Dynamic and Competitive Effects of Direct Mailings

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ABSTRACT AND KEYWORDS	
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Dynamic and Competitive Effects of Direct Mailings*

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Abstract

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Keywords: Dynamics, competition, direct mailings

1 Introduction

The use of direct marketing (DM) has increased steadily over the past decades, with companies in the US spending more than 160 billion dollar on DM activities in 2005. From all direct marketing activities, direct mailings are the most important one, accounting for 31% of total expenditures in DM. Expenditures on DM have even been growing at a faster pace than sales (Direct Marketing Association 2005). This rise in DM activities can be easily linked to the increased focus on building customer relationships (e.g. Reinartz and Kumar 2003; Rust and Verhoef 2005) and to the development of advanced targeting tools (Ansari and Mela 2003; Bodapati and Gupta 2004; Kim et al. 2005), which enhance the performance of DM.

Most research describing response behavior to direct mailing activities has focused on a static single-firm context, neglecting potential competitive and long-term effects (e.g. Bult and Wansbeek 1995). However, when multiple companies send multiple communications to individuals, there is likely to be interference and the response to a given message will be affected by messages received previously (Greyser 1973). Only recently, attention has been paid to the dynamics of response behavior at the individual level (e.g. Ansari et al. 2006; Simester et al. 2005) and corresponding improved mailing strategies (e.g. Campbell et al. 2001; Elsner et al. 2004; Gönül and Shi 1998; Gönül and Ter Hofstede 2006; Simester et al. 2006). However, these studies focus on a single company, ignoring competitive activity. Thus, so far, the direct marketing literature has focused on, and shown the effects of, messages sent by the focal firm, while interference is equally likely to result from messages received from competing firms (Unnava and Sirdeshmukh 1994; Yoo and Mandhachitara 2003), analogous to own and cross price elasticities in market share models (c.f. Kamakura and Russell 1989).

The present study addresses the above two issues by analyzing the dynamic competitive interactions among direct mailings at the household level. We focus on direct mailings that elicit a direct response, such as catalogs, all kinds of promotional offers, and solicitation letters from charities, with the latter being the subject of our application. Our main goals can be summarized as follows:

1) Establish that competitive interactions exist among direct marketing communications.
2) Illustrate the dynamic behavior of these competitive interactions.
3) Develop a parsimonious model that still captures the potential richness of these competitive dynamics.

Few messages (mailings in our context) generally have a positive impact, while tedium or irritation may arise when too many mailings are received (Elliot and Speck 1998; Greyser 1973). Hence, in line with Berlyne's two-factor theory (Berlyne 1970) direct mailings might have both positive and negative primary demand effects.

Negative primary demand effects might arise when individuals get bored or even irritated by the large number of direct mails and consequently develop defensive strategies against the direct mailings (Diamond and Noble 2001). Note that the term junk mail suggests that at least some people get irritated by direct mailings. At the same time, each direct mail could trigger an order from the catalog or a donation to charity that otherwise would not have been made, thereby enlarging total sales. To summarize, it is not immediately clear whether a company's own direct mailings have a positive or a negative effect on its own revenues.

For a given company, one might expect negative effects of competitive mailings, certainly in markets where market expansion effects are limited. When direct mailings enhance total spending, the effect is not known. In our application concerning charitable giving, one could imagine each letter creating some feeling of guilt of not donating. A letter of one charity might increase guilt enough for the household to donate to a subsequent solicitation letter of another charity, and hence positive externalities could exist.

Besides the signs of the effects, the dynamics are also not obvious in advance. How does the passage of time affect the influence of past mailings on today's response behavior? An individual will be more aware of recent events than of events in the distant past, as people tend to forget things (Zielske 1959). To model this, we implement a Koyck model where past events receive less weight (see Ansari et al. (2006) for a recent application), so that the effect of an event decays over time.

The remainder of this paper is organized as follows. Section 2 provides an overview of the relevant theory. Section 3 presents our model and Section 4 discusses the empirical application to charitable organizations. Finally, Section 5 concludes the paper.

2 Background

In this section we describe the relevant background of our study. The number of direct mailings seems unabatedly on the rise. Sending direct mailings could increase awareness and liking and provides customers a direct purchase opportunity. However, some companies are starting to realize the negative effect these high mailing frequencies could have in the long run.

In a recent survey amongst practitioners in direct marketing, long-term effects of direct mailings and direct mail induced irritation were suggested as two important research avenues (Verhoef et al. 2003). Also, Campbell et al. (2001) present an example of a company that recognized the cannibalization that occurred between essentially redundant mailings. The consequences of this are even more serious, as target selection results in the best customers receiving the largest number of mailings. If this results in irritation, the company is harming the relationship with its best customers. Indeed, Simester et al. (2005) find that for the best customers, increasing mailing frequency results in a loss in revenues. The negative impact of additional mailings is likely the result of irritation and/or budget constraints, for which competitive interference may be an important driving force in addition to the firm's own mailings.

In this paper we investigate the role of competitive interference in dynamic response behavior to direct mailings.

2.1 Dynamic effects

The first dimension we describe is the dynamic feature of the direct mailing process. Although in many marketing science studies attention has been given to dynamics (think, for example, of the short-/long-term distinction in Mela et al. (1998), Pauwels et al. (2002) and Sloot et al. (2006)), the issue has not received much attention in the direct mailing literature. Traditionally, both academics and practitioners have focused on a static context, sidestepping potential long-term effects. An example can be found in target selection literature and practice where often a selection is made for a one-event mail-shot without recognizing the overall effect on individuals (Kestnbaum et al. 1998). However, as people tend to (partially) remember past events and incorporate their memories into an overall attitude which may influence current decisions, omitting dynamics will generally lead to unreliable results and suboptimal choices. A direct mailing organization has to bear in mind that the decision to mail an individual today does influence the probability of response to future mailings (Campbell et al. 2001; Piersma and Jonker 2004). When we focus on the dynamics, we make a distinction between the promotion history and the purchase history of individuals, as has also been done by Elsner et al. (2004), for example.

Promotion history

We start with describing the relevance of the promotion history of an individual – and, accordingly, of the timing of mailings by a direct mailing company. Campbell et al. (2001) note that, in particular for the direct mailing context, timing next to content is an important factor in the saturation effect between two mailings. The more time between two mailings, the smaller is the saturative impact (Campbell et al. 2001). Also, Bult et al. (1997) suggest that the sequencing of direct mailings is an important issue.

Although a recent stream of research has acknowledged the importance of the appropriate number and timing of mailings for individuals over a long-term horizon (e.g. Elsner et al. 2004; Gönül and Shi 1998; Gönül and Ter Hofstede 2006; Piersma and Jonker 2004), the exact long-term effect of a company's direct mailings on revenues is not immediately clear.

On the positive side, repeated advertising exposures can lead to familiarity and liking of a company and can prevent forgetting over time (Naik and Piersma 2002, among others). Direct mailings can thus serve as a reinforcement of the message. Furthermore, sending many mailings could minimize the probability that an individual does not read the mailing because it gets lost in the mail or s/he is simply not interested. Also, each direct mail could trigger an order from the catalog or a donation to a charity, for example, that would otherwise not have been made, thereby enlarging total revenues.

Direct mailings may also have a negative long-run effect. For example, individuals might get bored or even irritated by the large number of direct mails and consequently develop defensive strategies against direct mailings (Diamond and Noble 2001). Elliott and Speck (1998) show that excessive direct mailing clutter can lead to a negative attitude, such as irritation, which reduces effectiveness of the mailings (see also Naik and Piersma (2002)). Causes could include that, due to the large stack of direct mailings, regular mail may easily be overlooked (Elliott and Speck 1998) or that individuals do not like being confronted with an appeal (in the case of soliciting mails of charities, see Diamond and Noble (2001)).

Finally, besides the direction of the direct mailing effect, also its shape is not straightforward as its effect may not be linear. In this respect, the dynamic response phenomena of buildup, wearout and decay from the advertising policy literature are particularly relevant. In short, buildup means that each promotion in the past contributes to the overall goodwill, or positive attitude towards the promotions. Wearout refers to the diminishing returns to scale of repetitive promotions, meaning that the effectiveness of each additional exposure is smaller than earlier exposures in case of continuous promotions (Little and Lodish 1969; Naik et al. 1998). Finally, decay represents the degree of forgetting when promotions are absent (Little and Lodish 1969; Naik et al. 1998). These decay effects have been found to be positive but diminishing over time (Bronnenberg 1998). However, almost all of these studies analyze effectiveness of advertising using measures like advertising awareness, brand name recall or brand attitudes. In contrast, we will focus on revenues as a measure of advertising effectiveness, which is known to be more reliable than stated preference data. To summarize, mailing frequency effects may be non-linear, could be positive or negative, and most likely decline with the passage of time.

Purchase history

We now describe the relevance of the purchase history of an individual in his/her response to direct mailings. From the state-dependence literature we know that past purchase behavior influences today's purchase behavior (e.g. Seetharaman and

Chintagunta 1998; Seetharaman et al. 1999). Indeed, it is well known that past behavior is a very good predictor of future behavior (Bult and Wansbeek 1995; Rossi et al. 1996). Many studies, investigating the effects of individuals' current choices on their future choices, have demonstrated the existence of both positive and negative state dependences.

Positive state dependence, or inertia, arises if an individual routinizes his/her purchases. In the case of direct mailings this could mean, for example, that the fact that an individual has purchased from a certain organization in the past has a positive influence on the current probability of purchasing from that company. Or, the more purchases in the past, the higher is the probability of purchase today, thereby capturing loyalty effects.

Negative state dependence, or variety seeking, arises if an individual satiates himself/herself with a brand / company, so that a purchase at a company in the past has a negative influence on the probability of purchase today. For example, an individual gets tired of ordering from the same direct mailing organization and hence decides to try a different one. Another negative purchase history effect might be due to budget restrictions. If an individual has already spent a lot, then s/he may not have much money left to spend, which could reduce the current amount. This phenomenon can be viewed as cannibalization.

We can conclude that purchase decisions in the past partially determine an individual's decision process today, although the sign of the effect is not clear a priori. Furthermore, state dependence is also subject to decay. Because of forgetting, a state-dependence effect can diminish, so that an individual does not exhibit the same level of state dependence over time (Ansari et al. 2006; Chintagunta 1998; Seetharaman et al. 1999). For example, if an amount was spent long ago it is likely that the individual now has some budget to spend again. Also, the then purchased product might now be out of fashion or in need of replacement due to usage. Indeed, although not always under this denomination, several studies acknowledge that variables covering more recent time periods (say, last week) may be more relevant predictors than variables covering the more distant past (say, past six months) (see Baesens et al. (2002) and Buckinx and Van den Poel (2005) for example).

Finally, as an example of non-linear effects of purchase history, we mention the situations of either a very recent or a very distant last response. In the first situation, an individual might be unwilling to respond again, while in the latter situation the individual might have lost interest. In both cases response behavior might be lower than in the case of a response in between. In sum, to understand responses to direct mailings, time matters and dynamics should be included in a model of response behavior.

2.2 Competitive effects

Although some studies do incorporate dynamics by acknowledging the importance of the total number and timing of mailings over a long-term horizon instead of focusing on a single mailing context, there is yet another dimension that is almost always overlooked, which is competitive effects. All researchers would agree that competitive effects are highly relevant to include in models, but mostly the lack of data has prevented the possibility of extensive research in this area. A company may have information on its own sales, but it generally has no insights into purchases from competitors or into the individuals' choice and consideration sets. This problem has frequently been acknowledged, for example by Allenby et al. (1999), and it has also often been brought up as either a limitation or as a further research suggestion (Gönül and Shi 1998; Naik et al. 1998).

Although much research has been devoted to the study of competitive interference on memory and brand evaluations (D'Souza and Rao 1995; Keller 1991), little is known about its effects on consumer behavior in general, and on responses to direct mailings in particular. Some studies do present little pieces of information, which at the least emphasize the importance of thorough research on competitive interactions in the direct mailing field. For example, Dwyer (1997) concludes that people typically divide their purchases across a number of competing organizations. For a comprehensive picture of direct mail response competition this is relevant, as many people likely receive mailings of multiple organizations. Furthermore, it is generally believed that own and cross effects, that is effects of a company's own actions vs. its competitors', differ and are thus of importance separately.

Looking at dynamic competitive effects, the promotion and purchase history distinction can again be applied. Regarding the competitive promotion history, several studies have shown that competitive interference can severely undermine the effectiveness of marketing actions (Unnava and Sirdeshmukh 1994). Therefore, one would generally expect negative competitive effects. An explanation can be found in the advertising clutter theory, where high mailing frequencies may lead to irritation and market shrinkage. On the other hand, there may be situations where positive competitive externalities exist. Examples are new products, where competitive advertising may increase awareness thereby enhancing total sales (Prins and Verhoef 2006), new attribute promotion, where competitive advertising may help remember old attributes thereby better distinguishing the new ones (Jewell and Unnava 2003) and charitable solicitations, where competitive advertising may increase guilt of not donating thereby increasing response probabilities (for the guilt motivation for donating, see Andreoni (1990) and Sargeant (1999) for example).

Regarding the competitive purchase history, the same phenomena arise as with the company's own purchase history. For example, the budget restriction implies that an individual who has just spent a lot, probably has not much left to spend now. Finally, also competitive effects are not necessarily linear. In sum, to understand one' own effectiveness in direct mailing, one needs to know what competitors do and what they have done.

2.3 The RFM framework

A well-known framework for describing purchase and promotion history that enables the incorporation of dynamic competitive effects into a mailing response model is the RFM framework. In marketing it is difficult to find variables more pervasive than the Recency, Frequency and Monetary value variables. Multiple variations have been proposed in each category. Examples are the number of time periods since the last purchase was made or an indicator for response to the last mailing for Recency, the number of purchases in the past or the fraction of mailings the individual responded to for Frequency, the total amount spent in the past or the average amount spent per purchase for Monetary value.

An important advantage of these variables is that they are often available at a low cost, as many companies keep track of their customers' purchase histories in databases (Rossi et al. 1996). Also, they have proven to be very effective behavioral predictors and are often the only type of data available (Donkers et al. 2006).

Many studies on a wide range of topics have used this RFM framework, if not in its original form then in a related format. Whereas the original RFM method boiled down to a straightforward (although rather subjective) customer classification, the literature now employs the RFM variables mostly as independent variables in modeling future response probability using regression methods (Colombo and Jiang 1999). Topics of studies exploiting RFM variables include optimal target selection (Colombo and Jiang 1999), mail order repeat purchasing (Baesens et al. 2002) and partial customer defection (Buckinx and Van den Poel 2005). Also, the RFM framework is frequently used by practitioners in segmentation, target selection and resource allocation (Reinartz and Kumar 2000; Verhoef et al. 2003).

The fact that firms generally assign the least importance to Frequency (Reinartz and Kumar 2000) is another indication that dynamics are indeed undervalued. They often focus on how recent the last purchase was made. We believe that this is a rather static approach that ignores the development of a customer-company relationship over time.

Sure enough, RFM variables are the best candidates for describing past events and in this way adding dynamics to a model. We will apply the framework's basic principles to describe both an individual's purchase and promotion history. In the next section, we will turn to our implementation of both dynamics and competition in a direct mailing response model, where we also address unobserved heterogeneity across individuals.

3 The model

In this section we present our model of individual response behavior to direct mailings of competing companies. Based on the well-known RFM framework, we assume that a response decision depends on purchase history and on promotion history. As described in the previous section, purchase history refers to what the individual has done in the past and promotion history refers to what the direct mailing organizations have done in the past (Elsner et al. 2004).

The key elements of our model originate from the following assumptions. In a given time period, an individual receives a number of direct mailings. For each receipt, the individual decides whether s/he will respond or not and if so, with what amount. These two variables constitute our dependent variables. We consider the prototypical individual who, upon receiving a direct mailing, instantly makes the response decision (see also Colombo and Jiang (1999)). The decision made is thus a response/non-response decision to a particular mailing, and not a choice between companies. Note that we assume that two mailings do not arrive at the very same time. As always, individuals are likely to vary in their response behavior. We mention loyal and variety-seeking individuals, who would react quite differently to an impulse. We accommodate for this by incorporating heterogeneity, that is, individual-specific parameters, thereby better capturing the true but unknown underlying decision processes.

3.1 Explanatory variables

Let $\tau=1,\ldots,T_i$ indicate the mailing events for individual *i*. As each individual receives a different number of mailings over time, the number of observations per individual varies and hence the data constitute an unbalanced panel. As described above, we relate the response decision at a mailing event τ to both promotion history variables and purchase history variables. More specifically, we expect this decision to depend on mailing actions from all companies in the past and all (or most) of the individual's past response behavior. For example, if an individual receives a mailing from a company today, then not only do all mailings from this company in the past count in the decision to respond today, but also do all mailings from the competition. Note that it is likely that past mailings from the company that sent today's mailing affect today's decision differently than mailings from other companies. To differentiate between such effects, we will make a distinction between own effects and cross effects. Below we will describe and motivate our explanatory variables in more detail.

Promotion history: mailings in the past

We include promotion history variables in our model as we expect that the extent to which an individual has been approached with direct mailings in the past influences the response decision today. Although they are usually used to describe purchase history, RFM variables also constitute the basis of our promotion history variables. However, as Monetary value is not applicable for the company's mailing decisions, we only take into account Recency and Frequency of mailings.

We expect that the response decision today is influenced by every mailing in the past, although it is likely that the effect is larger the more recent the mailing, as people tend to forget past events over time. In other words, the effect of a mailing is diminishing over time. Now, let the calendar time of mailing event τ for individual i be $t_{i\tau}$. Then $\Delta t_{is\tau} = t_{i\tau} - t_{is}$ denotes the number of time periods elapsed between mailing event s and τ. Hence, $\Delta t_{is\tau}$ constitutes a measure of the recency of mailing s at the time mailing τ is received. Then, instead of simply counting the number of direct mailings received in the past, which tends to grow over time and results in non-stationarity, we combine Frequency of mailings with Recency to create a single explanatory mailing variable. To account for the effects of forgetting we apply a multivariate finite duration adjustment of the geometric lag, or Koyck, model with unequally spaced observations, similar to Ansari et al. (2006). Using exponential decay dynamics with decay parameter λ_m the (discounted) number of mailings is given by:

$$mailings_{i\tau}^{c} = \sum_{s=1}^{\tau-1} \lambda_m^{\Delta t_{is\tau}} mail_{is\tau}^{c} \text{ with } c \in \{own, other\} \tag{1}$$

In (1), we sum over all mailing events before mailing event τ. Furthermore, as we expect different own and competitive effects, we distinguish between mailings of the company that sends the mailing at event τ and mailings from the competition. Thus, $mail_{is\tau}^{own}$ is a dummy variable that indicates that the mailing individual i received at mailing event s was sent by the same company as the mailing at event τ, while $mail_{is\tau}^{other}$ indicates that it was sent by a competing company.

To ensure that the effect of a mailing is diminishing over time the decay parameter λ_m must be in the interval (0,1). Then, the longer ago individual i received mailing s, the smaller will be the contribution of this mailing to the variable at time τ, which corresponds to forgetting. To achieve this, we specify the decay parameter λ_m as:

$$\lambda_m = \frac{\exp(\varphi_m)}{1+\exp(\varphi_m)} \tag{2}$$

The advantage of this approach is that it nullifies the initial conditions problem that inextricably goes with summing over all events in the past. That is, the longer the time period over which you calculate the total number of mailings, the larger it will be if every mailing counts without decay; this variable will explode over time. Through the decay parameter, the effect of mailings long ago will be negligible[1] so that the variable stabilizes if the time period is long enough, hence avoiding non-stationarity and the corresponding estimation problems.

We have no expectations concerning the effect of $mailings_{i\tau}^{c}$, as past research implies that it could go both ways. For example, competitive effects will generally be negative, but there could be some exceptions, such as new products (see Prins and Verhoef 2006) and charity organizations (because of increased guilt).

Furthermore, as the effect of the number of marketing communications need not be linear, we also include it quadratically in our model. In this way we allow for negative effects of very high and very low frequencies of mailings, which both seem plausible.

Purchase history: past response behavior

We include purchase history variables in our model as it is well known that past behavior is the best predictor for future behavior (Bult and Wansbeek 1995; Rossi et al. 1996). Again, RFM variables constitute the basis of our variables. We distinguish between own and competitive past behavior variables as the own and cross effects on response to the current mailing most likely differ.

Our first purchase history variable is a Frequency measure of response, namely a discounted version of the well-known response rate. As a response rate reflects the overall tendency to respond, it is related to the attitude an individual has towards a company. For example, if the response rate was high in the past, then it is likely to be high in the future, so that we expect this variable to have a positive influence on the probability of response, capturing an individual's general attitude and possible loyalty effects.

Instead of the commonly used response rate, we apply a weighted average of responses, placing more weight on recent events. Again, based on the Koyck structure, the weights are an exponential function of recency and the decay rate λ_r, to reflect the diminishing effect of past responses over time. Hence, as a Frequency measure for purchase history we use

$$response_{i\tau}^{c} = \frac{\sum_{s=1}^{\tau-1} \lambda_r^{\Delta t_{is\tau}} R_{is}\, mail_{is\tau}^{c}}{\sum_{s=1}^{\tau-1} \lambda_r^{\Delta t_{is\tau}}\, mail_{is\tau}^{c}} \quad \text{with } c \in \{own, other\} \tag{3}$$

In (3), R_{is} is a dummy variable that indicates if individual i responded to mailing s. Thus, we average over all mailing events before mailing event τ to obtain the weighted past response rate to either the mailing company itself ($mail_{is\tau}^{own}=1$) or to the competition ($mail_{is\tau}^{other}=1$).

Our second purchase history variable measures the Recency of responses, while at the same time accounting for their frequency. We use a discounted version of the number of responses in the past, either to the mailing company or to the competition, where again we use exponential discounting by recency to reflect that the effect of a response diminishes over time due to forgetting. Note that it might be important to also include responses before the last response, in particular for competitive mailings. It could well be that an individual responded twice, to different competitors, in a very short period and both events still affect today's response behavior.

$$response\_recency_{i\tau}^{c} = \sum_{s=1}^{\tau-1} \lambda_r^{\Delta t_{is\tau}} R_{is}\, mail_{is\tau}^{c} \quad \text{with } c \in \{own, other\} \tag{4}$$

To explain why we consider this a Recency measure we note the following. Conditional on the individual's general response tendency, captured by $response_{i\tau}^{c}$, this term is small if the last response was long ago, as the variable diminishes over time through the decay parameter when no new response is added. Furthermore, if the last response was very recent, this term is large. Thus, a high value of the Recency variable implies a very recent last response, whereas a low value implies a last response long ago. For the decay parameter λ_r we adopt the same formulation as for λ_m, although with its own parameter φ_r, and similarly for λ_a, which is used to discount the amounts of money spent, see (5) and (6) below.

There could be a non-linear effect of recency on current response behavior. For example, if an individual just responded this may strongly reduce the probability to respond again. Furthermore, if an individual has not responded in a very long time, there is a chance s/he has lapsed in the sense that s/he stopped being a customer with the company. To allow for such non-linear effects of Recency, we also include it quadratically in the final model below.

Finally, we present our Monetary value measures for purchase history. The first variable is the weighted average past amount. Although the effect on today's decision of an amount in the past decreases over time, the amount an individual spends at each purchase is often of the same order of magnitude. Thus, the level of the present amount is best explained (and predicted) by the weighted average amount in the past, where we again use an exponential function of recency and the decay rate as weights.

Furthermore, as average past spending is related to the attitude towards a company this variable will also capture loyalty effects.

Now, let A_{is} be the natural logarithm of the amount spent in response to mailing s, if a purchase is made, and zero otherwise. With the remaining variables defined as above, we model the (weighted) average natural logarithm of the amount spent with either the mailing company itself or with the competition as:

$$amount_{i\tau}^{c} = \frac{\sum_{s=1}^{\tau-1} \lambda_a^{\Delta t_{is\tau}} A_{is} mail_{is\tau}^{c}}{\sum_{s=1}^{\tau-1} \lambda_a^{\Delta t_{is\tau}} R_{is} mail_{is\tau}^{c}} \text{ with } c \in \{own, other\} \tag{5}$$

In (5), we average over all mailing events before mailing event τ to which individual i actually responded ($R_{is}=1$) to obtain the weighted average past amount[2] for either the mailing company itself ($mail_{is\tau}^{own}=1$) or the competition ($mail_{is\tau}^{other}=1$). Note that this formulation can approximate both the unweighted average (for $\lambda_a \uparrow 1$) and the last amount spent (for $\lambda_a \downarrow 0$), which are two other frequently used Monetary value measures.

Our second Monetary value measure is the total discounted amount in the past, either for the mailing company itself or for the competition, where each amount is discounted by its recency. This variable mimics the effects of budget restrictions, in the sense that if an individual has already spent much (either at the mailing company or at the competition), so that this variable is large, then s/he may not have much money left to spend, which could reduce the current amount. Furthermore, conditional on the average amount spent in (5), a low value indicates that the last amount has been spent long ago and it is likely that the individual now has some budget to spend again. Also, if the last amount has been spent long ago, the product then purchased might now be out of fashion or in need of replacement due to usage. Thus, our final explanatory variable is:

$$amounts\_recency_{i\tau}^{c} = \sum_{s=1}^{\tau-1} \lambda_a^{\Delta t_{is\tau}} A_{is} mail_{is\tau}^{c} \text{ with } c \in \{own, other\} \tag{6}$$

The classification of our explanatory variables is summarized in Table 1.

Insert Table 1

3.2 Direct mailing response model

We model the individual response decision at mailing event τ using a Tobit-II specification (Amemiya 1985, p.385). Thus, we assume that the individual jointly decides whether to respond or not and if so, with what amount. Although modeling both response and amount may seem like a logical step, in the direct mailing literature the focus is mostly on modeling response incidence only (Gönül and Ter Hofstede 2006).

In our explanatory variables we used R_{is} and A_{is} for $s=1,\ldots,\tau-1$, so that at mailing event τ the explanatory variables contain only lagged information. Now, let $R_{i\tau}$ indicate whether individual i responds at mailing event τ or not. Furthermore, $A_{i\tau}$ indicates the natural logarithm of the amount individual i spends at mailing event τ conditional on the decision to respond. Let $R^*_{i\tau}$ be the latent variable related to $R_{i\tau}$ and $A^*_{i\tau}$ the censored variable related to $A_{i\tau}$, where 'censored' means partially observed and partially latent. Note that we take the natural logarithm of the amount to ensure positive amount predictions. Then the Tobit-II model reads as:

$$R_{i\tau} = \begin{cases} 1 & \text{if } R^*_{i\tau} > 0 \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

$$A_{i\tau} = \begin{cases} A^*_{i\tau} & \text{if } R^*_{i\tau} > 0 \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

with

$$\begin{aligned} R^*_{i\tau} = \beta_{R0i} &+ \sum_{c\in C} \beta^c_{R1i} mailings^c_{i\tau} + \sum_{c\in C} \beta^c_{R2i} mailings^{c\,2}_{i\tau} + \\ &\sum_{c\in C} \beta^c_{R3i} response^c_{i\tau} + \\ &\sum_{c\in C} \beta^c_{R4i} response\_recency^c_{i\tau} + \sum_{c\in C} \beta^c_{R5i} response\_recency^{c\,2}_{i\tau} + \\ &\sum_{c\in C} \beta^c_{R6i} amount^c_{i\tau} + \sum_{c\in C} \beta^c_{R7i} amount\_recency^c_{i\tau} + \varepsilon_{Ri\tau} \end{aligned} \tag{9}$$

and

$$\begin{aligned} A^*_{i\tau} = \beta_{A0i} &+ \sum_{c\in C} \beta^c_{A1i} mailings^c_{i\tau} + \sum_{c\in C} \beta^c_{A2i} mailings^{c\,2}_{i\tau} + \\ &\sum_{c\in C} \beta^c_{A3i} response^c_{i\tau} + \\ &\sum_{c\in C} \beta^c_{A4i} response\_recency^c_{i\tau} + \sum_{c\in C} \beta^c_{A5i} response\_recency^{c\,2}_{i\tau} + \\ &\sum_{c\in C} \beta^c_{A6i} amount^c_{i\tau} + \sum_{c\in C} \beta^c_{A7i} amount\_recency^c_{i\tau} + \varepsilon_{Ai\tau} \end{aligned} \tag{10}$$

with $C = \{own, other\}$ and where $\varepsilon_{Ri\tau}$ and $\varepsilon_{Ai\tau}$ represent unobserved factors that influence the response decision and amount, respectively. Furthermore, $(\varepsilon_{Ri\tau}, \varepsilon_{Ai\tau}) \sim N(0, \Sigma_\varepsilon)$ with the restriction that $\Sigma_{\varepsilon,11}=1$ for identification of the response equation. Note that through the decay parameters the effects of the explanatory variables change over time. The subscripts R and A indicate that the parameters are equation-specific, as opposed to the lower case subscripts r and a for the decay parameters, that indicate variable-specificity.

Thus, as the parameters can be different for the response and amount equation, not all explanatory variables have to be equally relevant for the two dependents. Previous studies have established that decisions on whether or not to donate may be influenced differently by the same variables than decisions on how much to donate (see Smith et al. 1994 amongst others). For example, it has been found that past amounts have little explanatory power in the response equation, but are highly relevant in the amount equation (Donkers et al. 2006; Piersma and Jonker 2004)[3].

Unobserved heterogeneity

We specify individual-specific random effects for model intercepts, mailing and past behavior variables, so that individual-specific inferences can be made. All random effects may be correlated both within and across equations. We use Bayesian methods, where we model unobserved heterogeneity with a multivariate normal distribution. We apply MCMC techniques to obtain draws from the posterior distributions of the parameters and thus estimate the model. Further sampling details, such as prior and full conditional distributions, are described in the appendix.

4 Dynamic and competitive effects for charities

In this section we apply our model to donating behavior to charities, where we first describe our dataset and then present our results. We estimate our model in the charitable giving setting, as direct mailing forms an important part of charitable fundraising activity. Furthermore, as people often receive many soliciting mailings of various charities in a short period of time, this is also a setting where competition is indeed highly relevant.

4.1 Data

For this research we have a unique dataset at our disposal, consisting of the databases of three large charity organizations in the Netherlands that are active in the health sector. In these databases, the charities track their donators by recording who gave what and when. This means we have revealed preference data, that is, we have individual records of actual response behavior to competing organizations, which enable investigation of donating to multiple charities and hence competitive interactions between different charities.

The relevant information that is generally available for each individual in the database of a particular charity organization includes the following:

- name of the respondent
- complete address of the respondent
- for each soliciting mailing that was sent:

- date of the mailing
- if the individual responded: date of response
- if the individual responded: amount donated

Using the name and address data, we connect the three databases so that we can track for each individual when s/he received a mailing from one of the three charities and his/her exact response behavior towards these competing organizations.

We have 3½ years of data at our disposal on donations to three health charities, say charity 1, 2 and 3. The data period is January 2002 – June 2005. From the millions of individuals in the database we randomly select 2500 individuals, where we restrict attention to those that are mailed by multiple charities during the data period, to really focus on the competition aspect (see Kamakura and Russell 1989 for a similar approach). For the smallest charity, 57% of all individuals in the database are also being mailed by at least one of the other two charities and 23% by both. For the largest charity, the percentages are 23% and 3%.

For each individual in our sample we use as a start-up period one year after the first date each charity that mails him/her during the data period has sent a mailing. Thus, suppose an individual receives mailings from charity 1 and 2 in our period, where the first mailing of charity 1 is on January 20th 2002 and the first mailing of charity 2 on February 1st 2002. Then his/her start-up period is February 1st 2002 - January 31st 2003. The individual start-up period enables us to calculate reasonable initial values of the explanatory variables. The remainder of the data is used as the estimation period. Note that we only consider individuals who are active in the estimation period, where active is defined as being mailed at least once.

In our sample, 2220 individuals have received mailings from two charities during our time span, and 280 of three charities. Furthermore, 2163 individuals receive mailings from charity 1, 2421 from charity 2 and 695 from charity 3. These numbers are roughly proportional to the actual numbers of donators in the databases of the three charities, and are thus representative for the relative charity magnitudes. See Table 2 for some descriptives of the data. Here averages are taken over the whole sample, explaining the low values for the smallest charity (charity 3).

Insert Table 2

For example, we can deduce that at an overall response rate of 0.19, people on average respond to about one out of five mailings, although this varies somewhat across charities. This may seem high for direct mailings but is actually a reasonable response rate for the charity industry[4]. Furthermore, our observation period of 3.5 years contains over 75000 mailing events in total.

To get a better picture of what the data look like, Figure 1 depicts a possible scenario for an individual that receives mailings from all three charities. In the start-up period s/he received eight direct mailings, three of which s/he responded to. In the estimation period s/he donated twice out of the eight mailing events.

Insert Figure 1

As appears from Figure 1 and from the model described in the previous section, we assign each mailing event to a single date, while in practice we may have both a mailing and a response date. We chose to consider the mailing date as the mailing event date in the model, as we assumed an individual instantly makes the response decision upon receiving a mailing. Thus, as only the information known at that time can be taken into account in the response decision, we feel this should also be the only input in the explanatory variables. Furthermore, over 50 percent of the responses to a direct mailing were made within a week of the mailing date. Finally, varying the implementation of the mailing event date did not lead to qualitatively different results.

4.2 Results

To investigate the effects of mailing actions and the competitive interactions between charity 1, 2 and 3, we estimate the model described in Section 3, by applying MCMC techniques to obtain draws from the posterior distributions of the parameters.

Estimation results

Using the Gibbs sampling technique of Geman and Geman (1984) we estimate our model, where we use 40000 iterations as burn-in. After the chain has converged, we retain every tenth iteration of the next 40000 iterations to obtain an approximately random sample from the posterior distribution. Our posterior results are based on the resulting 4000 draws.

In Table 3 we present the posterior means of the effects of our variables in both the response and the amount equation, where posterior standard deviations are in parentheses. Below we will discuss the parameter estimates for the various types of variables.

Insert Table 3

Mailing variables

The effect of *mailings* on response to a future mailing of the same charity is significantly negative. Thus, each extra mailing a charity sends to an individual negatively affects the probability that this individual will respond to future mailings, possibly reflecting direct mailing irritation. For own mailings, we do not find evidence for a non-linear relationship of response incidence and mailing frequency, as the *square of mailings* is not significant.

For competitive mailings a non-linear relationship with response incidence is found. As the effect of mailings is significantly positive and the effect of square of mailings is significantly negative, small (discounted) numbers of competitive mailings have a positive effect but larger (discounted) numbers have a negative effect, suggesting irritation caused by too many mailings. Thus, it seems that a little competition can be reinforcing, but too much may be detrimental. However, as the decay parameter for mailings is small, it may be the case that for most events in our dataset the past discounted number of mailings is relatively small, so that an extra mailing will have a positive overall effect. To gain more insight, we therefore study whether the marginal effect of an extra mailing, which arises from the linear and quadratic term, is positive or negative for the actual mailing events in our data, ceteris paribus. For around two thirds of the cases we find a negative effect of an extra mailing. Or, in around two thirds of the cases too many competitive mailings are received.

We find similar results for the effects of mailings on the amount donated on subsequent donating occasions. Additionally, we find a non-linear effect of own mailings. The higher the (discounted) number of mailings, the stronger is the negative effect of an extra mailing on future donated amounts.

Response variables

The variable *response* reflects an exponentially weighted version of the response rate and has a positive effect on response, both to own and competitive mailing events. The own effect captures loyalty effects towards the charity. That is, if an individual has frequently donated to a certain charity in the past, this increases the probability that s/he will donate again. Furthermore, the competitive effect indicates a general positive attitude towards charitable donating. That is, if an individual has frequently donated to other competing charities in the past, this reflects a positive attitude towards charitable donating and increases the probability of response to this charity in the future. As all three charities in our data are from the health category, the cross effect reflects that individuals who frequently donate to one health charity are also more likely to donate to other health charities and thereby spread their donations over different health causes.

For the amount equation, only the own effect is significant. This positive effect indicates that individuals with high response rates at a charity also tend to donate larger amounts to this charity, again capturing loyalty effects.

For recency of response, we find both a significant main effect and a significant quadratic effect on response incidence. Hence, the effect of *response recency* is non-linear, in line with our expectations. More specifically, for both own and competitive responses, we find that very low and very high recency values decrease the probability of response, while intermediate values have a positive effect. Thus, if an individual just responded it is unlikely s/he will respond again, but if the last response has been very long ago, s/he may have lapsed in that s/he has stopped being a donator to the charity.

Regarding the effect of response recency on amount, we find that recency decreases the amount donated. Thus, an individual that has recently donated, or has donated frequently in the past, will donate a lower amount to the current mailing, although this effect is somewhat weakened by the positive quadratic term. Although we did not anticipate it, this effect corresponds to a budget restriction, in that individuals that have recently or frequently donated do not have budget left to donate a large amount now.

Amount variables

For the response equation, we find both own and competitive effects of the amount variables, although in opposite directions. The variable own *amount*, reflecting the weighted average past donation, has a positive effect on future response. This finding again suggests a positive attitude towards the charity and possibly loyalty. Thus, the higher the past donations to a certain charity, the higher the probability this individual will donate again. On the other hand, the variable competitive amount has a negative effect on future response, so that the higher the past donations to the competition, the lower the probability the individual will donate to this charity, suggesting loyalty towards the competition.

For the amount equation, we find both positive own and positive competitive effects. Particularly the own-effect is quite substantial, which one would expect as donation sizes tend to be rather stable over time. The competitive effect indicates that the higher the average donation at competitors of this charity, the higher the donated amount will be, suggesting a certain general generosity.

Next, we find a negative own effect of *amount recency* on response incidence, which we can interpret as a budget restriction. If an individual has recently donated money to a charity or has already donated a lot, s/he may not have budget left to donate to this charity again. The negative competitive effect of amount recency has a similar interpretation.

Finally, contrary to our expectations, both the own and competitive amount recency variables have a significant positive effect on amount donated. However, this effect cannot be completely separated from the response recency effect. After all, if one just responded than one just made a donation and vice versa. On average the positive amount recency effect does not compensate the negative effect of response recency, so that the recency effect overall does seem to reflect a budget restriction.

Decay parameters

Next, we consider the decay parameters for mailings, responses and amounts. Through the decay parameter the effect of, for example, a mailing varies over time. Although the decay parameter for mailings λ_m may seem very small at first sight, we have to keep in mind that these estimates are per year. Thus, if we consider for example the weekly and monthly decay rates for mailings we find that they are still 0.84 and 0.48, respectively. Hence, a mailing is half forgotten after a month. An alternative interpretation is that ten mailings only feel like five mailings a month later. Nonetheless, after a year a direct mailing is almost completely forgotten and its effect is negligible.

Past response behavior is much more persistent than past mailings however, as after a year both a past response and a past amount are still in people's memory for about one third, according to the model parameters. Or, after a year, the effect of a response or amount has decreased to about one third of the instantaneous effect.

Heterogeneity

Up till now we have discussed the effects at the posterior means of the parameter values. However, there is heterogeneity across individuals. In Table 4 we present the posterior mean of the variance in the random effects for the various model variables, indicating the spread in effects across individuals.

Insert Table 4

As the random effects may be highly dispersed, the story may be quite different for some individuals than for others. For example, the competitive effect of *response* on amount is not significant at the population level at a posterior mean of -0.011, but the 95% credible interval for the random effects that excludes 2.5% of the lowest and 2.5% of the highest individual parameter estimates, ranges from -0.26 to 0.13. Thus, on the one hand, the competitive response rate has a substantial negative effect on amount donated for some individuals, possibly indicating that people who frequently donate to multiple charities donate smaller amounts, because they spread their budget over various charities or various mailings. On the other hand, the competitive response rate increases the donated amount to future mailings for other individuals, for example reflecting a positive attitude towards charitable donating in general.

As an other example, although the quadratic effect of own mailings on response are not significant at the population level, they do have a negative quadratic effect for many donators, that is 87%. The 95% credible interval for random effects is [-0.23, 0.07] and for around 30% of the individuals the effect is even smaller than -0.1.

The effect of an extra mailing

Even though the separate posterior mean effects are quite clear-cut and straightforward to interpret, the explanatory variables are all interrelated and non-linear in the decay parameters and therefore their overall effect on response to a mailing is not immediately apparent. For example, although a higher number of mailings in the past tends to lower today's response probability to the same charity, it is reasonable to assume that a higher number of past mailings is related to a higher number of past responses (Elsner et al. 2004), which in turn increases the probability of response to a mailing today. Furthermore, as we allow for heterogeneity in parameters in our model, there may be certain patterns in response behavior that cannot be identified based on these population-averaged estimates alone. Thus, to get a clear view of all dynamic effects, we simulate impulse response functions (IRF's), which track the consequences of one extra mailing, the impulse, for response and amount on subsequent mailing events.

For a certain individual, averaging over impulses on different moments in time would result in an approximation of the effect of an extra mailing. However, choosing the impulse dates randomly would not be realistic, as not every point in time is a plausible candidate for sending an extra mailing. For example, charities would never (intentionally) send two direct mailings on one day, nor on consecutive days. Thus, to stay as close to the actual mailing strategies as possible, we opt for the following solution. Instead of adding an extra mailing on various days and averaging results, we remove an existing mailing and consider the difference in response propensity and donated amount on subsequent events. In this way, it is as if the mailing sequence minus the removed mailing forms the baseline, and the removed mailing the impulse. We follow this procedure for all existing mailings within a certain period. In particular, we remove a mailing and use the resulting values of the explanatory variables in combination with a draw of the estimated distribution of the error terms in our Tobit-II model to simulate the response and amount on the next mailing event. These simulated response and amount are then used to update the explanatory variables, which are in turn used to simulate the response and amount on the next mailing event, and so forth. Averaging over all mailings, over a number of error draws per individual, and over all individuals, results in estimates for the effect of an extra mailing, with the mailing strategy corresponding to the actual strategies used by the charities.

To obtain these IRF's, we divide our 3.5 year time span in three parts for each individual, an individual start-up period, as described above, a fixed holdout period of one year at the end of the period, and an impulse period in between that varies over individuals in line with the varying start-up period. See Figure 2 for two exemplary individual timelines.

Insert Figure 2

Thus, we remove all existing mailings in the impulse period, represented by the large dots, one by one, and simulate the effects on mailing events in the year following the impulse, represented by the connected dashed lines. For each impulse, we have an entire year of simulation mailings at our disposal, due to the holdout period at the end. The impulse period has a maximum length of around 1.5 years and on average around 3 quarters across all individuals.

Now, we simulate the IRF's for all charity combinations by averaging over 1000 draws from the error distribution per individual, where we use the posterior means of the individual parameters estimates, as opposed to the population level effects, to compute response probabilities and amounts. In Figure 3, the (somewhat smoothed) IRF for the donated amount per individual to charity 2 is depicted as an example. We do not show the direct individual effect of a direct mailing of charity 2 on its own revenues. Due to the relative magnitude of this effect compared to subsequent effects, this would make the graph rather uninformative.

Insert Figure 3

In Figure 3, the solid line represents the effect of an impulse of a mailing of charity 2 according to its mailing strategy on the individual amount donated to charity 2 over time. Furthermore, the two dashed lines represent the effects of impulses of both competing charities on the individual amount donated to charity 2. We find that the own effect is larger than competitive effects, but competitive interactions do exist. It appears that an extra mailing of charity 1 positively affects the amount donated to charity 2 at first, possibly due to goodwill or guilt creation, but has a negative effect in the long run. The effect of an impulse of charity 3 seems very small, but overall positive.

Although we did not depict it for reasons of clarity, an extra mailing clearly has a direct effect. As a mailing only has a direct effect for the mailing charity itself, there are no direct cross effects. However, a mailing sets a process in motion, which affects subsequent mailing events. For example, if an individual responds to the impulse mailing, this will have consequences for his/her response behavior to future mailings, both for the mailing charity itself and for the competition. To summarize these effects for all charity combinations we compute the indirect effects as the sum of effects over one year after, and not including, the impulse, where we apply an annual discount rate of 10%. In Table 5 we present the general classification of the various effects, with the expected sign of the effects in parentheses.

Insert Table 5

This table should be read as follows. The rows represent the charity sending the impulse mailing, and the columns the charities for which we compute the effects. Thus, the indirect effect C_{12}, for example, is the indirect effect for charity 2 generated by an extra mailing of charity 1, according to the mailing strategy of charity 1. We also present the terminology for the expected effects. For example, we expect a positive direct effect of a mailing for the mailing charity, which is the immediate gain. Furthermore, we expect a negative indirect effect for the mailing company itself, for example due to irritation or budget reasons, which we label cannibalization. Finally, all cross effects reflect competitive interactions. As past research suggests that these effects could go both ways (see section 2) and we already found this to be the case in Figure 3, we have no prior expectations regarding the signs of the effects. Note that asymmetries in cross effects are expected due to differences in the database compositions and in mailing strategies.

In Table 6 we present the total revenues in euros, that is, the total donated amount across all individuals over a year, generated by an extra mailing in accordance with actual mailing strategies.

Insert Table 6

As a bench mark, we note that the average total yearly revenues in our sample of 2500 individuals is €19689.03 for charity 1, €21838.51 for charity 2 and €4362.59 for charity 3. For all charities, we find strong positive direct effects. However, a direct mailing also has a substantial cannibalization effect. This effect is particularly strong for charity 2, where around two thirds of the own revenues are cancelled out within a year. We furthermore find some competitive effects, varying both in sign and size.

As we find some positive competitive effects and also saw in Figure 3 that effects may change from positive to negative or vice versa over time, we investigate these effects further. We break up the revenues into a short-run and a long-run effect by computing the effects over the first and second half year and present the results in Table 7.

Insert Table 7

Some clear patterns can be observed from these results. First, for all three charities we find that their mailings result in a strong initial decline in response behavior in the first six months followed by an improvement, although the effects are still negative in the long run. Next, concerning the competitive effects, we find that in the short run competitive mailings generally have a positive effect, which deteriorates into a negative effect in the long run. Thus, although these charities tend to be short run complements, in that they positively affect and support one another, for example due to goodwill or guilt creation, they are substitutes in the long run. Finally, note that although the effects seem to differ in size quite substantially, relative to yearly revenues they are roughly of the same order of magnitude.

5 Conclusion

We have proposed a new model to establish the existence of, and describe, dynamic and competitive effects of direct mailings, and we applied the model to a unique dataset concerning three charities in the health category. By combining the databases of these charities, we could retrieve which mailings were received by which households on which day. In this way, we were able to study competitive interactions between multiple direct mailing organizations over time.

The estimated model parameters in our illustration indicate that substantial dynamic and competitive effects exist. This result is quite interesting, as the relevant literature on direct mailings has largely overlooked these effects. Not only has the focus primarily been on a static context, ignoring potential long run effects, but also only one firm has been considered in general, passing over potential competitive interaction effects.

Firstly, our decay parameters indicate that past events (mailings, responses, amounts spent) are indeed still relevant today. Thus, for accurately describing direct mailing response behavior, the static context cannot be justified. Furthermore, for strategic purposes, a firm has to take into consideration that each mailing decision will affect response behavior well into the future. Even though the mailing itself is fairly quickly forgotten, the response the mailing is aimed to trigger is not.

Secondly, the fact that the number of direct mailings received significantly affects response behavior also indicates the inescapable dynamics of the process. We find that charitable direct mailings generally have a negative effect on future response propensities and amounts spent, possibly reflecting irritation. Also, we find some evidence of a non-linear relationship, in that the more mailings are sent, the larger the negative effect, which plausibly agrees with the concept of ‘too many mailings’.

Thirdly, we find that competitive interactions are indeed relevant. For example, a small number of competitive mailings appears to have a positive effect, possibly due to general goodwill or guilt creation. However, when the number of mailings gets larger, the effect gets smaller and turns negative, reflecting the ‘too many competitive mailings’ situation. Possibly due to lack of necessary data, these competitive effects have not been shown before. As the effects are quite substantial, however, it may be worth putting even more effort into data collection.

Finally, the impulse response functions and related direct and indirect effects were constructed to investigate the overall effects of an extra mailing, as the separate parameter estimates and heterogeneity prevent simple interpretation. The results emphasized once more the relevance of both dynamics and competitive interactions.

As a limitation of this study, we mention that the model is not particularly suited to develop optimal mailing strategies, as this requires extensive numerical simulation procedures. With the insights on the relevant competitive interactions, one might consider using more stylized models of individual response behavior to develop optimal mailing strategies (Naik et al., 2005; Simester et al., 2006).

The model can be refined in various ways. At present the estimated model considers three competitors. In principle, an extension to more than three is easy, although this would put a heavy burden on data collection. Hence, an interesting issue for further research would be to include an ‘other competitor’ category, without having to be very specific.

Further, for various reasons we adopted the Koyck lag structure and it would be of interest to see if other types of dynamic structures would give similar or very different results.

Finally, our model can be used to simulate the effects of too much or too little mailings on own and on competitor’s revenues. It would be challenging to see if a natural experiment would lead to comparable outcomes.

Appendix: Bayesian estimation of direct mailing response model parameters[5]

We have N individuals with T_i mailing event observations for individual i, i=1,..,N. Define for mailing event τ $y_{i\tau}^* = (R_{i\tau}^*, A_{i\tau}^*)^T$ and $\varepsilon_{i\tau} = (\varepsilon_{Ri\tau}, \varepsilon_{Ai\tau})^T$ and let the vector λ contain all decay parameters, so that $\lambda = (\lambda_m, \lambda_r, \lambda_a)^T$. Let $X_{i\tau}(\lambda)$ denote a (1xk)-matrix of k explanatory variables, where λ in parentheses indicates the dependence on the decay parameters. Then $X_i(\lambda)$ is the (T_ixk) matrix that stacks the k explanatory variables in $X_{i\tau}(\lambda)$ for the T_i mailing events of individual i. For y_i^* and ε_i similar definitions hold.

In our non-linear random-coefficients Tobit-II model specification in (7)-(10), we have $\varepsilon_{i\tau} \sim N(0, \Sigma_\varepsilon)$ with
$\Sigma_\varepsilon = \begin{bmatrix} 1 & \sigma_{RA} \\ \sigma_{AR} & \sigma_A^2 \end{bmatrix} = \begin{bmatrix} 1 & \rho\sigma_A \\ \rho\sigma_A & \sigma_A^2 \end{bmatrix}$, $\beta_i \sim N(\beta, \Sigma_\beta)$ and $\beta_i = (\beta_{Ri}^T, \beta_{Ai}^T)^T$ of size (*2kx1*).
The vector β_{Ri} contains all parameters in the response equation, excluding the decay parameters, that is $\beta_{Ri} = (\beta_{R0i}, \beta_{R1i}^{own}, \beta_{R1i}^{other}, \beta_{R2i}^{own}, \beta_{R2i}^{other}, \ldots, \beta_{R7i}^{own}, \beta_{R7i}^{other})^T$.

To obtain draws from the posterior distributions for the model parameters, we use the Gibbs sampling technique of Geman and Geman (1984) (see Casella and George (1992) for an introduction). Furthermore, we make use of data augmentation (Tanner and Wong 1987) for the latent variables in the model. The latent variables y_i^* and β_i $\forall i$ are sampled alongside the model parameters $\beta, \Sigma_\beta, \lambda$ and Σ_ε. We specify a flat prior for β and independent informative priors for the other model parameters, details of which will be discussed below. Finally, when a full conditional posterior distribution is of unknown form we use the Metropolis-Hastings algorithm (Chib and Greenberg 1995). In the remainder of this appendix we describe for each parameter and each latent variable the full conditional we use to obtain posterior results.

Sampling of $y_{i\tau}^*$

To sample the elements of $y_{i\tau}^*$, we use a data augmentation step by simulating the latent variables as follows. When a purchase is made, we set $A_{i\tau}^*$ equal to $A_{i\tau}$ and draw $R_{i\tau}^*$ from the conditional normal distribution[6]

$$N\left(X_{i\tau}(\lambda)\beta_{Ri} + \rho \frac{(A_{i\tau}^* - X_{i\tau}(\lambda)\beta_{Ai})}{\sigma_A}, 1 - \rho^2 \right),$$

truncated from below at zero. When no purchase is made, we start with drawing $R_{i\tau}^*$

from the conditional normal distribution $N\left(X_{i\tau}(\lambda)\beta_{Ri},1\right)$, truncated from above at zero. We then draw $A_{i\tau}^{*}$ from its conditional normal distribution $N\left(X_{i\tau}(\lambda)\beta_{Ai}+\sigma_A\rho(R_{i\tau}^{*}-X_{i\tau}(\lambda)\beta_{Ri}),(1-\rho^2)\sigma_A^2\right)$.

Sampling of β_i

As β_{Ri} and β_{Ai} are correlated, it is convenient to sample them simultaneously. For this purpose we define $Z_{i\tau}(\lambda)=I_2\otimes X_{i\tau}(\lambda)$ with I_2 the 2-dimensional identity matrix and $\otimes$ the Kronecker product. Let $Z_i(\lambda)$ be the ($2T_i$x$2k$) matrix that stacks the $Z_{i\tau}(\lambda)$ matrices for the T_i mailing events of individual *i*. Then $y_i^{*}=Z_i(\lambda)\beta_i+\varepsilon_i$ with $\varepsilon_i\sim N(0,I_{T_i}\otimes\Sigma_\varepsilon)$. In addition we have $\beta_i=\beta+\eta_i$ with $\eta_i\sim N(0,\Sigma_\beta)$.

Combining the two sources of information on β_i we obtain, $\beta_i\mid y_i^{*},Z_i(\lambda),\Sigma_\varepsilon,\Sigma_\beta,\beta\sim N(VW,V)$ with $V^{-1}=Z_i^T(\lambda)(I_{T_i}\otimes\Sigma_\varepsilon)^{-1}Z_i(\lambda)+\Sigma_\beta^{-1}$ and $W=Z_i^T(\lambda)(I_{T_i}\otimes\Sigma_\varepsilon)^{-1}y_i^{*}+\Sigma_\beta^{-1}\beta$ and a draw is made from this distribution.

Sampling of Σ_ε

Since $\Sigma_{\varepsilon 11}$ is restricted to 1 for identification purposes, sampling of Σ_ε is not straightforward. We follow the approach of McCulloch et al. (2000) and use the following reparametrization:

$\Sigma_\varepsilon=\begin{bmatrix}1 & \gamma\\ \gamma & S+\gamma^2\end{bmatrix}$ where *S* and γ are both scalars in our two-dimensional case.

This implies $\varepsilon_{Ri\tau}\sim N(0,1)$ and $\varepsilon_{Ai\tau}\mid\varepsilon_{Ri\tau},\gamma,S\sim N(\varepsilon_{Ri\tau}\gamma,S)$.

Now, consider $\varepsilon_{Ai\tau}=\varepsilon_{Ri\tau}\gamma+\omega_i$ and note that *S* is the variance of the error term in this model. Given conjugate priors $S\sim IG2(\kappa,C)$ and $\gamma\sim N(\bar{\gamma},B^{-1})$, the full conditional posteriors are $S\sim IG2\left(\kappa+\sum_{i=1}^{N}T_i,C+\sum_{i=1}^{N}\sum_{\tau=1}^{T_i}(\varepsilon_{Ai\tau}-\varepsilon_{Ri\tau}\gamma)^2\right)$ and

$$\gamma\sim N\left(A_\gamma\left(\frac{\sum_{i=1}^{N}\sum_{\tau=1}^{T_i}\varepsilon_{Ri\tau}\varepsilon_{Ai\tau}}{S}+B\bar{\gamma}\right),A_\gamma\right)\text{ with }A_\gamma=\left(\frac{\sum_{i=1}^{N}\sum_{\tau=1}^{T_i}\varepsilon_{Ri\tau}^{\;2}}{S}+B\right)^{-1}.$$

We take $\bar{\gamma}$ =0, B^{-1}=1/10, κ=3 and C=(1- B^{-1})(κ-1), in line with McCulloch et al. (2000) and draw *S* and γ from the full conditional posterior distributions.

Sampling of λ

As described in section 3, we apply the logit transformation to the vector λ to obtain a vector φ and generate draws for φ to ensure that the elements of λ are in the interval (0,1). We use the Metropolis-Hastings algorithm (Chib and Greenberg, 1995) to make independent draws for the separate elements in φ and specify a univariate N(0,1) prior distribution for each element φ_j, $j=1,\dots,J$ with J the number of elements of φ (see also Ansari et al. 2006). Then the full conditional posterior distribution for φ_j, $j=1,\dots,J$ is proportional to the likelihood times the prior and thus to

$$\prod_{i=1}^{N}\prod_{\tau=1}^{T_i}\exp\left(-\tfrac{1}{2}\left(y_{i\tau}^{*}-Z_{i\tau}\left(\frac{e^{\varphi_j}}{1+e^{\varphi_j}}\right)\beta_i\right)^{T}\Sigma_{\varepsilon}^{-1}\left(y_{i\tau}^{*}-Z_{i\tau}\left(\frac{e^{\varphi_j}}{1+e^{\varphi_j}}\right)\beta_i\right)\right)\cdot\exp\left(\frac{-\varphi_j^{\,2}}{2}\right).$$

Using a random walk Metropolis-Hastings algorithm with a normal candidate-generating density centered on the previous draw and with variance tuned to obtain reasonable acceptance rates (Koop 2003, p.98), we draw each element in φ independently.

Sampling of β

To sample β we consider the part of the model that depends on β which we can write as $\beta_i = \beta + \eta_i$ with $\eta_i \sim N(0,\Sigma_\beta)$. Given a flat prior $f(\beta) \propto 1$, β is drawn from $N\left(\frac{1}{N}\sum_{i=1}^{N}\beta_i, \frac{\Sigma_\beta}{N}\right)$.

Sampling of Σ_β

To sample Σ_β we again consider the regression model $\beta_i = \beta + \eta_i$ with $\eta_i \sim N(0,\Sigma_\beta)$. It follows that the full conditional posterior distribution of Σ_β is an inverted Wishart with scale parameter $\sum_{i=1}^{N}(\beta_i-\beta)(\beta_i-\beta)^T + \kappa_1 I_{2k}$ and $N+\kappa_2$ degrees of freedom, where the κ terms stem from the conjugate prior we impose to improve convergence of the Gibbs sampler, as recommended by Hobert and Casella (1996). We set $\kappa_1 = \frac{1}{10}$ and $\kappa_2=32$ to induce only a marginal influence of the prior on the posterior distribution and draw Σ_β from its full conditional posterior distribution.

Tables

Table 1: Classification of explanatory variables

Promotion history	*Frequency* + *Recency*	Discounted number of mailings Squared discounted number of mailings	(1)[a]
Purchase history	*Frequency*	Weighted response rate	(3)
	Recency	Discounted number of responses Squared discounted number of responses	(4)
	Monetary	Weighted average amount	(5)
	Value	Discounted total amount	(6)

[a] Relevant equation numbers are in parentheses

Table 2: Descriptive statistics

	Charity 1		Charity 2		Charity 3	
	Mean	Std.Err.	Mean	Std.Err.	Mean	Std.Err.
mailings (# per year)	3.35	2.04	4.74	2.83	0.73	1.41
responses (# per year)	0.68	0.84	0.83	1.00	0.16	0.48
total donation (€ per year)	7.93	20.06	8.79	20.78	1.76	9.16

Table 3: Posterior means and standard deviations

Explanatory variables		*Response equation*		*Amount equation*		*Decay*		
Constant	β_0	-1.188***	(0.014)	1.333***	(0.021)			
Mailings	β_1^{own}	-0.321***	(0.062)	-0.062*	(0.037)	λ_m	1.36e-4[a]	(6.54e-5)
	β_1^{other}	0.083***	(0.035)	0.072***	(0.031)			
Mailings^2	β_2^{own}	-0.055	(0.038)	-0.070**	(0.028)			
	β_2^{other}	-0.043**	(0.019)	-0.036***	(0.015)			
Response	β_3^{own}	0.372***	(0.051)	0.090**	(0.046)	λ_r	0.329[a]	(0.018)
	β_3^{other}	0.145***	(0.051)	-0.011	(0.026)			
Response recency	β_4^{own}	0.427***	(0.055)	-0.295***	(0.053)			
	β_4^{other}	0.378***	(0.043)	-0.224***	(0.026)			
Response recency^2	β_5^{own}	-0.047***	(0.016)	0.014**	(0.007)			
	β_5^{other}	-0.028***	(0.008)	0.001	(0.004)			
Amount	β_6^{own}	0.194***	(0.018)	0.444***	(0.024)	λ_a	0.337[a]	(0.018)
	β_6^{other}	-0.040***	(0.012)	0.018*	(0.009)			
Amount recency	β_7^{own}	-0.159***	(0.020)	0.110***	(0.020)			
	β_7^{other}	-0.044***	(0.016)	0.137***	(0.011)			

*, **, ***: Zero not contained in 90%, 95%, 99% Highest Posterior Density region, respectively.
[a]: Testing for significance is not relevant as implementation of the logit transformation automatically leads to exclusion of 0.

Table 4: Variance across individuals

		Response	Amount
Constant		0.027	0.058
Mailings	Own	0.242	0.089
	Other	0.076	0.047
Mailings^2	Own	0.098	0.050
	Other	0.014	0.009
Response	Own	0.265	0.096
	Other	0.193	0.049
Response recency	Own	0.234	0.194
	Other	0.049	0.073
Response recency^2	Own	0.028	0.006
	Other	0.002	0.001
Amount	Own	0.095	0.170
	Other	0.007	0.006
Amount recency	Own	0.069	0.022
	Other	0.009	0.010

Table 5: Classification of the effects of an extra mailing

	Direct effects	Indirect effects		
		Charity 1	Charity 2	Charity 3
Charity 1	A_1 (+) immediate gain	B_1 (-) cannibalization	C_{12} (+/-) competition	C_{13} (+/-) competition
Charity 2	A_2 (+) immediate gain	C_{21} (+/-) competition	B_2 (-) cannibalization	C_{23} (+/-) competition
Charity 3	A_3 (+) immediate gain	C_{31} (+/-) competition	C_{32} (+/-) competition	B_3 (-) cannibalization

Table 6: Direct and indirect effects of an extra mailing on revenues

	Direct effects	Indirect effects		
		Charity 1	Charity 2	Charity 3
Charity 1	3059.56	-851.52	8.48	0.14
Charity 2	2235.36	-274.91	-1480.28	9.35
Charity 3	749.23	-15.45	49.38	-148.16

Table 7: Short- and long-run indirect effects

	Charity 1		Charity 2		Charity 3	
	Short run	Long run	Short run	Long run	Short run	Long run
Charity 1	-569.18	-282.34	105.94	-97.46	9.85	-9.71
Charity 2	-76.21	-198.69	-1134.34	-345.94	15.78	-6.43
Charity 3	6.35	-21.80	58.78	-9.40	-100.25	-47.91

Figures

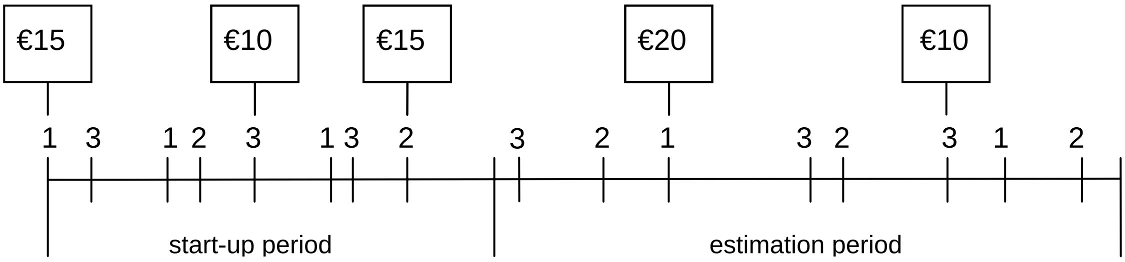

Figure 1: A possible scenario

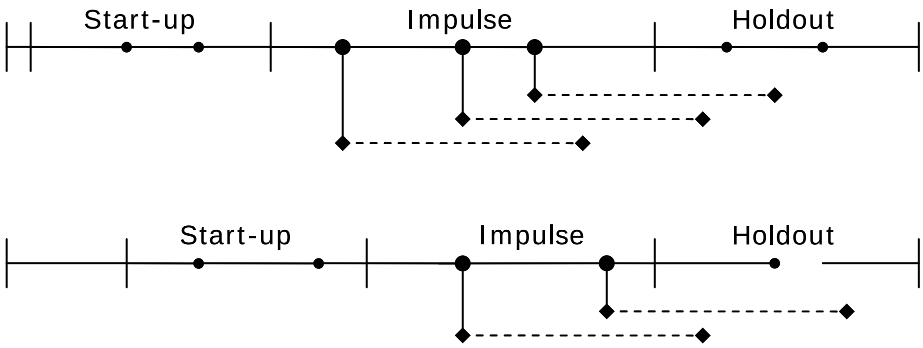

Figure 2: Individual time line divisions

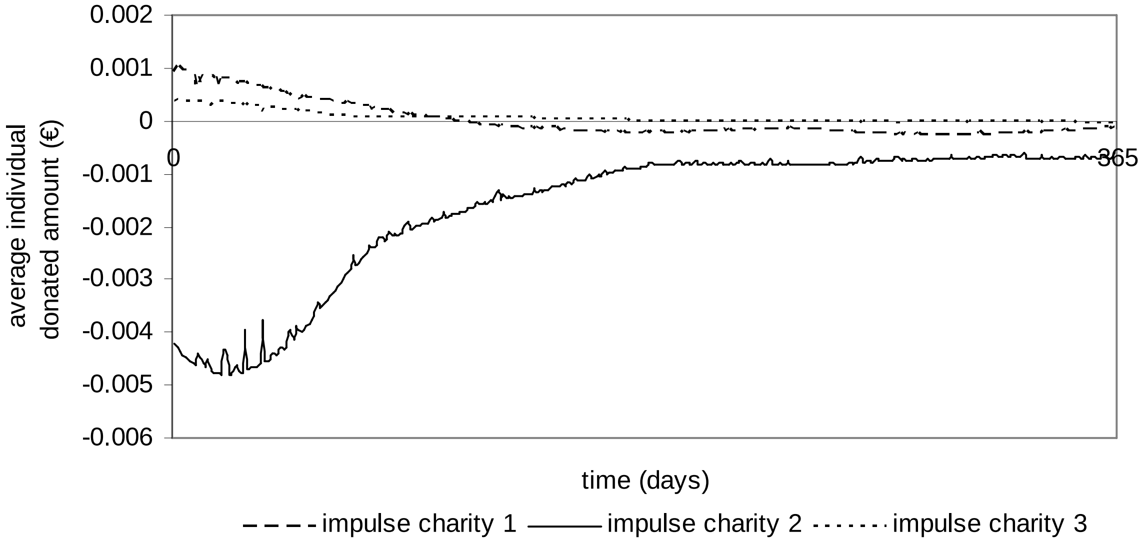

Figure 3: IRF for donated amount to charity 2

References

Allenby, G.M., R.P. Leone and L. Jen (1999), "A Dynamic Model of Purchase Timing With Application to Direct Marketing", *Journal of the American Statistical Association*, 94(446), 365-374

Andreoni, J. (1990), "Impure Altruism and Donations to Public goods: A theory of Warm-glow Giving", *The Economic Journal,* 100(401), 464-477

Ansari, A. and Mela, C. (2003), "E-Customization", *Journal of Marketing Research*, 40(2) 131- 146

Ansari, A., C.F. Mela and S. Nesslin (2006), "Customer Channel Migration", *working paper under 4th review, Journal of Marketing Research*

Baesens, B., S. Viaene, D. Van den Poel, J. Vanthienen and G. Dedene (2002), "Bayesian Neural Network Learning for Repeat Purchase Modelling in Direct Marketing", *European Journal of Operational Research*, 138(1), 191-211

Berlyne, D.E. (1970), "Novelty, Complexity, and Hedonic Value," *Perception and Psychophysics*, 8(5), 279–286

Bodapati, A. and S. Gupta (2004), "A Direct Approach to Predicting Discretized Response in Target Marketing", *Journal of Marketing Research*, 41(1), 73–85

Bronnenberg, B.J. (1998), "Advertising Frequency Decisions in a Discrete Markov Process Under a Budget Constraint", *Journal of Marketing Research*, 35(3), 399-406

Buckinx, W. and D. Van den Poel (2005), "Customer Base Analysis: Partial Defection of Behaviorally Loyal Clients in a Non-Contractual FMCG Retail Setting", *European Journal of Operational Research*, 164(1), 252-268

Bult, J.R., H. Van der Scheer and T. Wansbeek (1997), "Interaction Between Target and Mailing Characteristics in Direct Marketing, with an Application to Health Care Fund Raising", *International Journal of Research in Marketing*, 14(4), 301-308

Bult, J.R. and T. Wansbeek (1995), "Optimal Selection for Direct Mail", *Marketing Science*, 14(4), 378-394

Campbell, D., R. Erdahl, D. Johnson, E. Bibelnieks, M. Haydock, M. Bullock and H. Crowder (2001), "Optimizing Customer Mail Streams at Fingerhut", *Interfaces*, 31(1), 77-90

Chintagunta, P.K. (1998), "Inertia and Variety Seeking in a Model of Brand-Purchase Timing", *Marketing Science*, 17(3), 253-270

Colombo, R. and W. Jiang (1999), "A Stochastic RFM Model", *Journal of Interactive Marketing*, 13(3), 2-12

Diamond, W.D. and S.M. Noble (2001), "Defensive Responses to Charitable Direct Mail Solicitations", *Journal of Interactive Marketing*, 15(3), 2-12

Direct Marketing Association (2005), "US Direct Marketing Today: Economic Impact 2005, Executive Summary for 2005", *http://www.the-dma.org/research/economicimpact 2005ExecSummary.pdf*

Donkers, B., R. Paap. J.J. Jonker and P.H. Franses (2006), "Deriving Target Selection Rules from Endogenously Selected Samples", *Journal of Applied Econometrics*, 21(5), 549-562

D'Souza, G. and R.C. Rao (1995), "Can Repeating an Advertisement More Frequently than the Competition Affect Brand Preference in a Mature Market", *Journal of Marketing*, 59(2), 32-42

Dwyer, F.R. (1997), "Customer Lifetime Valuation to Support Marketing Decision Making", *Journal of Direct Marketing*, 11(4), 6-13

Elliott, M.T. and P.S. Speck (1998), "Consumer Perceptions of Advertising Clutter and Its Impact across Various Media", *Journal of Advertising Research*, 38(1), 29-41

Elsner, R., M. Krafft and A. Huchzermeier (2004), "The 2003 ISMS Practice Prize Winner – Optimizing Rhenania's Direct Marketing Business Through Dynamic Multilevel Modeling (DMLM) in a Multicatalog-Brand Environment", *Marketing Science*, 23(2), 192-206

Geman, S. and D. Geman (1984), "Stochastic Relaxations, Gibbs Distributions, and the Bayesian Restoration of Images", *IEEE Transaction on Pattern Analysis and Machine Intelligence*, 6(6), 721-741

Gönül. F.F. and M.Z. Shi (1998), “Optimal Mailing of Catalogs: A New Methodology Using Estimable Structural Dynamic Programming Models”, *Management Science*, 44(9), 1249-1262

Gönül, F.F. and F. Ter Hofstede (2006), “How to Compute Optimal Catalog Mailing Decisions”, *Marketing Science*, 25(1), 65-74

Greyser, S.A. (1973), “Irritation in Advertising”, *Journal of Advertising Research*, 13(1), 3-10

Jewell, R.D. and H.R. Unnava (2003), “When Competitive Interference can be Beneficial”, *Journal of Consumer Research*, 30(2), 283-291

Kamakura, W.A. and G.J. Russell (1989), “A Probabilistic Choice Model for Market Segmentation and Elasticity Structure”, *Journal of Marketing Research*, 26(4), 379-390

Keller, K.L. (1991), “Memory and Evaluation Effects in Competitive Advertising Environments,” *Journal of Consumer Research*, 17(4), 463-476

Kestnbaum, R.D., K.T. Kestnbaum and P.W. Ames (1998), “Building a Longitudinal Contact Strategy”, *Journal of Interactive Marketing*, 12(1), 56-62

Kim, Y.S., W.N. Street, G.J. Russell and F. Menczer (2005), “Customer Targeting: A Neural Network Approach Guided by Genetic Algorithms”, *Management Science*, 51(2), 264-276

Koop, G. (2003), “Bayesian Econometrics”, *John Wiley and Sons*, Chichester, England

Little, J.D.C. and L.M. Lodish (1969), “A Media Planning Calculus”, *Operations Research*, 17(1), 1-35

Mela, C.F., K. Jedidi and D. Bowman (1998). “The Long-term Impact of Promotions on Consumer Stockpiling Behavior”, *Journal of Marketing Research,* 35(2), 250-262

Naik, P.A., M.K. Mantrala and A.G. Sawyer (1998), “Planning Media Schedules in the Presence of Dynamic Advertising Quality”, *Marketing Science*, 17(3), 214-235

Naik P.A. and N. Piersma (2002), “Understanding the role of marketing communications in direct marketing”, *Econometric Institute Report EI 2002-13*, Erasmus University Rotterdam, Econometric Institute.

Naik, P.A., K. Raman and R.S. Winer (2005), “Planning Marketing-Mix Strategies in the Presence of Interaction Effects”, *Marketing Science*, 24(1), 25-34

Pauwels, K., D.M. Hanssens and S. Siddarth (2002), “The Long-Term Effects of Price Promotions on Category Incidence, Brand Choice, and Purchase Quantity,” *Journal of Marketing Research*, 39(4), 421–449

Piersma, N. and J.J. Jonker (2004), “Determining the Optimal Direct Mailing Frequency”, *Eurpean Journal of Operational Research*, 158(1), 173-182

Prins, R. and P.C. Verhoef (2006), “Marketing Communication Drivers of Adoption Timing of a New E-Service among Existing Customers”, *Working Paper*, Erasmus Research Institute of Management, Erasmus University Rotterdam

Reinartz, W.J. and V. Kumar (2000), “On the Profitability of Long-Life Customers in a Noncontractual Setting: An Empirical Investigation and Implications for Marketing”, *Journal of Marketing*, 64(4), 17-35

Reinartz, W.J. and V. Kumar (2003), “The Impact of Customer Relationship Characteristics on Profitable Lifetime Duration”, *Journal of Marketing*, 67(1), 77-99

Rossi, P.E., R.E. McCulloch and G.M. Allenby (1996), “The Value of Purchase History Data in Target Marketing”, *Marketing Science*, 15(4), 321-340

Rust, R.T. and P.C. Verhoef (2005), “Optimizing the Marketing Interventions Mix in Intermediate-Term CRM”, *Marketing Science*, 24(3), 477–489

Sargeant, A. (1999), “Charitable Giving: towards a Model of donor Behaviour”, *Journal of Marketing Management*, 15(4), 215-238

Seetharaman, P.B., A. Ainslie and P.K. Chintagunta (1999), “Investigating Household State Dependence Effects Across Categories”, *Journal of Marketing Research*, 36(4), 488-500

Seetharaman, P.B. and P.K. Chintagunta (1998), “A Model of Inertia and Variety-Seeking with Marketing Variables”, *International Journal of Research in Marketing*, 15(1), 1-17

Simester, D.I., Y. Hu, E. Brynjolfsson and E.T. Anderson (2005), “Does Current Advertising Cause Future Sales? Evidence from the Direct Mail Industry", *working paper December 2005*

Simester, D.I., P. Sun and J.N. Tsitsiklis (2006), “Dynamic Catalog Mailing Policies", *Management Science,* 52(5), 683-696

Sloot, L.M., D. Fok and P.C. Verhoef (2006), “The Short- and Long-term Impact of an Assortment Reduction on Category Sales”, *Journal of Marketing Research,* forthcoming

Smith, V.H., M.R. Kehoe and M.E. Cremer (1995), “The Private Provision of Public Goods: Altruism and Voluntary Giving”, *Journal of Public Economics*, 58(1), 107-126

Unnava, H.R. and D. Sirdeshmukh (1994), “Reducing Competitive Ad Interference”, *Journal of Marketing Research*, 31(3), 403-411

Verbeek, M. (2004), “A Guide to Modern Econometrics”, 2nd edition, *John Wiley and Sons*, Chichester, England

Verhoef, P.C., P.N. Spring, J.C. Hoekstra and P.S.H. Leeflang (2003), “The Commercial Use of Segmentation and Predictive Modeling Techniques for Database Marketing in the Netherlands”, *Decision Support Systems*, 34(4), 471-481

Yoo, B. and R. Mandhachitara (2003), “Estimating Advertising Effects on Sales in a Competitive Setting”, *Journal of Advertising Research*, 43(3), 310-321

Zielske, H.A. (1959), “The Remembering and Forgetting of Advertising”, *Journal of Marketing*, 23(3), 239-243

Footnotes

[1] Note that this also implies that our Koyck based model theoretically includes all events in the infinite past, but that events very long ago are negligible. Thus, although our notation in (1) indicates a finite duration, we essentially model the infinite past.

[2] For brevity we will often use amount to denote the natural logarithm of amount.

[3] Note that the decay parameters in the explanatory variables are not equation-specific and are the same for own and competitive variables, as these represent forgetting behavior.

[4] Based on personal communication with the relevant fund managers.

[5] For basic results on Bayesian estimation, see for example Koop (2003).

[6] For the derivation of conditional distributions of two normal variables, see for example Verbeek (2004, p. 404).

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