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Optimizing the Marketing Interventions Mix in Intermediate-Term CRM

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We provide a fully personalized model for optimizing multiple marketing interventions in intermediate-term customer relationship management (CRM). We derive theoretically based propositions on the moderating effects of past customer behavior and conduct a longitudinal validation test to compare the performance of our model with that of commonly used segmentation models in predicting intermediate-term, customer-specific gross profit change. Our findings show that response to marketing interventions is highly heterogeneous, that heterogeneity of response varies across different marketing interventions, and that the heterogeneity of response to marketing interventions may be partially explained by customer-specific variables related to customer characteristics and the customer's past interactions with the company. One important result from these moderating effects is that relationship-oriented interventions are more effective with loyal customers, while action-oriented interventions are more effective with nonloyal customers. We show that our proposed model outperformed models based on demographics, recency-frequency-monetary value (RFM), or finite mixture segmentation in predicting the effectiveness of intermediate-term CRM. The empirical results project a significant increase in intermediate-term profitability over all of the competing segmentation approaches and a significant increase in intermediate-term profitability over current practice.

Key words: customer relationship management (CRM); one-to-one marketing; personalization; customer heterogeneity; segmentation; direct marketing
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1. Introduction

CRM differs from traditional direct marketing in that it usually involves customer contact over a variety of contact media. For example, although the typical direct marketing problem may involve only one type of marketing intervention (e.g., a regularly mailed catalog), the CRM marketing problem typically involves a mix of marketing interventions (e.g., direct mail, Internet contacts, personal selling contacts, telephone contacts, etc.). This leads to the problem that we address—how to design a mix of marketing interventions for each customer individually.

The database marketing literature (e.g., Schmittlein and Peterson 1994) has provided individual-level prediction models of future purchase but has stopped short of providing a general optimization model for marketing interventions. The direct marketing literature (e.g., Bult and Wansbeek 1995, Gönül and Shi 1998) has provided individual-level optimization models for the case of one kind of direct mailing. A gap in the literature is a solution to the general CRM problem of how to optimize a mix of marketing interventions at the individual level. Traditionally, the direct marketing literature has focused on which customers in a company's database should be targeted with a direct mailing or catalog. The standard approach has been to select profitable customers for each mailing using several methods, such as RFM, CHAID, and logit models (e.g., Bult and Wansbeek 1995, David Sheppard Associates 1990). However, these methods optimize profitability only in the short run. Some studies have advocated a longer term orientation and developed individual-level models that optimize the number of mailings sent to a customer in a certain time period (e.g., Bitran and Mondschein 1996, Gönül and Shi 1998). In a very recent study, Elsner et al. (2004) proposed the use of dynamic multilevel modeling to find out, for the intermediate timeframe, the optimal number of direct mailings sent to each customer.

Visionaries and consultants have touted one-to-one marketing, in which companies completely personalize their marketing efforts, as the ultimate form of CRM (Peppers and Rogers 1997) in practice, though, many companies that apply CRM do not fully personalize their marketing interventions, in that they do not fully accommodate heterogeneity of response. Personalization in CRM can take two forms. First, companies can differentiate their marketing efforts based on customer differences in personal characteristics and history with the company. Such efforts do not necessarily imply any modeling of heterogeneity of response. For example, a company might estimate an aggregate regression equation that includes personal variables as independent variables. Second, companies can further differentiate their marketing efforts based also on customer differences in response. Such methods permit heterogeneity in not only personal characteristics and history but also model heterogeneity in responsiveness to marketing efforts.

Typically, firms model heterogeneity of response through various forms of response segmentation (Levin and Zahavi 2001, Verhoef et al. 2003). These segmentation approaches can be segmentation based on customer characteristics, such as demographic segmentation, or segmentation based on history with the company, such as RFM segmentation (Roberts and Berger 1989, Bitran and Mondschein 1996). Other CRM models account for customer heterogeneity (e.g., Bult and Wittink 1996, DeSarbo and Ramaswamy 1994), using latent class/finite mixture models.

All the aforementioned approaches result in segmentized (rather than truly personalized) marketing interventions. From a CRM perspective, personalized marketing interventions—methods that fully accommodate individualized responsiveness, based on customers' characteristics and their purchase history with the firm—are preferred (Libai et al. 2002, Peppers and Rogers 1999). Although direct marketing models that fully capture heterogeneity have been devised to model interpurchase times (Allenby et al. 1999) and response to couponing (Rossi et al. 1996), no models have been published that fully capture heterogeneity of response to a mix of marketing interventions in CRM, either in the long term or the intermediate term.

It has been noted that different types of interventions can have different impacts across customers, depending on their customer characteristics (e.g., DeWulf et al. 2001). CRM interventions can have different purposes. For example, the CRM literature generally distinguishes between interventions with a call for action focusing on cross-selling (i.e., direct mailings) and more relationship-oriented instruments (i.e., relationship magazines) (Berry 1995, Bhattacharya and Bolton 1999, McDonald 1998). In this research, we therefore investigate whether the intermediate-term effects of these two types of interventions differ across customers. We also explore whether moderating variables can work differently for these two types of interventions.

The objectives of this paper are fourfold. First, this study develops an intermediate-term CRM optimization model that models heterogeneity in responsiveness to the marketing intervention mix, as well as heterogeneity of past behavior and personal characteristics. Second, we compare empirically whether a fully personalized CRM approach performs better than traditional segmentation approaches in predicting intermediate-term customer profitability. Third, we investigate the moderating effects of past behavior on action-oriented and relationship-oriented interventions, with particular interest in whether these moderating variables affect the relative effectiveness of marketing interventions, depending on the purpose of the intervention. Fourth, we explore whether fully personalized CRM can significantly increase intermediate-term profitability over commonly used segmentation approaches and current practice.

2. The Model

2.1. The Managerial Problem

The objective of a firm's CRM strategy is to optimize each individual customer's profitability over time (Reinartz and Kumar 2003). In our model, we consider the yearly profit of an individual customer. We assume that the firm's aim is to determine the customer-specific marketing interventions mix that maximizes the profit change of each customer in this year.[1] We refer to this as the intermediate-term CRM problem, as opposed to the long-term CRM problem of determining the customer-specific future marketing interventions trajectory that will optimize customer lifetime value (CLV). This profit change consists of changes in gross profits from a customer over time because of, for example, cross-buying, minus the marketing costs allocated to a customer to achieve this. Mathematically, the change in profitability of customer i between t and $t-1$ is formulated as follows:

$$\Delta Profit_{i,(t-1)\to t} = (R_{i,t} - R_{i,t-1}) - C_{i,(t-1)\to t},^{2} \qquad (1)$$

where $R_{i,t}$ is the gross profit (revenues minus direct costs) obtained from customer i in time t, and $C_{i,(t-1)\to t}$ is the marketing costs allocated to customer i in time t. In our model, we take a CRM perspective on

[1] Ideally the firm would instead maximize its customer equity (Rust et al. 2004) by individually maximizing each CLV (the long-term approach) (Reinartz and Kumar 2000). We use next period profit change (the intermediate-term approach) instead, because the optimization results in a closed-form solution, and because research shows a close relationship between current profitability and CLV in this industry (Donkers et al. 2003).

[2] The gross profits in our model are equal to the contributions to profit received from an individual customer. The contribution margin is a figure that is constant across customers.

defining the marketing costs. These costs only include those instruments that a firm can personalize. In most CRM applications, these instruments concern direct communication instruments, such as direct mailings (Roberts and Berger 1989). The marketing costs of a customer i in a given time period are defined as

$$C_{i,(t-1)\to t} = \sum_{k=1}^{K} M_{k,i} * C_k, \tag{2}$$

where k is a marketing instrument, $M_{k,i}$ is the marketing allocation to customer i between t and $t-1$, and C_k is the variable costs of instrument k. The objective function for firms maximizing the profitability change of their individual customers becomes as follows:

$$\Pi_{i,(t-1)\to t} = \Delta R_{i,(t-1)\to t} - \sum_{k=1}^{K} M_{k,i} * C_k. \tag{3}$$

2.2. Optimizing the Intervention Mix

If $\mathbf{M}_i$ is a vector of nonnegative marketing allocations to customer i, and $\boldsymbol{\beta}_i$ is a coefficient vector that captures the impact of the marketing allocations on the profitability of customer i, then we have

$$\Pi_{i,(t-1)\to t} = \mathbf{X}_i\boldsymbol{\beta}_i - \mathbf{M}_i\mathbf{C} + \epsilon_i, \tag{4}$$

where $\mathbf{X}_i$ is a vector containing the marketing intervention levels targeted to customer i (equal to the elements $\ln(M_{ik}+1)$ for all elements k of $\mathbf{M}_i$), $\mathbf{C}$ is a vector containing the costs, C_k, and ϵ_i is a normally distributed error term. The logarithmic transformation is employed to capture the phenomenon of diminishing returns to marketing efforts and to facilitate tractability of obtaining optimal marketing allocation levels.

The marketing allocation problem in intermediate-term CRM is best modeled as a profit maximization problem (Bult and Wansbeek 1995). The objective is to maximize $\Pi_{i,t-(t-1)}$ with respect to $\mathbf{M}_i$ for each customer i. Based on this formulation, it is easy to obtain that the optimal level of marketing allocation M_{ik} is

$$M'_{ik} = (\underline{\beta}_{ik}/C_k) - 1, \tag{5}$$

where $\underline{\beta}_{ik}$ is the element of $\boldsymbol{\beta}_i$ corresponding to marketing allocation k. In many cases, the marketing allocation, M_{ik}, is constrained to a maximum of $M_{ik}^{\max}$. In such a case, the optimal allocation is given as $\min(M'_{ik}, M_{ik}^{\max})$.[3]

If a segmentized marketing approach is used, then the coefficient vector $\boldsymbol{\beta}_i$ will be estimated by segment. That is, for segment s, the marketing allocation will be identical across customers. This leads to the optimal allocation rule

$$M'_{sk} = (\underline{\beta}_{sk}/C_k) - 1. \tag{6}$$

2.3. A Hierarchical Model for Customer-Level Effects

To optimize individual customer profitability, the impact of marketing interventions on customers' changes in gross profits must be modeled. As we aim to account for customer heterogeneity at the customer level to develop a personalized intermediate-term CRM intervention strategy, we propose a hierarchical model (Rossi and Allenby 2003). The general shift in gross profit model is formulated as follows:

$$\Delta R_{i,(t-1)\to t} = \mathbf{X}_i\boldsymbol{\beta}_i + \epsilon_i. \tag{7}$$

Equation (7) may also be formulated to include interaction terms.[4] We now specify the customer-specific response parameter vector, $\boldsymbol{\beta}_i$ as

$$\boldsymbol{\beta}_i = \mathbf{Z}_i\boldsymbol{\alpha} + \boldsymbol{\delta}_i, \tag{8}$$

where $\mathbf{Z}_i$ is a vector of the past behavior and customer characteristics of customer i, available from the firms' customer database, and $\boldsymbol{\alpha}$ is a coefficient vector representing the moderating effect of $\mathbf{Z}_i$ on the effect of CRM interventions on the intermediate-term shift in gross profits of customer i. In all alternative models, the alpha variables are instead used as covariates.

3. Moderating Effects

In our model, we distinguish two types of interventions: direct mailings and relationship magazines. The direct mailings have a call for action and often provide short-term economic rewards (i.e., price discounts). Relationship magazines provide more social benefits (i.e., information on services and lifestyle information) and focus on both relationship building and the creation of additional sales. We hypothesize that past behavior will have differential impact on the two types of marketing interventions.

3.1. The Effects of Past Behavior

In our model, we distinguish the following six past behavioral variables: (1) last period profit, (2) relationship duration, (3) loyalty program membership, (4) number of current products used, (5) time since last purchase, and (6) cumulative number of purchases. There is ample evidence that these variables

[3] In practice, the allocation level must generally be nonnegative, and it often must be integer. In such a case, we determine the objective function value for the nonnegative integers above and below $\min(M'_{ik}, M_{ik}^{\max})$ or simply round to the nearest nonnegative integer.

[4] In our case, we also tested a model with interaction terms, but the prediction error turned out to be slightly worse than the model without interaction terms. For that reason, and to save space, we focus our attention on the simpler main-effect model.

might moderate the effect of CRM interventions. In our propositions, we consider relationship duration, number of current products used, time since last purchase, and cumulative number of purchases as indicators of behavioral loyalty (e.g., Bolton et al. 2004, Reichheld 1996, Reinartz and Kumar 2000). Our assumption that past behavior might moderate the effect of CRM interventions is also based on the direct marketing literature, which acknowledges that there are microsegments based on prior behavior that respond differently to the sent direct mailings Elsner et al. (2004).

Behavioral Loyalty. Bawa and Shoemaker (1987) show that direct mailings with coupons are less effective among behavioral loyals, while Kahn and Louie (1990) also report on a weaker effect of sales promotions among brand loyals. Thus, this might suggest that the effect of action-oriented CRM interventions will be lower among loyal customers. Also, from a relationship perspective, there is a reason to support this expectation. Loyal customers might have reached their potential value in the relationship with respect to the number of services purchased (Dwyer et al. 1987, Grant and Schlesinger 1995). Thus, they might be less likely to purchase additional services, despite a received direct mailing with a call for action.

Although loyal customers might be less inclined to respond to direct mailings, they might be more responsive to relationship magazines. Loyal customers expect more relational value from the firm (e.g., Fournier et al. 1998, Reinartz and Kumar 2000). As a result, they highly value relationship-oriented actions. These actions provide a deeper meaning to the relationship with the firm, which at that time should go beyond pure economic transaction-oriented value (Dwyer et al. 1987). Less loyal customers will be less receptive for this relational value, as they will prefer economic-oriented value seducing them to purchase an additional service. Moreover, loyal customers are also likely to be more committed to the firm (Verhoef et al. 2002), which leads to more attention for relationship-oriented interventions. Hence, we expect that relationship-oriented interventions will be more effective among behavioral loyals. There are several potential measures of behavioral loyalty, and each has its own strengths and weaknesses. Nevertheless, the weight of past research leads us to propose the following:

PROPOSITION 1A. *Past behavioral loyalty, which is indicated by longer relationship duration, greater number of current products used, shorter time since last purchase,*[5] *and larger cumulative number of purchases, will be negatively related to response to action-oriented interventions.*

PROPOSITION 1B. *Past behavioral loyalty, which is indicated by longer relationship duration, greater number of current products used, shorter time since last purchase, and larger cumulative number of purchases, will be positively related to response to relationship-oriented interventions.*

Loyalty Program Membership. Loyalty program membership has been shown to positively impact customer behavior such as retention, service usage, and customer share (Bolton et al. 2000, Verhoef 2003). A theoretical explanation for this positive effect is that customers might view program incentives as a motive to repeatedly purchase the programs' sponsors' brand (Kivetz 2003, Roehm et al. 2002). No research has yet considered the moderating effect of loyalty program membership on the effect of pure CRM interventions. Our contention is that the motivating nature of the loyalty program might strengthen the effect of CRM interventions independent of the purpose of the intervention (Duncan and Moriarty 1998). Thus, we propose the following:

PROPOSITION 2. *Loyalty program membership will be positively related to response to CRM interventions.*

3.2. Other Moderating Variables

For completeness, we also include a number of other variables that may have a moderating effect on the effectiveness of CRM interventions. Although they are not the substantive focus of our current investigation, past research indicates that Sex (Blattberg and Neslin 1990, Spring et al. 2001), Education (Bell et al. 1999), Number of Wage Earners (Darian 1987), Income (Ailawadi et al. 2001, Bawa and Gosh 1999), Age (Bell et al. 1999, Kamakura et al. 1991, Urbany et al. 1996), and whether the customer purchases from catalogs (Spring et al. 2001) may have an impact on the effectiveness of CRM interventions. For this reason, we include all of these variables in our model as potential moderators as well as last period profit.

4. Empirical Test of the Heterogeneity Models

4.1. Data

We obtained data from a financial service provider that specializes in insurance. The data consist of the purchases of insurance of 1,580 customers over a two-year period. For each service category (n), the firm has calculated a contribution margin $(CM)_n$. This contribution margin is not customer specific and is thus the same across all customers. Based on these data, the gross profit per customer can be calculated as follows:

$$R_{i,t} = \sum_{n=1}^{N} Service_{i,n,t} * (CM)_n. \tag{9}$$

[5] Shorter time since last purchase is not an infallible indicator of loyalty. For a customer with a high baseline purchase rate, even a short gap in purchases may indicate disloyalty, whereas a customer with a low baseline purchase rate may be loyal, even with large gaps in the purchase record (e.g., see Schmittlein and Peterson 1994).

In this equation, $Service_{i,n,t}$ stands for the number of services (insurances) purchased by customer i in product category n in time t. Given the two-year time period, we have customer gross profit information at one-year intervals—at $t = 0$, $t = 1$, and $t = 2$.

Besides gross profit information and information on the number of services purchased, we also have data on the relationship age of the customer, which are calculated as the time between the starting date of the relationship with the firm (first purchase) and $t = 0$ (Bolton 1998). Furthermore, as we observe the purchase dates of services, we can calculate the time since the last purchase. Finally, the data also provide information on whether a customer i is a member of a loyalty program. From these 1,580 customers, the firm also observed sociodemographic characteristics using questionnaires. We have information on each customer's age, income, household size, education, and gender. On average, the customers of the financial service provider can be characterized as rather prosperous and well educated.

During the period of our study, the firm did not employ an allocation strategy that optimized the total value of the customer. They instead employed distinct strategies for the direct mailings and the relationship magazine. For the direct mailings, they used two types of strategies. First, they sent out mailings based on the expected response rate to that mailing, which might be considered the traditional direct marketing approach. Second, they sent out some mailings without consideration of expected response. On average, the firm sent 2.2 direct mailings to a customer in the first year and 3.1 in the second year.

The company's policy was to send the relationship magazine to all active customers. However, during a period of our study, in both Year 1 and Year 2, they randomly split the customer base into one group that received that issue of the magazine, and another group that did not. This provided a controlled experiment in which the variation in number of magazines sent was not based on any profit optimization decision rule. The company sent an average of 3.4 magazines in the first year, and 2.4 magazines in the second year.

For the purposes of our study, we split the data into an estimation sample and a validation sample. The estimation sample employed the data from $t = 1$, except for last period profit, loyalty program, and number of company insurances, which were from $t = 0$, so as not to make the analysis circular. The validation sample used the data from $t = 2$, with the lagged variables from $t = 1$. Descriptive statistics from both samples are shown in Table 1. We note, in particular, that the percentage of people for whom gross profit changes from year to year is 21% in Year 1 and 24% in Year 2. This sort of pattern is typical of continuing services such as financial services, subscriptions, and memberships.

Table 1 Descriptive Statistics

	Mean (std. dev.)	
Variable	Year 1	Year 2
Gross profit (guilders)	192.81 (204.68)	212.47 (220.28)
% with changing profit	21%	24%
Relationship duration (years)	10.78 (6.40)	11.78 (6.40)
% in loyalty program	31%	35%
No. of insurances purchased	1.14 (1.79)	1.22 (1.90)
Time since purchase (years)	4.18 (5.13)	4.38 (5.06)
Cumulative number of purchases	2.69 (2.30)	2.87 (2.41)
% male	75%	75%
Catalogs	1.71 (1.05)	1.71 (1.05)
Median education	5.04[1] (1.22)	5.04[1] (1.22)
No. of wage earners	1.52 (0.56)	1.52 (0.56)
Median income	3.25[2] (1.47)	3.25[2] (1.47)
Age	42.18 (8.89)	43.18 (8.89)

[1]Advanced high school.
[2]Higher than the average income.

4.2. Competing Models

A Priori Segmentation. One method of accounting for heterogeneity is to define customer segments a priori. This is an often-applied method in CRM, with its most famous example the segmentation on RFM characteristics. For each segment, linear models are estimated that explain the shift in gross profits over time. In this research, we consider two frequently used segmentations (Roberts and Berger 1989, Verhoef et al. 2003): demographic segmentation and RFM segmentation. Within each of these segmentation schemes a response model is estimated for each segment. These result in the following linear models for each segment s:

$$\Delta R_{i,(t-1)\to t} = \mathbf{X}_i \boldsymbol{\beta}_s + \mathbf{Z}_i \boldsymbol{\gamma} + \epsilon_i \tag{10}$$

that are estimated to assess the effect of CRM interventions on the shift in intermediate-term gross profits. (The variables are defined in §§2.1–2.3.)

Ex Post Segmentation. While the often-applied segmentation methods in CRM concern a priori segmentations, the segments can also be derived ex post. To do so, a finite mixture formulation may be used (Wedel and Kamakura 1999). In this study, we use the following well-known formulation by Kamakura and Russell (1989):

$$\mathrm{E}[\Delta R_{i,(t-1)\to t}] = \sum_s p_s [X_i \beta_s + Z_i \gamma_s], \tag{11}$$

where p_s is the posterior probability of segment membership.

Because segment membership is known probabilistically rather than with certainty, the optimization formula in Equation (5) must be modified. Reformulating the objective function to reflect the probabilistic nature of the finite mixture model, we wish to maximize $\mathrm{E}[\Pi_{i,(t-1)\to t}]$ with respect to $\mathbf{M}_i$. We have

$$\begin{aligned}\mathrm{E}\big[\Pi_{i,(t-1)\to t};\mathbf{M}_i\big] &= \left\{\sum_s \Pr(s;Z_i)\mathrm{E}\big[\Pi_{i,(t-1)\to t};X_i,s\big]\right\} - \mathbf{M}_i\mathbf{C}\\ &= \mathbf{X}_i\sum_s\{\Pr(s;Z_i)\beta_s\} - \mathbf{M}_i\mathbf{C}. \qquad (12)\end{aligned}$$

This expression is maximized for marketing allocation k when

$$M'_{ik} = \left[\left\{\sum_s \Pr(s;Z_i)\beta_{ks}\right\}\Big/C_k\right] - 1. \qquad (13)$$

4.3. Estimation of the Hierarchical Model

The hierarchical model described in §2.3 is estimated using Markov Chain Monte Carlo (MCMC) methods (Gelfand and Smith 1990). Denoting $Y_i = \Pi_{i,t-(t-1)}$, we can specify our model as the following:

$$Y_i \sim N(\mu_i, \tau_1), \qquad (14)$$

where $N(\cdot)$ is the normal distribution, μ_i is the mean, and τ_1 is the precision (inverse of the variance). The mean μ_i is a function of the marketing efforts, $\mathbf{X}_i$, according to

$$\mu_i = \mathbf{X}_i\boldsymbol{\beta}_i + \beta_0, \qquad (15)$$

where β_0 is a normally distributed error term and the marketing responsiveness vector, $\boldsymbol{\beta}_i$, is itself a function of the customer characteristics and history, $\mathbf{Z}_i$, according to the relationship,

$$\beta_{ik} \sim N(\mathbf{Z}_i\boldsymbol{\alpha}_k, \tau_2), \qquad (16)$$

where τ_2 is the precision and $\boldsymbol{\alpha}_k$ is the transformation between the customer characteristics and history, $\mathbf{Z}_i$, and the average responsiveness to marketing intervention k. We specify the following priors to enable estimation:

$$\begin{aligned}&\tau_1 \sim \text{gamma}(1.0, 1.0), \qquad \tau_2 \sim \text{gamma}(1.0, 1.0),\\ &\beta_0 \sim N(0, 1.0), \qquad \alpha_{jk} \sim N(0, 1.0),\end{aligned} \qquad (17)$$

where α_{jk} is the element of $\boldsymbol{\alpha}_k$ that relates customer characteristic j to marketing intervention k, the first argument is the mean, and the second argument is the precision.

Estimation is accomplished using MCMC, based on a Gibbs sampling scheme (Geman and Geman 1984) in which we approximate the (analytically intractable) posterior distribution by sampling from the full conditional distribution. Equations (14)–(17) are used to specify the model. We ran 60,000 iterations using the WinBUGS software package, combating autocorrelation by thinning the observations—using only every fifth observation. The first 55,000 iterations were used for burn-in, and the last 5,000 were used for estimation.

4.4. Operationalizing the Segmentation Models

We operationalized the demographic segments using income (low, high) × age (younger, older), using median splits, with low income defined as less than 4,000 guilders[6] per month, and younger defined as age 40 or less. The RFM segments were defined by recency (recent, lapsed) × frequency (frequent, infrequent) × monetary value (high, low), where recent was defined as purchase in the last four years, frequency was defined as two or more previous purchases, and low monetary value was defined as less than 194 guilders profit in the previous time period. To maintain adequate sample sizes in all cells, we combined all of the low monetary value RFM cells into one cell before estimating.

The finite mixture model was operationalized by estimating model parameters for one, two, etc., segments individually, using 100 random starting points for each number of segments. For each number of segments, we chose the solution with the highest likelihood. The number of segments was determined by considering the AIC, BIC, and AIC3 (Andrews and Currim 2003, Bozdogan 1994) statistics. The lowest value for each of the three criteria was obtained for the seven-segment solution, so we use the best seven-segment solution as our finite mixture model.

5. Results

5.1. Convergence Diagnostics

Because the hierarchical model is estimated using MCMC, we must concern ourselves with whether or not the coefficient estimates have converged. We apply two tests for convergence, using the Business Operations Analysis (BOA) program, accessible in *R*. The Geweke convergence test (Geweke 1992) compares data early in the test period (after the burn-in period) with data late in the test period, to see whether they are significantly different. We see that all 29 nodes are nonsignificant, implying that there is no reason to doubt convergence. We also test for convergence using the Heidelberger and Welch stationarity test (Heidelberger and Welch 1983), which tests the null hypothesis that the chain is stationary. Again, we find that all of the nodes in our analysis pass the stationarity test. Between the two tests, we conclude that our estimation is reasonably stable and convergent.

5.2. Model Estimation

Changes in Gross Profit. The estimation sample was used to estimate the change in gross profit model in Equations (3)–(8). Table 2 shows the marketing

[6] In the period of study, the currency of The Netherlands was still guilders, which had not yet been converted to the euro.

Table 2 Segmentation Models' Marketing Responsiveness and Optimal Allocations

Model	Segment	Marketing responsiveness: Relationship magazine	Marketing responsiveness: Direct mailings	Holdout sample optimal allocations: R.M.[1]	Holdout sample optimal allocations: D.M.[2]
Demographic	Low income/younger	7.09	−7.09	2	0
	Low income/older	−3.85	12.53	0	7
	High income/younger	18.01	26.57	4	9
	High income/older	12.15	20.00	4	9
RFM	Low $	13.42	12.48	4	7
	High $/lapsed/infrequent	5.56	13.32	2	7
	High $/recent/infrequent	9.09	22.73	3	9
	High $/lapsed/frequent	−32.44	29.28	0	9
	High $/recent/frequent	26.45	−16.10	4	0
Finite mixture	1	−181.77*	105.41*	0	9
	2	109.03*	26.54*	4	9
	3	−67.12*	38.28*	0	9
	4	−33.42*	45.43*	0	9
	5	−2.86	−24.20	0	0
	6	8.95	−26.10*	3	0
	7	0.04	0.24	0	0
Hierarchical (median)		2.76	15.07	0	8

*Significant at the 0.05 level.
[1]Relationship magazines.
[2]Direct mailings.

responsiveness parameter estimates obtained from the various segmentation methods. We see from the table that the effect of the relationship magazines is found to be significant only for finite mixture segments one through four, while the effect of the direct mailings is significant for five of the finite mixture segments.

The parameter estimates for the hierarchical model are shown in Table 3. Because of the Bayesian nature of the analysis, it is not appropriate to discuss statistical significance, but we can construct an approximate analog. The table shows the mean for each parameter, along with a Monte Carlo standard error (Spiegelhalter et al. 2000), calculated using the method of batched means (Roberts 1996, p. 50). The final column shows the mean divided by the Monte Carlo standard error. The absolute value of this quotient exceeds two in all but one case. The heterogeneity of response is illustrated in Figure 1. In the figure, the horizontal axis is the size of the regression coefficient related to the marketing intervention, and the vertical axis represents the frequency with which that level of responsiveness was encountered across the customers studied. We can see that the hierarchical model reveals considerable heterogeneity of response, with the shape of the response being skewed toward ineffectiveness in the relationship magazine case, and more symmetrically distributed in the case of direct mailings. To address the stability of the individual-level coefficient estimates, we conducted split-half analyses (using both the estimation and validation samples) in which we calculated the standard errors of the individual-level coefficients for relationship magazine and direct marketing across the samples. The result was that the hierarchical model coefficients were about as stable as those produced by demographic segmentation or RFM segmentation, and were much more stable than those produced by finite mixture analysis.

The results are largely consistent with the propositions posited in §3. Proposition 1a is supported, in that longer relationship duration, larger number of current products used (number of insurances), and cumulative number of purchases all have a negative impact on response to direct mailings, and longer time since last purchase has the expected positive impact. Proposition 1b is also mostly supported, in that larger number of insurances, and larger cumulative number of purchases have a positive impact on response to relationship magazines, and larger time since last purchase has the expected negative impact. However, the effect of relationship duration is essentially zero. Proposition 2 is also supported, in that loyalty program membership is positively related to responsiveness to both direct mailings and relationship magazines.

The effects of the other moderating variables are similar across both marketing interventions. Both interventions are more effective for men than for women. Also, the higher the education level, the higher the income, and the more wage earners in

Table 3 Hierarchical Model Parameter Estimates

Parameter	Dependent variable	Independent variable	Mean	Monte Carlo S.E.	Mean/M.C.S.E.
α_{11}	Relationship magazines	Last period profit	−0.05	7.6E−4	−59.5
α_{12}	Relationship magazines	Relationship duration	0.00	0.02	0.1
α_{13}	Relationship magazines	Loyalty program	0.41	0.01	32.1
α_{14}	Relationship magazines	No. of insurances	0.28	0.01	26.2
α_{15}	Relationship magazines	Time since purchase	−0.12	0.01	−13.3
α_{16}	Relationship magazines	Cumulative no. of purchases	0.24	0.01	19.4
α_{17}	Relationship magazines	Sex (1 = male, 2 = female)	0.11	0.01	7.3
α_{18}	Relationship magazines	Catalogs	0.23	0.01	23.1
α_{19}	Relationship magazines	Education	0.43	0.01	33.9
$\alpha_{1,10}$	Relationship magazines	No. of wage earners	0.54	0.01	51.5
$\alpha_{1,11}$	Relationship magazines	Income	0.81	0.01	77.0
$\alpha_{1,12}$	Relationship magazines	Age	0.11	0.01	17.0
α_{21}	Direct mail	Last period profit	0.02	9.6E−4	24.5
α_{22}	Direct mail	Relationship duration	−0.88	0.02	−44.4
α_{23}	Direct mail	Loyalty program	0.26	0.01	19.1
α_{24}	Direct mail	No. of insurances	−0.08	0.01	−6.8
α_{25}	Direct mail	Time since purchase	0.46	0.01	33.5
α_{26}	Direct mail	Cumulative no. of purchases	−0.41	0.01	−29.5
α_{27}	Direct mail	Sex (1 = male, 2 = female)	0.18	0.01	15.4
α_{28}	Direct mail	Catalogs	0.29	0.01	28.5
α_{29}	Direct mail	Education	0.30	0.01	21.7
$\alpha_{2,10}$	Direct mail	No. of wage earners	0.40	0.01	35.6
$\alpha_{2,11}$	Direct mail	Income	0.45	0.01	36.8
$\alpha_{2,12}$	Direct mail	Age	0.36	0.01	44.3
avgbeta[1]	Revenue shift	Relationship magazines	2.78	0.11	26.0
avgbeta[2]	Revenue shift	Direct mail	15.12	0.14	107.8
β_0	Revenue shift	Constant	0.17	0.01	12.4
τ_1	Revenue shift	Error precision	2.2E−4	4.6E−7	542.5
τ_2	Independent variables	Error precision	7.9E−4	2.8E−6	292.2

the household; and the higher the income, the more the responsiveness to marketing. Older customers and catalog-buying customers are more responsive to the marketing interventions.

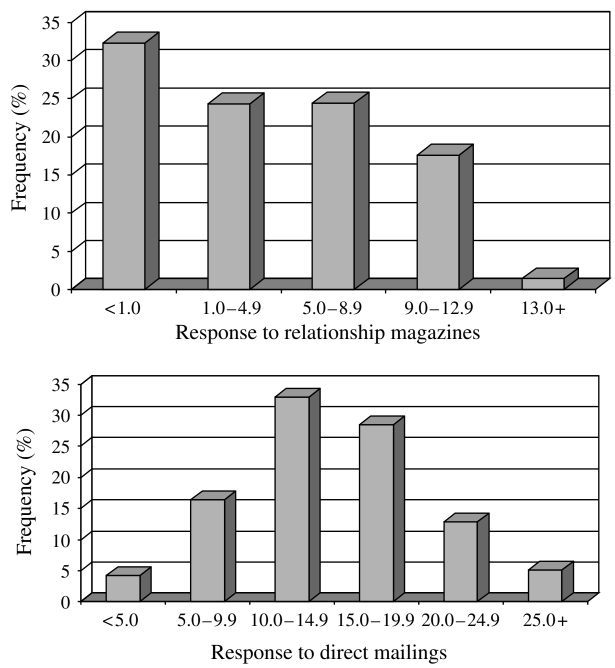
Optimal Marketing. Based on the parameter estimates from the estimation sample, plus the cost of the marketing interventions, it is possible to derive optimal marketing allocations. In the validation sample period ($t = 2$), the maximum number of relationship magazines was four, and the maximum number of direct mailings was nine. Each relationship magazine cost 2.20 guilders, and each direct mailing cost 1.65 guilders. Using Equations (5), (6), and (13), plus each customer's segment memberships, we can set the optimal marketing allocations for each customer, for each of the competing models. Allocations are by segment, except for the finite mixture model, which involves a mixture of segments, and the hierarchical model, in which case the allocations are fully personalized.

The last two columns of Table 2 show the optimal marketing allocations for each of the competing models. It is notable that there are many insignificant effects for the segmentation models despite a fairly large sample size. For this reason, we calculated optimal marketing allocations in two ways. Table 2 shows the optimal allocations without regard to statistical significance. We also employed an alternative allocation, in which all insignificant effects were set to an allocation of zero. For all models, the allocation was set to zero if there was a negative effect. The median hierarchical model allocations are zero relationship magazines and eight direct mailings, but the optimal allocation varies across customers. Figure 2 shows the optimal marketing allocations suggested by the hierarchical model. We can see that while 32.9% of customers would receive no relationship magazines, 27.7% would receive all four. The distribution of optimal allocations is more skewed for the direct mailings, with 41.5% of customers receiving the maximum number of mailings.

5.3. Predictive Validation

Table 4 shows the results from the validation test, predicting change in gross profit. We see from the holdout sample results that the hierarchical model resulted in the smallest mean square error (MSE) of prediction, 12.42 (all MSE numbers are expressed in thousands). By comparison, the demographic model (using only significant marketing allocations) produced a MSE of 15.48, the demographic model (using all allocations, significant or not) produced a MSE of 12.98, the RFM model (significant only) had a MSE of 15.03,

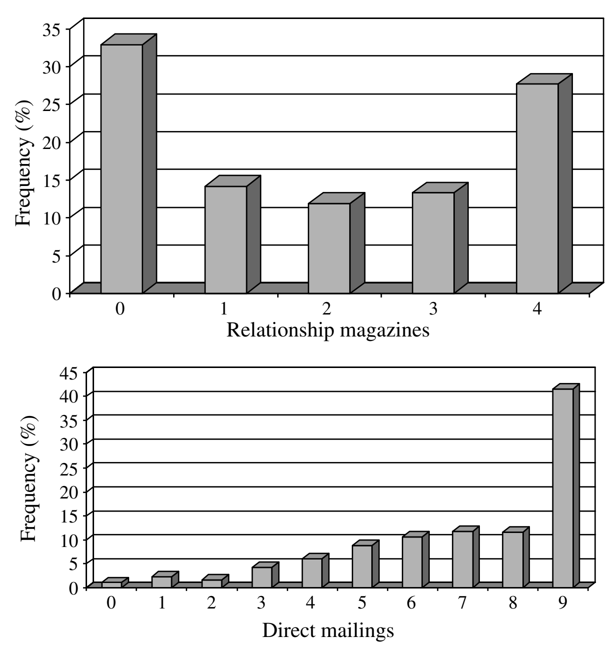
Figure 1 Heterogeneity of Response—Hierarchical Model



and the RFM model (all) had a MSE of 13.44. The finite mixture model (significant only) had a MSE of 23.05, and the finite mixture model (all) had a MSE of 23.49. We note that the performance of the segmentation models was usually better when statistical significance was ignored. Each of the competing models was significantly worse than the hierarchical model in a pairwise difference test. Particularly notable was the poor performance of the finite mixture model. This could be because the method is poorly suited to this problem, because a fairly large number of customers in the data set have no change in gross profit, leading the finite mixture model to try to make those customers into an inertial segment with coefficients close to zero.[7]

We also evaluated the bias of the gross profit change predictions. The demographic model (significant) underestimated gross profit change by an average of 45.34 guilders (significant at the 0.01 level), and the demographic (all) model underestimated by an insignificant 2.46 guilders. The RFM (significant) model underestimated by 33.38 guilders (significant at 0.01), and the RFM (all) model underestimated by 20.04 guilders (also significant at 0.01). The finite mixture (significant) model overestimated by an insignificant average of 2.56 guilders, and the finite mixture (all) model overestimated by an insignificant 1.06 guilders. The hierarchical model underestimated by an insignificant average of 3.28 guilders. Thus, the demographic model that uses all significant variables and both versions of the RFM model exhibit significant bias in predicting gross profit change.

Figure 2 Distribution of Optimal Marketing Allocations



5.4. Profit Impact

Ultimately, the goal is to increase customers' profitability, so we conducted a test of how profitable the strategies suggested by the competing model would be. We used the model estimates from the estimation sample and the corresponding optimal allocations, as shown in Table 2 and Figure 2, and projected the profitability that would result. We also tested the actual marketing allocations that were selected by the firm, to determine whether any of these models would result in improved profitability over current practice.

Because the hierarchical model had the best predictive performance, we treated that estimated model as "truth." Because the hierarchical model in Equations (7)–(8) models the error distributions around the coefficient estimates, it would not be correct to assume that the hierarchical model's coefficient estimates for individual customers were precisely correct. Rather, we conducted a Monte Carlo simulation in which we regenerated the "true" coefficient estimates anew in each replication, using the hierarchical model specification in Equations (14)–(17). The "true" coefficients were multiplied by the optimal marketing allocations in Table 3 and Figure 2, to yield the change in gross profit, and the cost of the marketing program was subtracted from this, yielding the projected profitability of the marketing program in the holdout sample.

[7] As an attempt to alleviate this effect, we split out the inertial segment and re-estimated the finite mixture model on the remainder of the data. The results were similar, in both the estimation sample and predictive validation.

Table 4 Validation Test—Predicted Gross Profit Change

Model	MSE (000)	Standard deviation (000)	Average worse than hierarchical model	Standard error of difference	t
Demographic (significant)	15.48	116.70	3,052.8	389.2	7.15**
Demographic (all)	12.98	113.95	559.6	228.2	2.45*
RFM (significant)	15.03	96.73	2,611.5	939.6	2.49*
RFM (all)	13.44	96.63	1,016.0	508.4	2.00*
Finite mixture (significant)	23.05	139.32	10,629.6	2,589.2	7.06**
Finite mixture (all)	23.49	140.98	11,063.7	1,836.4	6.02**
Hierarchical	12.42	110.34	—	—	—

*Significant at 0.05, **significant at 0.01.

The projected incremental profitability of each of the competing methods is seen in Table 5. The demographic (significant) and RFM (significant) models propose no marketing allocations—nevertheless the gross profit was projected to decline by an average of 0.02 guilders, solely because of the random influence of the error term in Equation (4). The demographic (all) model produced an average projected profit of 14.46, the RFM (all) model produced an average profit of 8.61, the finite mixture (significant) model yielded an average profit of 3.22, and the finite mixture (all) model resulted in a profit of 3.12. The hierarchical model had the highest projected incremental profitability, at 23.12 guilders, compared to 10.57 for the actual allocation employed by the company. Pairwise t-tests show that the hierarchical model's profitability level is significantly better than each of the other methods.

6. Discussion

This paper provides an approach to the problem of determining a profit-maximizing mix of marketing interventions for each customer individually in the intermediate term. Personalization of marketing effort is key to the success of CRM, yet many previous approaches do not fully personalize. Many of these approaches (e.g., RFM) implicitly or explicitly assume that response to marketing interventions is homogeneous within market segment. Thus, even though these techniques might personalize to the extent of controlling for individual characteristics and history, they do not create a truly unique marketing program for each customer. The direct marketing literature, on the other hand, includes individual-level models, but only for the simpler case of one type of marketing intervention—not a mix of types of interventions. These models focus on one single marketing intervention (i.e., direct mailings), instead of multiple interventions (e.g., Bult and Wansbeek 1995, Elsner et al. 2004).

The results show that a profitability estimation model of the intermediate-term CRM marketing intervention mix, implemented via a hierarchical model, and estimated using MCMC, produced better predictive results in a holdout sample than segment-based approaches. We found that the traditional a priori segmentation approaches (e.g., RFM) produced reasonably good parameter estimates but were outperformed by the hierarchical model. The finite mixture model approach performed very poorly in prediction, probably because of estimation problems arising from the nature of the data. A simulation showed that, at least in these data, the proposed model projected to be more than twice as profitable as the actual marketing allocations used by the company studied and more profitable than any of the competing segmentation approaches.

Responsiveness to marketing interventions was found to be highly heterogeneous, and the result was that even marketing interventions that were unprofitable on average could be used profitably on

Table 5 Holdout Sample—Projected Incremental Profitability

Model	Average gross profit	Average cost	Average profit	t of profit vs. hierarchical	Profit difference vs. actual
Actual allocation	20.83	10.26	10.57	7.61**	—
Demographic (significant)	−0.02	0.00	−0.02	9.00**	−10.59
Demographic (all)	32.49	18.03	14.46	5.62**	3.89
RFM (significant)	−0.02	0.00	−0.02	9.00**	−10.59
RFM (all)	25.63	17.02	8.61	7.33**	−1.96
Finite mixture (significant)	5.67	2.45	3.22	8.19**	−7.35
Finite mixture (all)	5.70	2.58	3.12	8.23**	−7.45
Hierarchical	37.60	14.48	23.12	—	12.55

*Significant at 0.05, **significant at 0.01.

selected customers. The segmentation approaches, for the most part, were not granular enough to recover these effects and likely would not do so without creating very narrow segments. Furthermore, the use of very narrow segments would have the drawback of greatly increasing the total sample size necessary for estimation. With responsiveness being very heterogeneous, the distribution of optimal marketing allocations turns out to be equally heterogeneous. In one case (relationship magazines), we found a bimodal distribution of optimal marketing allocation, with optimal allocation usually implying either no exposure or full exposure, and the intermediate levels being less preferred.

Based on existing research, we formulated and tested propositions about how past behavior should moderate the effect of CRM interventions. Our analysis suggests that relationship-oriented instruments are more effective among loyal customers, while action-oriented instruments are less effective among loyal customers. Our explanation is that loyal customers value relationship marketing activities more than nonloyal customers. Less loyal customers value short-term rewards and are less receptive to relationship-oriented actions. Thus, our results suggest that firms should mainly target their relationship-oriented programs at loyal customers, while action-oriented interventions should mainly be targeted at less loyal customers. Interestingly, this recommendation is largely inconsistent with the intermediate-term CRM strategies actually employed by the company studied, indicating that current practice could likely be improved in at least some companies.

Although the model presented produced better predictions and higher intermediate-term profitability, it may not be the answer for all companies. The complexity and conceptual difficulty of the hierarchical Bayes approach may be a barrier to some companies, which might instead wish to use simpler methods such as RFM. Simpler methods might also be advisable when there is not much heterogeneity across the customer base or when a small number of variables (e.g., recency) explain a high percentage of the variance of change in profitability. We should also note that the superiority of the hierarchical model is based on the analysis of only one data set and should be tested on other data sets before definitive conclusions can be drawn.

The limitations of our study include the fact that only a limited array of marketing interventions were studied (both involving direct marketing communications), and that we could not conduct a controlled experiment (manipulating the marketing interventions) to further validate the performance of the hierarchical model. Selection of change in intermediate-term profit as dependent variable is a limitation, to the extent that next period profits fail to predict long-term profits and customer lifetime value. The generalization of our findings would be more confident if there were replication on additional data sets. For example, one might be more confident in generalizing our findings about heterogeneous response to scenarios involving other marketing interventions that are similar to our direct mail interventions, and less confident in generalizing our heterogeneity findings to other types of interventions (e.g., direct sales calls). Likewise, one might be more confident in generalizing the response model to other financial services scenarios but less confident in generalizing to other types of products. In addition, our sample size was limited to 1,580 customers. It is possible that the segment-based approaches might have performed better with a larger sample size, because more of their estimated effects might have been significant. Our model has a limited time horizon in that it looks ahead only one year. Application of our model, and all similar models, is limited to firms that have built a database of customer-specific characteristics, history, marketing interventions, and sales response. Such companies are commonplace in business-to-business, direct marketing, and subscription businesses, but rare in industries such as consumer packaged goods.

We believe that a fully dynamic CRM optimization model (e.g., extending the Gönül and Shi 1998 approach to a mix of marketing interventions) would be very useful. Development of such a model is complicated by the fact that the future marketing interventions are endogenous. Existing CRM optimization models do not adequately capture this endogeneity. In fact, fairness dictates that we admit that endogeneity is also an issue in our model, because the marketing intervention levels that appear in our estimation models may be (probably are) the result of analyzing past observations. Remedying this problem is not feasible in our application, because extensive additional longitudinal data would be required, that are currently unavailable to us, and are generally unavailable to most companies applying this sort of intermediate-term model.

To conclude, our research provides a model for optimizing a mix of intermediate-term CRM interventions at the individual level. Our empirical results show that such a model, at least on the data studied here, may result in substantially higher profitability than that obtained by more commonly used approaches or by current managerial practice.

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