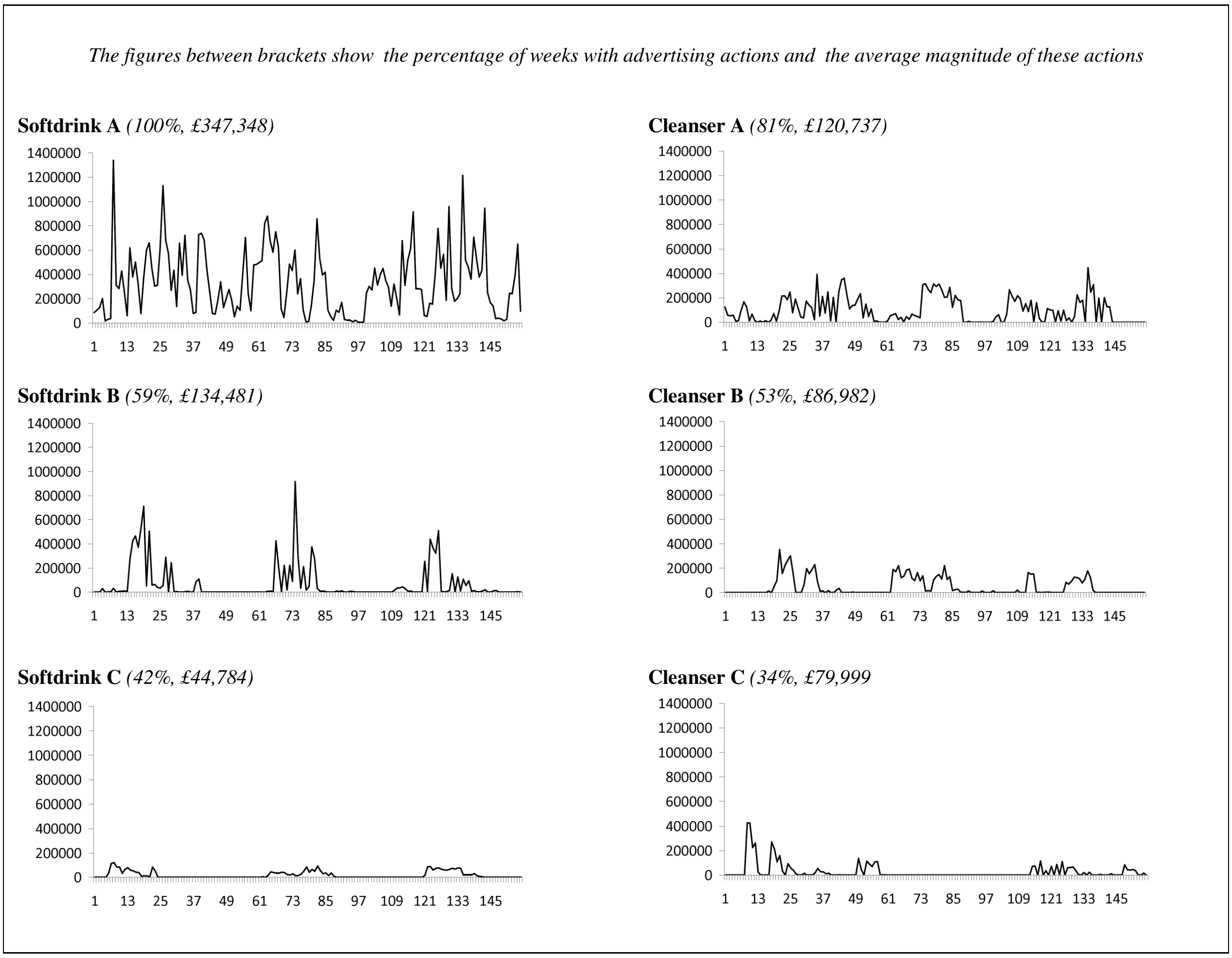


Figure 2. Advertising, Adstock level, and Adstock change

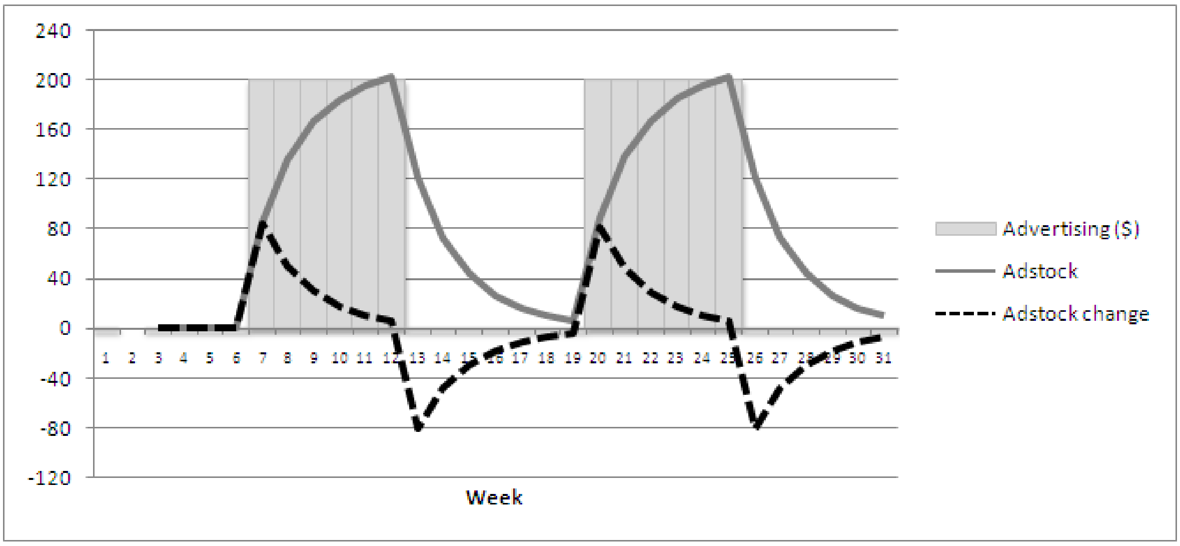


Figure 3. Conceptual framework

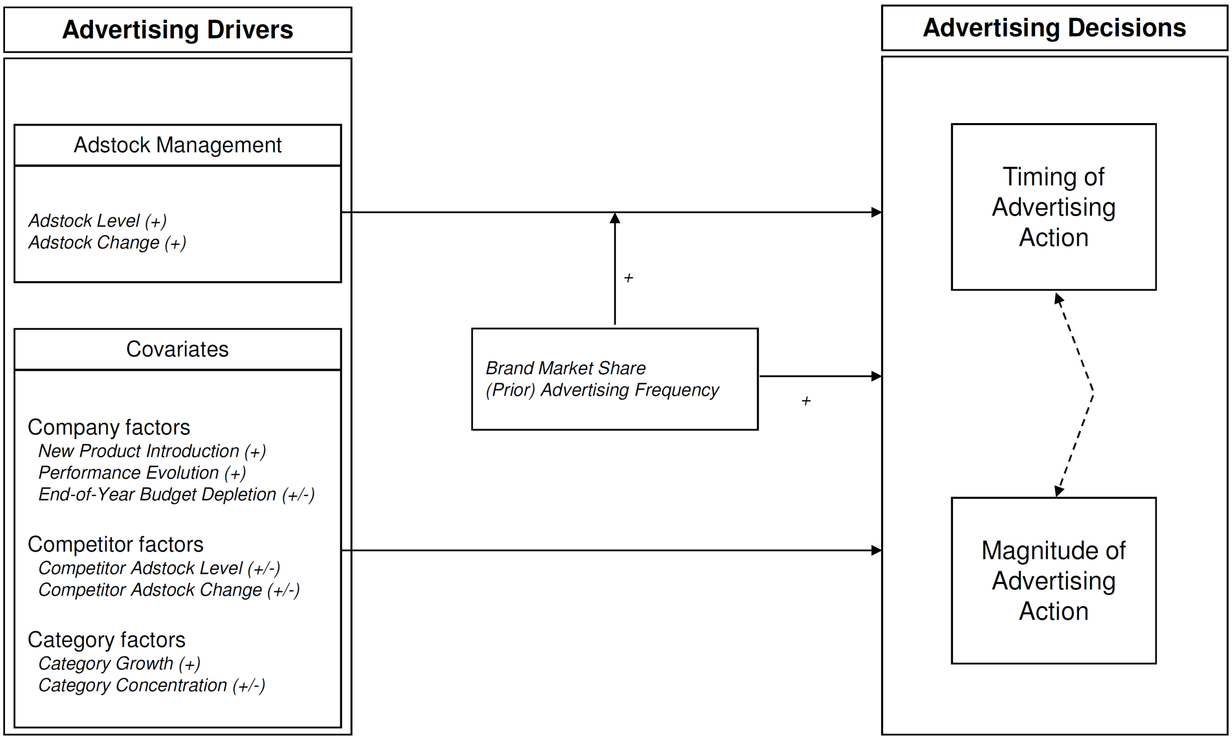


Figure 4. Distribution of the percentage of advertising weeks

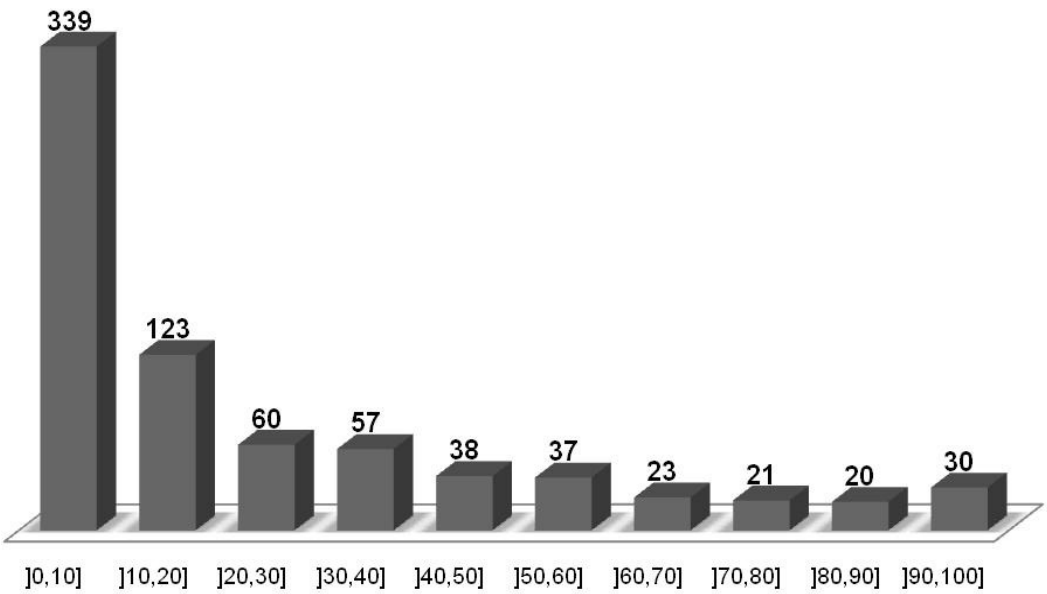


Figure 5. Difference in advertising effectiveness for brands relying on adstock level and/or change in timing decision compared to benchmark of no adstock reliance.

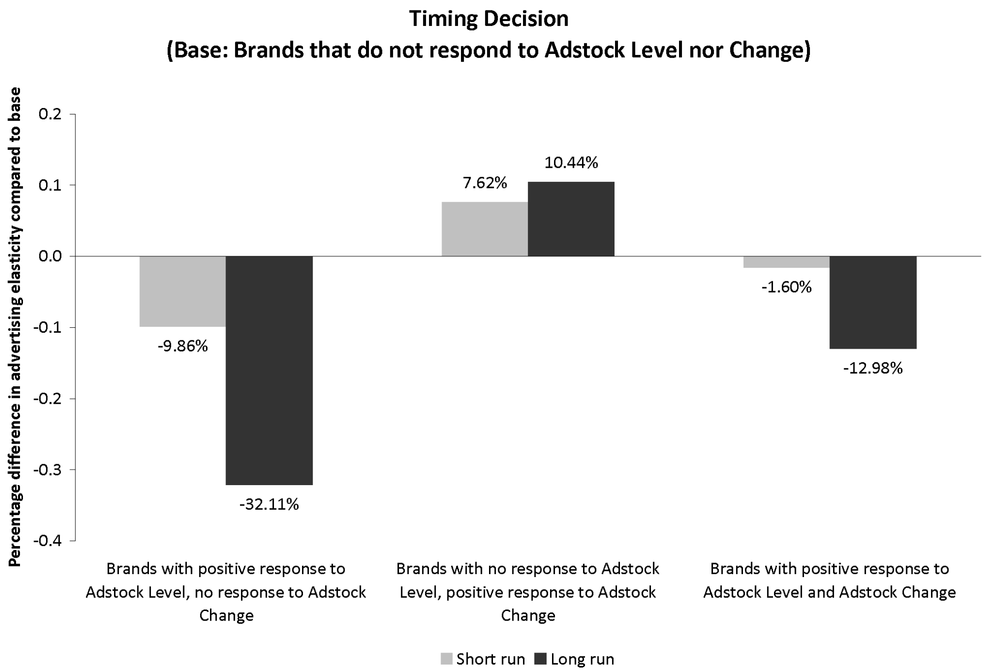
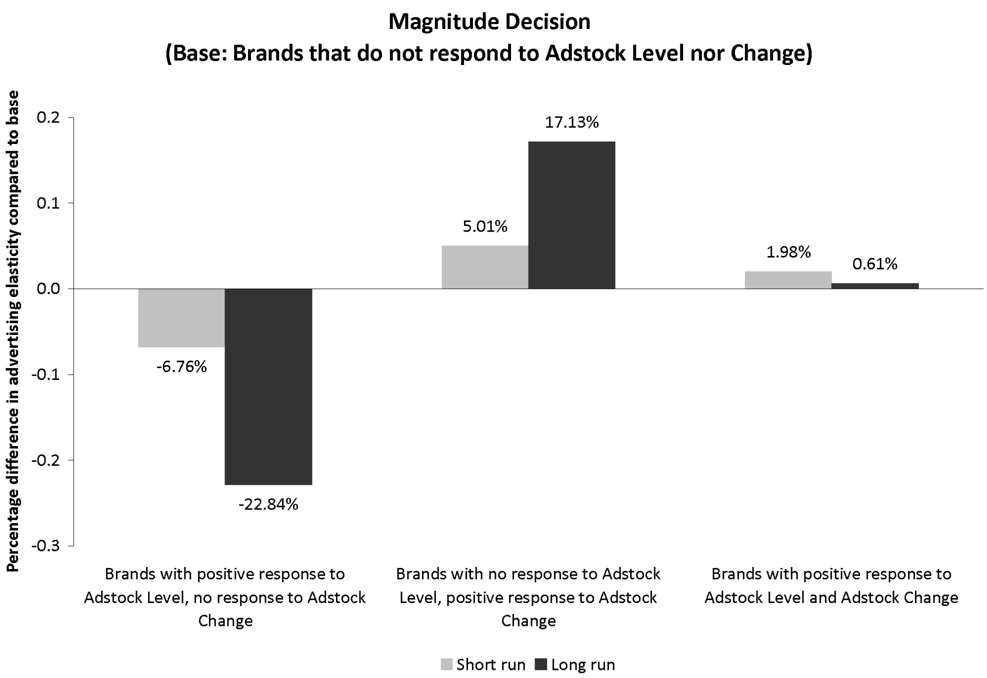


Figure 6. Difference in advertising effectiveness for brands relying on adstock level and/or change in magnitude decision compared to benchmark of no adstock reliance.



APPENDIX: OPERATIONALIZATION OF THE VARIABLES

Variable	Measurement
Adstock management	
Adstock Level	$Adstock_{cb,t} = (1-\lambda_{cb}) * \ln Advertising_{cb,t} + \lambda_{cb} Adstock_{cb,t-1}$
Adstock Change	$\Delta Adstock_{cb,t} = Adstock_{cb,t} - Adstock_{cb,t-1}$
Moderators	
Brand Market Share	Average volume share over the 156 week estimation period (cfr. Gatignon et al., 1990)
(Prior) Advertising Frequency	Percentage of time the brand was advertised during the 52 week initialization period
Company factors	
New Product Introduction	Dummy variable; 1 = if within four weeks after product introduction, 0 = otherwise
Performance Evolution	First difference of the log-transformed volume share of the brand over a moving window of previous 26 weeks (cfr. Franses and Koop, 1998)
End-Of-Year budget depletion	Dummy variable; 1 = if within last four weeks of the year, 0 = otherwise
Competitor factors	
Competitor Adstock Level	$CompetitorAdstock_{cb,t} = \sum_{i \neq b} \left(MarketShare_{ci,t} * Adstock_{ci,t} \right)$
Competitor Adstock Change	$\Delta CompetitorAdstock_{cb,t} = CompetitorAdstock_{cb,t} - CompetitorAdstock_{cb,t-1}$
Category factors	
Category Growth	First difference of the log-transformed category volume sales over a moving window of previous 26 weeks (cfr. Franses and Koop, 1998)
Category Concentration	Herfindahl index of volume shares of the brand over a moving window of previous 26 weeks