UNDERSTANDING THE ROLE OF MARKETING COMMUNICATIONS IN DIRECT MARKETING

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ABSTRACT

The standard RFM models used by direct marketers include behavioral variables, but ignore the role of marketing communications. In addition, RFM models allow customer responsiveness to vary across different customers, but not across different time periods. Hence, the authors first extend RFM models by incorporating the effects of marketing communications and temporal heterogeneity. Then, using direct-marketing data from a Dutch charity organization, they calibrate the proposed model, and find that it better explains customer behavior because it includes information on both the past behavior and marketing communications. More specifically, they show that direct mail communication builds goodwill, which, in turn, enhances customer's likelihood to buy. However, cumulative exposure to direct mail creates irritation, and erodes goodwill. The two opposite effects induce a cyclic pattern of goodwill formation, which repeats over four quarters. Next, the authors find that, when they control for these communications effects, the standard result — customer's likelihood to buy increases as shopping frequency increases — reverses. That is, in contrast to the extant literature, customers who donate frequently are *less* likely to donate in the near future. These findings are not only stable over time, but also replicate across two large data sets. Finally, the authors discuss the need for implementing pulsing strategy to mitigate irritation, and the possibility of practicing one-to-one marketing by using information on customer responsiveness, which can be estimated for each customer via the proposed model.

INTRODUCTION

Direct marketers collect transaction information on customer's purchases and create large customer databases. Using the databases, they construct variables such as *recency* (time elapsed since last purchase), *frequency* (how often they buy), and *monetary value* (of purchase transactions) to target prospective customers. They can extract further information from the databases to improve customer selection and devise optimal mailing strategies (see Wedel, DeSarbo, Bult and Ramaswamy 1993, DeSarbo and Ramaswamy 1994, Bult and Wansbeek 1995, Bitran and Mondschein 1996, Gönül and Shi 1998, and Donkers, Jonker, Franses and Paap 2002). In addition, they can use the databases to shed light on customer behavior and understand the consequences of their own actions.

Previous studies indicate that customer's *shopping* frequency is an important variable because customers who bought the product often are more likely to buy it again. In other words, customer's response probability is positively related to shopping frequency. Consequently, frequent shoppers are inundated with marketing communications that persuade them to buy something or travel somewhere or donate money to some charity. What, then, is the impact of *communications* frequency on customer's response probability? Does repeated exposure to a company's products evokes familiarity and liking, thus enhancing goodwill? Or does cumulative exposure creates irritation, thus eroding goodwill? How do the effects of communications frequency moderate those of shopping frequency? To address these and related issues, we aim to incorporate communications effects in direct-marketing response models so that we better understand its role in influencing customer's behavior and marketer's actions.

While RFM models typically include customers past behavior (i.e., recency, shopping frequency, monetary value), we extend it by incorporating the effects of marketing communications. Specifically, using advertising theory, we introduce the concept of goodwill formation, whose dynamics is driven by communications frequency and cumulative exposures. We calibrate the proposed dynamic response model using direct-marketing data from a major Dutch charity organization. We find that communications frequency does build goodwill, which positively impacts customer's response probability. Interestingly, cumulative exposure diminishes goodwill formation. But most importantly, once we control for the impact of communications, the effect of shopping frequency reverses. In other words, customer's response probability is *negatively* related to shopping frequency. To ascertain that this reversal is not transient, we estimate the RFM effects for each of the twenty-two quarters, and find them to be stable in sign, albeit varying in magnitude. In addition, to verify that these findings are not statistical or sampling artifacts, we re-analyze another large data set and find similar results, ensuring convergent validity of the findings via replication. Thus, in contrast to the extant literature, we show that customers who donate frequently are *less* likely to donate in the future.

An important policy implication for marketers is that it is beneficial *not* to communicate with frequent donors incessantly. Rather, they may consider implementing a *pulsing strategy* (see Mahajan and Muller 1986, Naik, Mantrala and Sawyer 1998) in which bursts of intense contacts are punctuated by periods of no contact so that irritation resulting from the high mailing pressure wanes during the hiatus.

An important consequence of the proposed approach is the possibility to estimate customer's responsiveness for each individual customer. We discuss its implications for modeling customer heterogeneity (see Wedel and Kamakura 2000, Ch. 19) and practicing one-to-one marketing (see Peppers, Rogers, Dorf 1999).

We organize the rest of this paper as follows. In the next section, we first review the literature on direct-marketing and advertising. Using this knowledge, we then formulate a dynamic response model that incorporates goodwill formation. We next describe the data and estimation approach used to calibrate this model, and subsequently present the empirical results. We then discuss the marketing implications, and finally conclude by summarizing the contributions.

LITERATURE REVIEW

Here we review the recent advances in direct marketing, followed by relevant studies on marketing communications effects, and then draw the implications for building direct-marketing response models.

Advances in Direct Marketing

Direct marketing is one of the oldest techniques of marketing products, and typically involves contacting customers directly without using salesforce or retail distribution. For example, *Land's End* contacts a set of prospective customers directly via catalogs. Traditionally, to identify prospective customers, direct marketers apply RFM models, which are linear or logistic regression models that predict customer's likelihood to buy — known as *response probability* in technical terms — using behavioral variables such as recency, frequency and monetary value. Recently, marketing science advanced several valuable approaches to improve the understanding and practice of direct marketing. For example, to understand customer retention, statistical models are developed to predict when customers might become inactive or switch suppliers (Schmittlein, Morrison and Colombo 1987, Allenby, Leone and Jen 1999). To improve mailing decisions, Bitran and Mondschein (1996) and Gönül and Shi (1998) develop decision-theoretic heuristics and algorithms. To better characterize response probability, Bult and Wansbeek (1995) extend RFM-type models by incorporating non-parametric link between customer response and behavior variables (instead of logistic or probit functions); Wedel et al. (1993), DeSarbo and Ramaswamy (1994), Donkers et al. (2002) extend RFM-type models by accounting for customer heterogeneity via finite mixtures of Poisson, binary, and tobit models, respectively. To calibrate RFM-type models using many regressor variables, Naik, Hagerty and Tsai (2000) apply sliced inverse regression for dimension-reduction of regressor-space without specifying any link function and with minimal loss of information.

For a comprehensive review of direct marketing literature, see Jonker, Franses and Piersma (1998). We note here that direct marketing models assume that (a) RFM effects remain constant over time, and (b) they do not focus on the impact of marketing communications.

Marketing Communications Effects

Advertising research has shown that advertising repetition affects consumers positively and negatively. On the positive side, several studies find that repeated exposure to advertisements builds goodwill toward product or company (e.g., Nerlove and Arrow 1962) because it enhances consumers' familiarity and liking (e.g., Zajonc

1968). In the absence of ad exposure, consumers forget the advertised product; hence goodwill decays over time, but does so gradually because of carryover effects from past goodwill (e.g., Zielske and Henry 1980). On the negative side, Pieters, Rosbergen and Wedel (1999) show that consumer's visual attention to print advertisement decreases by about 50% from the first to the third exposure (also see Rosbergen, Pieters and Wedel 1997). In addition, cumulative exposure can induce irritation (e.g., Greyser 1973) and wearout (e.g., Grass and Wallace 1969), reducing the rate of goodwill formation. Thus, ad repetition both helps and hurts goodwill formation. Hence, to effectively manage repetitive advertising, Naik, Mantrala and Sawyer (1998) suggest that advertisers should not advertise continually; rather they take the ads off the air intermittently so that, during the media hiatus, the effectiveness of advertising can restore (also see Burke and Edell 1986). Such "on-off" media plans are known as *pulsing strategy* (Mahajan and Muller 1986).

For comprehensive reviews of this advertising literature, see Sawyer and Ward (1981) and Pechmann and Stewart (1988). We note here that advertising models of goodwill formation are (a) specified for market-level data (e.g., awareness, sales), and (b) they estimate the effects of mass media (e.g., TV, print). Consequently, we do not know the dynamics of individual-level goodwill formation due to non-broadcast media such as direct-mail communications.

Implications for Direct Marketing Response Models

We draw three implications based on the above discussion. First, it reveals a fundamental distinction between *shopping* frequency and *communications* frequency. Shopping frequency (i.e., how often does a customer buy?) affects customer response probability, and is not under the control of direct marketers. In contrast, communications frequency (i.e., how often does a direct marketer contact the customer?) affects goodwill formation, and is controlled by the direct marketer. Recognizing this distinction, we should study the impacts of both kinds of frequency to understand their differential effects on customer response probability.

Second, does goodwill affect customer response probability? The empirical marketing literature is silent on this issue because advertising models, which are typically calibrated using aggregate data, show that goodwill affects brand sales — not individual customer's likelihood to buy. Thus, direct marketing context provides an opportunity to augment our understanding of goodwill formation at individual-level using customer response data and media vehicle other than broadcast ads (e.g., direct mail).

Finally, direct marketing response models are typically cross-sectional models, which can account for customer heterogeneity, but not for "temporal" heterogeneity in customer response. Consequently, we do not know empirically whether and how the effects of recency, frequency and monetary value change over time? To this end, the assumption of constancy of model parameters over time needs to be relaxed. By incorporating these issues, we next formulate a dynamic RFM model that includes the roles of communications frequency, goodwill formation, and temporal heterogeneity.

MODEL DEVELOPMENT

We first describe the standard RFM model commonly used by direct marketers, and then extend it to address the above three implications.

Standard RFM model

Direct marketers utilize RFM models to predict the probability of favorable response (e.g., buy, donate). Let $x_{it} = (R_{it}, F_{it}, M_{it})'$ denote the information on customer i's recency, frequency, and monetary value in quarter t, and y_{it} be the binary response (i.e., buy or not buy). Then, applying logistic regression, they predict the customer's *response probability* by

$$\begin{aligned} p_{it} &= \Pr(y_{it} = 1) \\ &= F(\alpha + x_{it}'\beta) \\ &= \frac{\exp(\alpha + x_{it}'\beta)}{1 + \exp(\alpha + x_{it}'\beta)}, \end{aligned} \tag{1}$$

where α is the intercept, and $\beta = (\beta_1, \beta_2, \beta_3)'$ are the effects of recency, frequency, and monetary value, respectively. Equation (1) is the standard logistic model. When $F(\cdot)$ represents the cumulative distribution for a uniform random variable, equation (1) becomes a linear regression model; when F is a normal distribution function, we obtain the probit model. Next, we extend equation (1) by incorporating goodwill, and by allowing the parameters in β to evolve over time.

Incorporating Goodwill Formation and Communications Effects

For any customer i, let G_{it} denote goodwill toward the direct marketer's product in quarter t. Based on the advertising literature, goodwill formation depends on marketer's frequency of communications as well as carryover effect from past goodwill. Specifically, goodwill dynamics is modeled as

$$G_{it} = \phi G_{i,t-1} + \gamma u_{it} + \eta v_{it}, \tag{2}$$

where u_{it} denotes the communications frequency, and v_{it} is the cumulative exposure to direct mail communications. In equation (2), ϕ represents the carryover effect (see Leone

1995), γ is the effect of communications frequency, η is the irritation effect due to repetitive exposure to direct mails. Based on aggregate advertising studies, we expect that ϕ is a positive fraction, γ is positive, and η is negative. In contrast to those studies, however, we specify equation (2) for each individual customer i in the database — not a market-level model of goodwill.

To incorporate communications effects in RFM models, we replace the intercept in equation (1) by goodwill in equation (2); that is, $\alpha \leftarrow G_{it}$. Consequently, we generalize the fixed α to individual-specific intercepts, G_{i0}, for the initial period t = 0 when no dynamic effects arise from the carryover effect (see equation 2). In the future periods, G_{it} evolves according to equation (2), and so its temporal path is unique to each customer i who receives different sequence of inputs $\{u_{it}\}$. For example, if two customers A and B receive mailing patterns {1, 0, 1, 0} and {1, 0, 0, 1}, respectively, then their goodwill dynamics resulting from equation (2) are not identical even though they both get two contacts in four quarters. Thus, we not only endow the dormant intercept α with dynamic goodwill properties, but also ensure that customer's response probability p_{it} depends on both the past behavior and marketing communications.

Introducing Temporal Heterogeneity

RFM models such as equation (1) often assume parameter constancy, i.e., $\beta_t = \beta$ for all t. We propose to relax this assumption so that parameters in β evolve over time. Specifically, we let

$$\beta_{jt} = \beta_{j,t-1} + \varepsilon_{jt}, \tag{3}$$

where j = 1, 2, 3 refers to the elements of vector $\beta_t = (\beta_{1t}, \beta_{2t}, \beta_{3t})'$. In words, equation (3) says that each parameter β_{jt} changes from one period to the next due to the net effect of many events, $\varepsilon_{jt} \sim N(0, \sigma^2)$, that are likely to be present in consumer's environment unbeknownst to us. Thus, we introduce the notion of *temporal heterogeneity*, i.e., customer responsiveness to a given variable x_j need not be fixed forever, and may vary stochastically across time periods. As we explain later, this notion complements the ideas of customer heterogeneity in market segmentation literature (see the section *Marketing Implications*). But first, we describe the data set and estimation approach to calibrate the system of dynamic equations (1), (2) and (3).

DATA AND ESTIMATION

Data Description

A large Dutch charitable organization initiated a direct mail campaign to raise funds. They provided us the history on their mailing patterns and donor responses during February 1994 through December 1999. During these 22 quarters, they contacted 725,093 potential donors who received different mailing patterns. For example, some people received a direct mail every quarter; some received it in alternate quarters; others received it intermittently. The database contains personal information (e.g., postal code, registration number), mailing information (e.g., date of each mailing sent), and donor response (e.g., date of each response, amount donated). For empirical analyses, we randomly select a large sample of 25,000 cases from this database.

We note that a small sample (900 cases) from this database was used by Donkers et al. (2002). However, their data set differs from ours because, by construction, the two samples do not overlap. Furthermore, our focus of inquiry is different. Specifically, while Donkers et al. (2002) develop an improved methodology for customer selection, we aim to understand the differential effects of shopping and communications frequency, the carryover and irritation effects, and the dynamics of goodwill formation in RFM models.

To that end, we operationalize the variables as follows. Specifically, for person i in quarter t, *recency* (R_{it}) is measured by the number of quarters elapsed since the last donation. *Shopping frequency* (F_{it}) is the number of donations in the past four quarters, and *monetary value* (M_{it}) is the average amount donated during this period. To properly scale the data set, we measure monetary value in thousands of Dutch Guilders, and divide recency and shopping frequency by their maximum values (namely, 22 and 4, respectively). This operationalization is consistent with the extant literature (e.g., Bitran and Mondschein 1996, Bult and Wansbeek 1995, Gönül and Shi 1998). Furthermore, as Donkers et al. (2002) recommend, we construct these variables over four quarters (rather than past four mailing instances) so that they do not depend on the firm's mailing policy. To understand goodwill formation, we measure *communications frequency* (u_{it}) by the number of direct mails sent to person i in quarter t, and so *cumulative exposure* (v_{it}) is the sum total of u_{it} over the campaign period. The binary response variable (y_{it}) indicates whether or not person i donated in quarter t. We next explain the estimation approach to calibrate the dynamic RFM model.

Estimation Approach

We estimate standard RFM models by maximizing the log-likelihood function,

$$L(\Theta_1) = \sum_{i=1}^{N} \sum_{t=1}^{T} [y_{it} \ln p_{it} + (1 - y_{it}) \ln(1 - p_{it})], \tag{4}$$

where the vector $\Theta_1 = (\alpha, \beta_1, \beta_2, \beta_3)'$, the sample size N = 25,000 cases, and T = 22 quarters. When dynamics are absent, we compute p_{it} using equation (1), which assumes that model parameters are time-invariant. In the presence of dynamics, however, consumer responsiveness evolves over time, resulting in inter-temporal dependence that may persist in the long run (Dekimpe and Hanssens 1995). Equations (2) and (3) capture such dynamics; and so response probability not just evolves, but does so in a non-stationary manner (i.e., exhibits persistence).

To account for these dynamics in computing the likelihood function, we first stack equations (2) and (3) together as,

$$\begin{bmatrix} G_{it} \\ \beta_{1t} \\ \beta_{2t} \\ \beta_{3t} \end{bmatrix} = \begin{bmatrix} \phi & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} G_{it-1} \\ \beta_{1t-1} \\ \beta_{2t-1} \\ \beta_{3t-1} \end{bmatrix} + \begin{bmatrix} \gamma u_{it} + \eta v_{it} \\ 0 \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} 0 \\ \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \end{bmatrix}, \tag{5}$$

and compactly represent equation (5) by the *transition equation*,

$$\alpha_t^i = T\alpha_{t-1}^i + d_{it} + \varepsilon_t, \tag{6}$$

where $\alpha_t^i = (G_{it}, \beta_{1t}, \beta_{2t}, \beta_{3t})'$, T = diag($\phi$,1,1,1), $d_{it} = (\gamma u_{it} + \eta v_{it}, 0,0,0)'$, and $\varepsilon_t = (\tilde{\varepsilon}_t$, ε_{1t}, ε_{2t}, $\varepsilon_{3t})' \sim$ MVN(0, Q). It follows from equations (2) and (3) that var($\tilde{\varepsilon}_t$) = 0 and var(ε_{jt}) = σ^2, and hence Q = diag(0, σ^2, σ^2, σ^2).

We then let $\Im_{t-1}^i$ denote the *information set* for person i after direct mail for the quarter t is sent out, but *prior* to observing the response y_{it} in quarter t. Based on this information set and equation (6), we determine the means and variances of α_t^i respectively, as

$$
\begin{aligned}
a^{i}_{t|t-1} &= E[\alpha^{i}_{t} \mid \Im^{i}_{t-1}] \\
&= Ta^{i}_{t-1} + d_{it},
\end{aligned}
\tag{7a}
$$

and

$$
\begin{aligned}
V^{i}_{t|t-1} &= V[\alpha^{i}_{t} \mid \Im^{i}_{t-1}] \\
&= TV^{i}_{t-1}T' + Q.
\end{aligned}
\tag{7b}
$$

The subscript "t | t −1" in equations (7a, b) indicates that we evaluate the moments in period t based on the information set $\Im^{i}_{t-1}$. Using equation (7a), we compute the response probability for person i as

$$
\begin{aligned}
p^{i}_{t|t-1} &= \Pr(y_{it} = 1 \mid \Im^{i}_{t-1}) \\
&= \frac{\exp(X'_{it} a^{i}_{t|t-1})}{1 + \exp(X'_{it} a^{i}_{t|t-1})},
\end{aligned}
\tag{8}
$$

where $X_{it} = (1, R_{it}, F_{it}, M_{it})'$, thus incorporating both the goodwill and time-varying RFM effects — unlike p_{it} in equation (1). Consequently, the log-likelihood contribution from person i in quarter t is

$$
l_{it} = y_{it} \ln p^{i}_{t|t-1} + (1 - y_{it}) \ln(1 - p^{i}_{t|t-1}). \tag{9}
$$

After observing the response y_{it}, we augment the information set so that $\Im^{i}_{t} = \{y_{it} \cup \Im^{i}_{t-1}\}$, and thus no more uncertainty remains on what the customer i's response is. But it raises the question, how do we update the means and variances of α^{i}_{t} given in equations (7a, b) in the light of this new information? Following Tanizaki (1993), who develops non-linear filtering for qualitative response models, we obtain *posterior* means and variances of α^{i}_{t}, respectively,

$$
\begin{aligned}
a^{i}_{t|t} &= E[\alpha^{i}_{t} \mid \Im^{i}_{t}] \\
&= a^{i}_{t|t-1} + \lambda_{it}(y_{it} - p^{i}_{t|t-1}),
\end{aligned}
\tag{10a}
$$

and

$$\begin{aligned} V^i_{t|t} &= V[\alpha^i_t \mid \Im^i_t] \\ &= V^i_{t|t-1} - \lambda_{it}\nabla'_{it}V^i_{t|t-1}, \end{aligned} \qquad (10b)$$

where $\lambda_{it} = V^i_{t|t-1}\nabla_{it} / (\nabla'_{it}V^i_{t|t-1}\nabla_{it} + p^i_{t|t-1}(1 - p^i_{t|t-1}))$ represents the gain factor and, from equation (8), the gradient $\nabla_{it} = \dfrac{\partial p^i_{t|t-1}}{\partial a^i_{t|t-1}} = X_{it}p^i_{t|t-1}(1 - p^i_{t|t-1})$. Both λ_{it} and ∇_{it} are vectors of dimension 4 x 1. As before, the subscript "t | t" in equations (10a, b) indicates that we evaluate the moments in period t based on the information set $\Im^i_t$.

We next advance by one period, replace t by (t + 1) in equations (7a, b), compute the log-likelihood contribution using equation (9), and update the moments via equations (10a, b). Applying the recursions in equations (7, 10) sequentially for periods t =1, 2, …,T, we assess the likelihood of observing the entire sequence $\{y_{it}\}$ for person i,

$$L_i = \sum_{t=1}^{T} l_{it} \ . \qquad (11)$$

The total log-likelihood is the sum of L_i across all cases:

$$\tilde{L}(\Theta_2) = \sum_{i=1}^{N} L_i \ , \qquad (12)$$

where $\Theta_2 = (G_0, \beta_{10}, \beta_{20}, \beta_{30}, \phi, \gamma, \eta, \sigma)'$. Finally, we maximize equation (12) to obtain parameter estimates, and determine their standard errors via the estimated information matrix.

In closing this section, it is worth noting that the order of double summation in (4) is inconsequential. Why? Because the inter-temporal dynamics for every person is ignored. For example, we could first sum the total log-likelihood contribution across all cases for the period t = 22; then we repeat this cross-sectional sum for the period t = 2 (say); then for the period t = 13; and so proceed randomly (say) for all other periods.

Indeed, in the standard approach, one pays no heed to the unidirectional flow of time; disregards dependence in decisions over time; just so long as all cross-sectional likelihoods are added once.

In contrast, the order of summation in (11) must follow the increasing sequence of natural numbers. For example, to compute the likelihood l_{it} for (say) quarter 13, we not only need information for the period t = 13, but also require all the information *up to* that period, $\Im^{i}_{12}$, which contains information from previous periods (i.e., $\Im^{i}_{12} \supset \Im^{i}_{11} \supset \Im^{i}_{10} \cdots$ and so on), so that the temporal dependence in choices are explicitly accounted for. Thus, the proposed approach respects the time sequence of information arrival by properly augmenting the information set $\Im^{i}_{t}$, accounts for inter-temporal dynamics via equations (7, 10), and computes the likelihood of observing an entire *time-path* (see equation 11). That is, we assess the chance of observing each person's *history* of responses $\{y_{i1}, y_{i2}, \ldots, y_{it}, \ldots, y_{iT}\}$ — not just the current response y_{it}, independent of past and future responses. In the next section, we present the empirical results obtained from both the approaches.

EMPIRICAL RESULTS

Using direct marketing data from the Dutch charity, we calibrate (a) the standard RFM model in equation (1) by maximizing the likelihood function (4) and, (b) the proposed dynamic model in equations (1), (2) and (3) via the likelihood function (12). We note that the standard RFM model is a nested version of the dynamic one with parameter space $\phi = \gamma = \eta = \sigma = 0$, and $G_{i0} = \alpha$. Preliminary analyses indicate that initial goodwill and carryover effect are negligible and insignificant; so we set them to zero in the final estimation run. Table 1 reports the estimation results for both the models (see the columns (2) and (3)).

Insert Table 1 here

Model Comparisons

We note that the dynamic RFM model outperforms the standard one. First, the log-likelihood value improves from -211,054.2 to -187,400.9. Formally, the likelihood ratio test statistic, minus two times the difference in log-likelihood values, is 47306.6, which is significantly larger than the critical χ^2 = 5.99 for 2 degrees of freedom (i.e., difference in dimensions of $\hat{\Theta}_1$ and $\hat{\Theta}_2$) at the 95% confidence level. Second, because goodness-of-fit improves with the addition of more parameters, we apply the Akaike information criterion (AIC) for model selection, which imposes parameter penalty to balance the trade-off between improved fit and model parsimony. A model associated with the smallest AIC value is preferred; hence, based on Table 1, we retain the dynamic model over the standard RFM model. Third, the adjusted R^2 also shows improvement from 18.83% (standard) to 29.38% (dynamic). Together, these results suggest that the proposed dynamic model fits this donor response data better than the standard RFM model. This is because the dynamic model includes information not only on past behavior (recency, frequency, and monetary value), but also on marketing communications (goodwill formation, direct mail impact, and irritation effect).

Reversal of Shopping Frequency Effect

A striking insight from this research is the following: when we apply the standard and dynamic RFM models to the *same* data set, we find that the estimated effect of shopping frequency is reversed. In Table 1, we observe from the standard model that shopping frequency has a positive effect on response probability; whereas, from the dynamic model, it has a negative effect on response probability. Why is this so?

This is because, in the standard model, we compare across different people at a fixed point in time (i.e., inter-personal comparison); whereas in the dynamic model, we compare a fixed person across different points in time (i.e., inter-temporal comparison). Consequently, a positive effect of shopping frequency in the standard model means that people who donate frequently are more likely to donate than *those* who donate less frequently. In the dynamic model, however, a negative effect of shopping frequency means that people who donate more frequently *now* are less likely to donate in the *future*. Thus, both the quantitative results and qualitative interpretations obtained from standard and dynamic models are different.

Are these Results Stable?

It is important that this reversal is not a transient phenomenon. In other words, does the negative effect disappear over time, or changes sign to become positive effect eventually? To ascertain this, we estimate the RFM effects for each of the twenty-two quarters. In Figure 1, Panels A, B, and C display the time-varying effects of recency, shopping frequency, and monetary value, respectively. We observe that their magnitudes vary over time, but their directional impact (i.e., the sign) remains unchanged. In particular, this reversal is stable over time: the shopping frequency effect remains negative for every quarter (see Panel B). Therefore, a customer's response probability *decreases* as shopping frequency increases.

A stronger test[1] of stability is, "Would these effects replicate with new data?" To verify it, we draw another random sample of 25,000 cases from this database. We re-estimate the dynamic model, and report the estimation results in the column (4) of Table 1. Evidently, the signs, magnitudes, and significance levels of the estimates based on replication data are similar to those from the original data (see column (3) in Table 1). Hence, the above findings are robust across two large data sets.

Insert Figure 1 here

Marketing Communications Effects

One of the main differences between the standard RFM model and its dynamic counterpart is the introduction of communications variables. Specifically, we hypothesized that direct mail communications and cumulative exposure influence goodwill. Our data lends support for these hypotheses. Table 1 indicates that communications frequency positively and significantly affects goodwill. This result is consistent with the theory that enhanced familiarity leads to liking towards a direct marketer (e.g., Zajonc 1968). Similarly, cumulative exposure negatively and significantly affects goodwill. This finding is a consequence of irritation resulting from "junk-mail" (e.g., Greyser 1973, Grass and Wallace 1969, Pechmann and Stewart 1988).

[1] A standard statistical test involves bootstrap replication, which is weak because it uses the same data set for sampling.

The above results are important because they complement our understanding of how advertising works. In the extant literature, similar effects of communications frequency and cumulative exposure are known based on either (a) experimental data at the individual-level (e.g., Calder and Sternthal 1980), or (b) field data at the aggregate-level (e.g., Naik, Mantrala and Sawyer 1998). Here, we utilize field data, but at an individual-level, thus extending the validity of previous findings. Furthermore, the previous findings typically are based on *broadcast* advertising such as television or print commercials. Here, we use direct mail communications, thus generalizing the findings across different types of media vehicles. Finally, we understand the *differential* effects of two kinds of frequency: shopping frequency and communications frequency. The former reduces response probability, while the latter lifts it by enhancing goodwill.

Cyclic Goodwill Formation

As mentioned before, we found that initial goodwill and carryover effects were negligible and insignificant. The substantive implications are (a) the initial endowment of brand equity for this charity is limited, and (b) the charity benefits little from the carryover of past goodwill-building efforts. But more importantly, we find a cyclic pattern of goodwill formation (see Figure 2). This result is driven by two opposing forces: the positive effect of direct mail communications, and the negative effect of irritation. Together, they set in a periodic evolution of goodwill over time, with a cycle of approximately 4 quarters. These findings have important implications for pulsing strategy and customer heterogeneity, which are discussed next.

Insert Figure 2 here

Marketing Implications

Pulsing Mailing Strategy

The cyclic dynamics of goodwill suggests that the firm should consider a pulsing mailing strategy. That is, the firm sends mail to a set of donors who are most likely to donate, and tries to build their goodwill and raise donation. However, as cumulative contacts increase, the donation drive itself creates irritation. Hence, to mitigate it, they should stop sending mail to this set of donors. Instead, they may direct their mailing effort to another set of donors, perhaps those who are not the most likely to donate, so that they build goodwill and raise funds from this segment. Thus, one way to manage donation drive is to alternate between two action-states — keep-mailing and stop-mailing — across two or more segments of potential donors.

Customer Heterogeneity

To implement such a pulsing strategy, the firm should identify "segments" in the population. Typically, market segments are identified using latent class models (see Wedel and Kamakura 2000), which characterize customer heterogeneity by finite number of latent segments that are assumed homogenous within-segment and heterogeneous across-segments. Alternatively, when each consumer is viewed as uniquely different from other consumers, we model their heterogeneity via continuous distributions of response parameters (e.g., Allenby and Ginter 1995). Wedel and Kamakura (2000, Ch. 19) offer a comparative discussion of these approaches.

In the proposed approach, we neither formulated latent class response models, nor assumed continuous distributions for response parameters. To be precise, we note that the response parameters in equation (3) are not randomly distributed across customers.

Rather, the response parameters evolve stochastically over *time* to capture temporal heterogeneity (see Figure 1). In doing so, we obtain the estimates of response parameters for each and every customer via equation (10a), which incorporates feedback from each customer's response y_{it}. Consequently, we have the ability to estimate the RFM effects for Mr. Jack, for Ms. Jill, and so on for every customer. To illustrate this feature of the proposed model, in Figure 3, we display the histograms obtained from these customer-specific estimates of recency, shopping frequency, and monetary effects. This information is valuable for both academic and managerial purposes.

Insert Figure 3 here

Academically, the debate of whether customer heterogeneity is better represented by latent class models or continuous distributions of parameters remains unresolved (see Wedel and Kamakura 2000, p. 326), perhaps because researchers have had to adopt one or the other representation. Because we did not assume either representation of customer heterogeneity, we take the disinterested position and "let the data speak." Panel A in Figure 3 presents the most interesting case with *bimodal* distribution of recency effects. Here, one can consider either a two-segment model allowing for within-segment heterogeneity (Böckenholt 1993), or a *mixture* of continuous distributions of parameters (Allenby, Arora, and Ginter 1998). On the other hand, Panel B depicts a uni-modal and skewed distribution of shopping frequency effects, lending support for modeling heterogeneity by a continuous distribution. Panel C shows *homogeneity* in the monetary effect, indicating that most people react similarly in the matters of money. In sum, our results suggest that the richness of consumer responsiveness necessitates the multiplicity of models and methods, and so the “correct” representation remains elusive.

Managerially, using the proposed approach, direct-marketers can implement the concept of *one-to-one marketing* (Peppers, Rogers, and Dorf 1999). In essence, this concept entails four steps: identify best customers, differentiate among them, interact with them, and configure products or services to meet each customer’s needs. The existing models in the literature empower direct marketers to identify the best set of customers — either based on response probability (Bult and Wansbeek 1995) or expected transaction value (Donkers et al. 2002). Having identified the best set of customers, the direct marketer’s next step is to differentiate amongst them; here, the direct marketer needs customer-specific information on responsiveness, which is available from the proposed model. Subsequently, the direct marketer can interact differently with Mr. Jack and with Ms. Jill, and customize its products and services.

CONCLUDING REMARKS

Direct marketers utilize RFM models, which include behavioral variables such as time elapsed since last purchase, how often one buys, and the amount spent. However, these models ignore the role of communications variables, which are actions initiated by the marketer, and which may influence customer’s behavior. In addition, while recent advances in RFM models incorporate customer heterogeneity, they ignore temporal heterogeneity. In other words, these models recognize that customer responsiveness varies across different customers, but not across different quarters. By addressing these issues, this paper makes the following contributions to modeling, methodological, substantive and conceptual domains of direct-marketing literature.

We introduce communications effects in the RFM models via the construct of goodwill. Applying advertising theory, we formulate a model of goodwill formation, whose dynamics are driven by both repeated and cumulative exposures to marketing commuications. In addition, we relax the assumption that customer responsiveness reamins fixed over time, introducing the notion of temproal heterogeneity. Thus, the modeling contributions are: (a) dynamics induced by communications effects are introduced in RFM models; and (b) time-varying paramaters are incorporated in RFM models.

Methodologically, we noted that the standard estimation approach ignores inter-temporal dynamics, unidirectional flow of time, and dependence in decisions over time. In contrast, via the concept of information set, the proposed estimation approach takes into account the time sequence of information arrival and computes the likelihood of the entire time-path of observed choices. Consequently, we make the following methodological contribution: direct marketers can estimate responsiveness of each specific customer, without specifying either latent-class models or continuous parametric distributions for customer heterogeneity.

Substantively, we show that direct mail communications (as opposed to broadcast television or print ads) affect goodwill formation, which, in turn, influences customer's repsonse probability (as opposed to aggregate brand awareness or sales). Furthermore, direct mail builds goodwill, whereas cumulative exposure creates irritaion and erodes it. The two opposing forces induce a periodic pattern of goodwill formation, with a cylce of four quarters. Hence, to mitigate irritation, direct marketer should apply pulsing strategy in which customers receive no mail contacts during two intense mailing bursts.

Conceptually, we made a distinction between two kinds of frequency: shopping and communications frequency. The former is controlled by the customer, the latter, by the marketer. Once we introduce communications frequency in the standard RFM model, we observe reversal in the shopping frequency effect. That is, in contrast to the extant literature, we find that response probability *decreases* as shopping frequency increases, and so customers who donate frequently are *less* likely to donate in the future.

In conclusion, we hope that these contributions provide new insights and tools for direct marketers to improve their practice.

TABLE 1

PARAMETER ESTIMATES FROM STANDARD AND DYNAMIC RFM MODELS

(1)	(2)	(3)	(4)
	Standard Model	*Dynamic Model*	*Dynaimc Model (Replication)*
Parameters	*Estimates (t-values)*	*Estimates (t-values)*	*Estimates (t-values)*
Intercept, α	-1.2448	–	–
	(-136.2)		
Recency, β_{10}	-3.9042	-12.121	-12.064
	(-120.0)	(-257.2)	(-250.3)
Shopping Frequency, β_{20}	2.2425	-2.6931	-3.2279
	(137.8)	(-88.9)	(-95.0)
Monetary Effect, β_{30}	-0.9768	-18.446	-10.902
	(-5.3)	(-44.3)	(-30.6)
Communications Frequency, γ	–	2.3888	2.4450
		(215.0)	(200.0)
Irritation Effect, η	–	-0.0558	-0.0555
		(-53.4)	(-48.3)
Transition Error, σ	–	0.4981	0.5569
		(85.3)	(70.2)
Max. Log-likelihood, L^*	-211054.2	-187400.9	-183325.2
AIC	422116.4	374813.8	366664.4
Adjusted R^2	18.83%	29.38%	29.62%

FIGURE 1

TIME-VARYING RFM EFFECTS

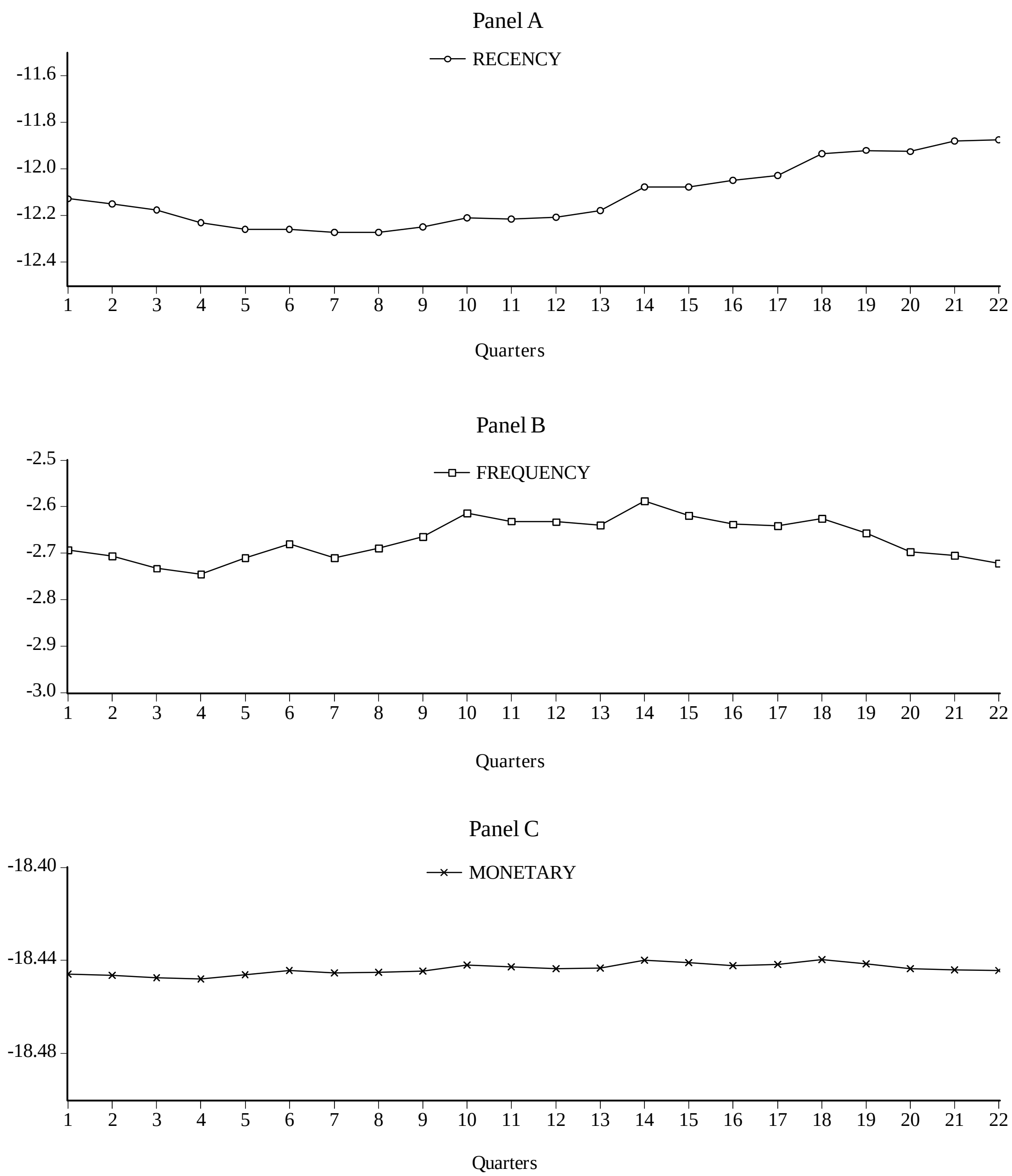


FIGURE 2

CYCLIC DYNAMICS OF GOODWILL FORMATION

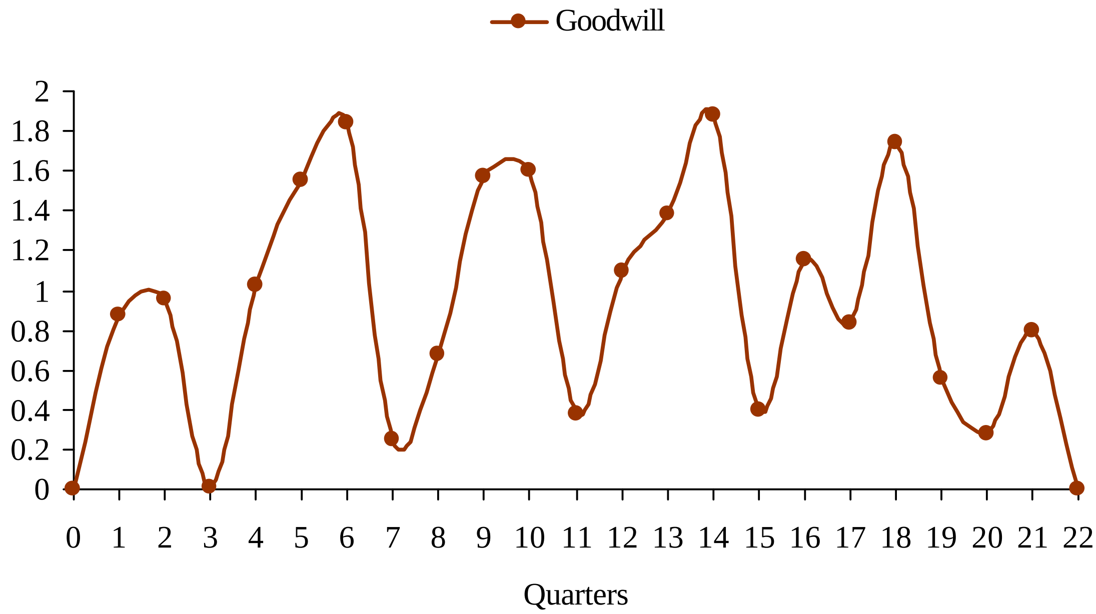
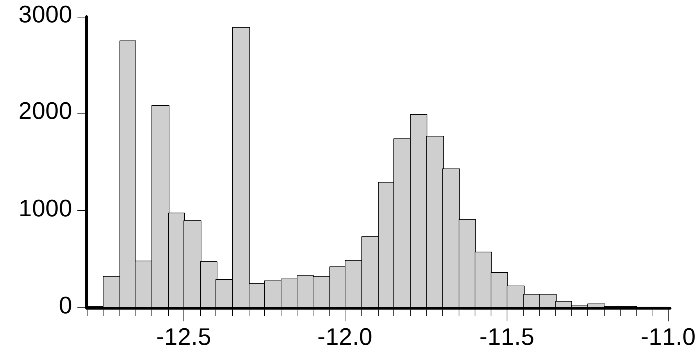


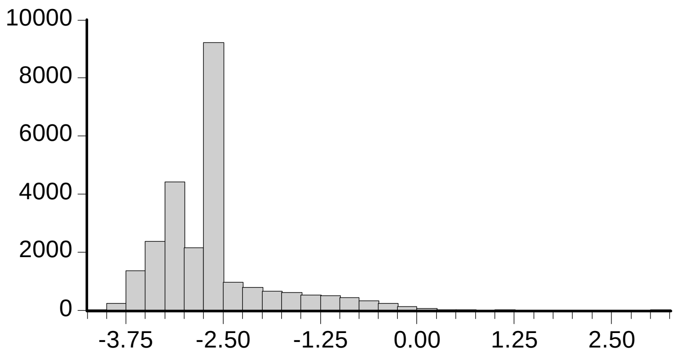
FIGURE 3

HISTOGRAMS OF DONOR-SPECIFIC RFM EFFECTS



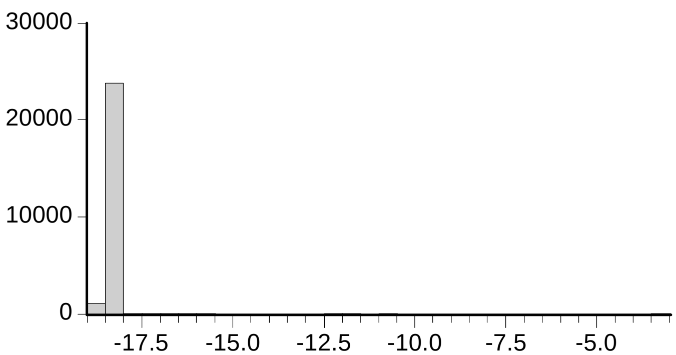
RECENCY EFFECT

Cases	25000
Mean	-12.11744
Median	-12.07510
Maximum	-11.01694
Minimum	-12.78507
Std. Dev.	0.395910
Skewness	-0.026603
Kurtosis	1.581722



FREQUENCY EFFECT

Cases	25000
Mean	-2.670341
Median	-2.693088
Maximum	3.116097
Minimum	-4.178674
Std. Dev.	0.714312
Skewness	1.504224
Kurtosis	5.640724



MONETARY EFFECT

Cases	25000
Mean	-18.44378
Median	-18.44596
Maximum	-3.012160
Minimum	-18.67161
Std. Dev.	0.139641
Skewness	70.24503
Kurtosis	6710.937

REFERENCES

Allenby, G. M. and J. L. Ginter (1995), "Using Extremes to Design Products and Segment Markets," *Journal of Marketing Research*, Vol. 32, No. 4, p. 392-403.

Allenby, G. M., N. Arora, and J. L. Ginter (1998), "On the Heterogeneity of Demand," *Journal of Marketing Research*, Vol. 35, No. 3, p. 384-389.

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*, Vol. 94, 365-374.

Bitran, G. R. and S.V. Mondschein (1996), "Mailing Decisions in the Catalog Sales Industry," *Management Science*, Vol. 42, No. 9, p. 1364-1381.

Böckenholt, U. (1993), "Estimating Latent Distributions in Recurrent Choice Data," *Psychometrika*, Vol. 58, No. 3, p. 489-509.

Bult, J. R. and T. Wansbeek (1995), "Optimal Selection for Direct Mail", *Marketing Science*, Vol. 14, No. 4, p. 378-394.

Burke, M. C. and J. A. Edell (1986), "Ad Reactions Over Time: Capturing Changes in the Real World," *Journal of Consumer Research*, Vol. 13, No. 1, p. 114-118.

Calder, B. J. and B. Sternthal (1980), "Television Commercial Wearout: An Information Processing View," *Journal of Marketing Research*, Vol. 17, No. 2, p. 173-186.

Dekimpe, M. G. and D. M. Hanssens (1995), "The Persistence of Marketing Effects on Sales," *Marketing Science*, Vol. 14, No. 1, p. 1-21.

DeSarbo, W.S. and V. Ramaswamy (1994), "CRISP: Customer Response Based Iterative Segmentation Procedures for Response Modeling in Direct Marketing, *Journal of Direct Marketing*, Vol. 8, No. 3, p. 7-20.

Donkers, B., J. J. Jonker, P. H. Franses, and R. Paap (2002), "Modeling Target Selection", *Marketing Science*, forthcoming.

Gönül, F. and M. Z. Shi (1998), "Optimal Mailing of Catalogs: A New Methodology Using Estimable Structural Dynamic Programming Models, *Management Science*, Vol. 44, No. 9, p. 1249-1262.

Grass, R. and W. H. Wallace (1969), "Satiation Effects of TV Commercials," *Journal of Advertising Research*, Vol. 9, No. 4, p. 3-8.

Greyser, S. (1973), "Irritation in Advertising," *Journal of Advertising Research*, Vol. 13, No. 1, p. 3-10.

Jonker, J.J., P. H. Franses, and N. Piersma (1998), "Evaluating Direct Marketing Campaigns; Recent findings and Future Research Topics", *Research Report*, Econometric Institute, Erasmus University Rotterdam.

Leone, R. P. (1995), "Generalizing What is Known About Temporal Aggregation and Advertising Carryover," *Marketing Science*, Vol. 14, No. 3, Part 2, p. G141-G150.

Mahajan, V. and E. Muller (1986), "Advertising Pulsing Policies for Generating Awareness for New Products," *Marketing Science*, Vol. 5, No. 2, p. 89-111.

Naik, P. A., M. K. Mantrala, and A. G. Sawyer (1998), "Planning Pulsing Media Schedules in the Presence of Dynamic Advertising Quality," *Marketing Science*, Vol. 17, No. 3, p. 214-235.

Naik, P. A., M. R. Hagerty, and C.-L. Tsai (2000), "A New Dimension Reduction Approach for Data-Rich Marketing Environments: Sliced Inverse Regression," *Journal of Marketing Research*, Vol. 37, No. 1, p. 88-101.

Nerlove, M. and K. Arrow (1962), "Optimal Advertising Policy Under Dynamic Conditions," *Economica*, Vol. 29, May, p. 129-42.

Pechmann, C. and D. W. Stewart (1988), "Advertising Repetition: A Critical Review of Wearin and Wearout," in *Current Issues and Research in Advertising*, Eds. J. H. Leigh and C.R. Martin, Ann Arbor, MI: The University of Michigan Press, p. 285-330.

Peppers, D., M. Rogers, and B. Dorf (1999), "Is Your Company Ready for One-to-One Marketing," *Harvard Business Review*, Vol. 77, No. 1, p. 151-160.

Pieters, R., E. Rosbergen, and M. Wedel (1999), "Visual Attention to Repeated Print Advertising: A Test of Scanpath Theory," *Journal of Marketing Research*, Vol. 36, No. 4, p. 424-438.

Rosbergen, E., R. Pieters, and M. Wedel (1997), "Visual Attention to Advertising: A Segment-Level Analysis," *Journal of Consumer Research*, Vol. 24, No. 3, p. 305-314.

Sawyer, A. G. and S. Ward (1981), "Carryover Effects in Advertising Communication," in *Research in Marketing*, Vol. 2, JAI Press Inc., p. 259-314.

Schmittlein, D. C., D. G. Morrison, and R. Colombo (1987), "Counting Your Customers: Who are They and What Will They Do Next?," *Management Science*, Vol. 33, No. 1, p. 1-24.

Tanizaki, H. (1993), "Kalman Filter Model with Qualitative Dependent Variables," *Review of Economics & Statistics*, Vol. 75, No. 4, P. 747-752.

Wedel, M, W. S. DeSarbo, J. R. Bult, and V. Ramaswamy (1993), "A Latent Class Poisson Regression Model for Heterogeneous Count Data," *Journal of Applied Econometrics,* Vol. 8, No. 4, p. 397-411.

Wedel, M. and W. Kamakura (2000), *Market Segmentation: Conceptual and Methodological Foundations*, 2nd edition, Boston, M.A.: Kluwer Academic.

Zajonc, R. B. (1968), "Attitudinal Effects of Mere Exposure," *Journal of Personality and Social Psychology*, Vol. 9, No. 2, p. 1-28.

Zielske, H. A and W. Henry (1980), "Remembering and Forgetting Television Ads," *Journal of Advertising Research*, Vol. 20, No. 2, p. 7-13.