# EVALUATING DIRECT MARKETING CAMPAIGNS; RECENT FINDINGS AND FUTURE RESEARCH TOPICS

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| ERIM REPORT SERIES *RESEARCH IN MANAGEMENT* | |
|---|---|
| ERIM Report Series reference number | ERS-2002-26-MKT |
| Publication | February 2002 |
| Number of pages | 40 |
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# REPORT SERIES
## *RESEARCH IN MANAGEMENT*

| BIBLIOGRAPHIC DATA AND CLASSIFICATIONS | | |
|---|---|---|
| Abstract | This paper contains a survey of the recent literature on the evaluation of direct marketing campaigns. We give an outline of the various stages included in such a campaign. Next, we review the statistical methods most frequently used and we review the general findings from using these methods. | |
| Library of Congress Classification (LCC) | 5001-6182 | Business |
| | 5410-5417.5 | Marketing |
| | HF 5415.126 | Direct marketing |
| Journal of Economic Literature (JEL) | M | Business Administration and Business Economics |
| | M 31<br>C 44 | Marketing<br>Statistical Decision Theory |
| | M 31 | Marketing |
| European Business Schools Library Group (EBSLG) | 85 A | Business General |
| | 280 G<br>255 A | Managing the marketing function<br>Decision theory (general) |
| | 290 R | Direct marketing |
| Gemeenschappelijke Onderwerpsontsluiting (GOO) | | |
| Classification GOO | 85.00 | Bedrijfskunde, Organisatiekunde: algemeen |
| | 85.40<br>85.03 | Marketing<br>Methoden en technieken, operations research |
| | 85.40 | Marketing |
| Keywords GOO | Bedrijfskunde / Bedrijfseconomie | |
| | Marketing / Besliskunde | |
| | Direct marketing, Statistische methoden | |
| Free keywords | Direct marketing, evaluation, quantitative models, target selection | |

# Evaluating Direct Marketing Campaigns; Recent Findings and Future Research Topics

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February 21, 2002

**Abstract**

This paper contains a survey of the recent literature on the evaluation of direct marketing campaigns. We give an outline of the various stages included in such a campaign. Next, we review the statistical methods most frequently used and we review the general findings from using these methods.

Keywords: direct marketing; evaluation; quantitative models; target selection

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# 1 Introduction

Many firms are aware of the fact that to acquire and keep customers some form of personal attention is required. Often products are targeted at a specific subset of the entire customer population. Also, it appears more expensive to obtain new customers than to maintain current ones (Peppers and Rogers (1993)). So, firms understand the importance of developing good relationships with current and new customers. Direct marketing is an important tool in this process, because its goal is to develop and maintain long-term relationships with (individual) customers. Direct marketing has become an important business. Already in 1995, 12% of total sales in business-to-business markets and 5% of total sales in consumer markets in the United States were generated by direct marketing (DMA (1995)).

There is no consensus in the literature on the definition of direct marketing. In this chapter direct marketing is defined as a form of marketing that is aimed at obtaining and maintaining direct relations between individual suppliers and buyers within one or more product/market combinations. These marketing activities are usually based on (partial or full) knowledge of the individual (potential) customers. The use of marketing instruments can thus be tuned to the individual buyer. An important characteristic of direct marketing is the use of direct communication and/or direct delivery (Hoekstra, 1998, p. 22).

Being part of the marketing activities of a firm, direct marketing has become a serious research topic in the last 10 years in the marketing research literature. This paper provides an overview of the literature, in order to describe the theoretical and empirical insights that have been obtained so far, and to determine areas for possible future research. Our main interest lies in the quantitative aspects of direct marketing, because we believe that this is an area with numerous opportunities for future research. Also, improved data collection and processing techniques, due to advanced Information and Communication Technology (ICT), facilitates the quantitative evaluation of direct marketing.

In this paper, the focus will be limited to analyzing direct marketing by looking at direct marketing campaigns. A direct marketing campaign consists of a number of sequential steps or stages. Almost all of the major issues concerning direct marketing can be addressed by analyzing these different stages. The objective of direct marketing is to obtain a long-term relationship with customers, naturally this goal can not be reached by a single campaign. Therefore, it is necessary to have multiple campaigns, aimed at current (and possibly new) customers. By communicating regularly with customers, the company can try to build a relationship with the customer. This relationship can be improved by monitoring the satisfaction with current (offers of) products and by trying to determine future demand for these and other products, see (Roberts and Berger, 1999, p. 10) and (Stone, 1994, p. 44).

The outline of this paper is as follows. In Section 2 , a general (theoretical) framework for analyzing direct marketing campaigns is presented. The campaigns can be described by a number of stages, such as determining the product and selecting the customers, and each of these stages is discussed. These stages can be divided into three parts: (1) setting up the framework of the campaign; (2) operationalisation of the campaign and (3) execution of the campaign and handling of the response. Section 3 looks at setting up the framework of the campaign. This consists of determining the goal of the campaign, deciding who the (general) target audience should be and determining which media vehicles will be used. Next, one has to decide how to operationalize the campaign. This concerns selecting individuals from the target audience, developing the format of the campaign and perhaps executing a test campaign. This is discussed in Section 4. The final part, described in Section 5, consists of the campaign and the consecutive steps: monotoring response, fulfilment and feedback to the customers. Section 6 concludes.

# 2 Stages in a DM Campaign

A direct marketing campaign consists of a number of stages. These stages are encountered sequentially, although some can occur simultaneously. The stages can be divided into three parts.

First, the general framework of the campaign has to be determined. This framework consists of four parts. First and foremost, the direct marketer has to decide what will be the goal of the campaign. Usually the goal will be to generate sales, but a campaign can have other goals. After the marketer has determined what (s)he wants to accomplish, (s)he has to determine which (potential) customers to approach. In this stage of the campaign this is formulated in general terms: are current customers approached or is attention focused on obtaining new customers (prospects). In the third step of the general framework we look at the media vehicles that will be used. Each vehicle (mail, telephone, tv, internet, etc) has certain advantages and disadvantages. Which vehicle is most appropriate for the campaign depends (among other things) on the previous two steps, that is the goal of the campaign and the target audience. Finally, the direct marketer has to determine when the campaign should be held.

The second stage of the campaign consists of the operationalization. The goal of this stage is to select the most profitable (potential) customers from the total target audience. For such a selection, information on the target audience has to be available. For current customers, this information is usually internally available, but for new customers this information has to be obtained from external sources. Next, this information has to be analyzed, in order to determine to the most profitable customers. There are various selection methods available in order to determine these customers. These are discussed extensively in Section 4.2. In order to examine the quality of this selection, a test campaign can be held. With the results of a test campaign, different versions of the product or different ways of presenting the product can be evaluated. Furthermore, the response to the test campaign can be analyzed to determine whether the individuals who did respond have distinguishing characteristics.

The final part of a direct marketing campaign consists of the execution of the campaign itself, and the handling of the response. Monitoring the response can help to provide early indicators of the performance of the campaign. If the performance is below expectations, one can decide to take steps to help to improve the response rates. The customers' response should be handled quickly and adequately, as customers appreciate good fulfilment, where fulfilment is defined as all producer actions after a consumer has decided to buy the product. Such fulfilment consists for instance of distributing the product quickly and in a good condition. It also deals with handling complaints and answering questions. By registering and handling dissatisfaction in an early stage, the company can prevent or reduce customer withdrawal. This can lead to a deepening of the relationship with a customer, and it will stimulate repeat purchases and cross-selling. The final step of this part of the direct marketing campaign consists of determining the profitability of the campaign. A careful inspection of the results of a campaign can help to determine the factors that caused the campaign to be (un)successful.

All of these aspects of the direct marketing campaign will be discussed in more detail in the subsequent sections.

# 3 Preparation of the Campaign

The first part of a direct marketing campaign consists of determining:

1. The goal of the campaign. What do we want to achieve? Sales or awareness?
2. The target audience. Are we going to approach existing or new customers?
3. The media vehicles. Do we use direct mail, catalogs, mass media sources or a combination of those?
4. The timing of the campaign. When will the campaign be held? During which time of the year and which day of the week?

In the following subsections, each of these steps will be discussed.

## 3.1 Goal of the Campaign

A company first has to decide on the goal of the campaign. This goal can be ((Roberts and Berger, 1999, p. 9)):

1. sales of a product or a service;
2. lead generation (obtaining response from potential customers);
3. lead qualification (determining whether the respondents who asks for information can be qualified as having a genuine intention to buy);

4. creating brand knowledge;
5. maintenance of customer relationships.

The first three goals are directly measurable. The audience targeted by the campaign is usually known, so the sales can be related to the total number of people targeted. The last two have to be measured indirectly.

A direct marketing campaign can be used to offer certain products to the customer. The campaign can also be used to obtain the names and addresses of potential customers (leads), for example when the product is too complex to be sold by mail. In this case, most respondents will first ask for more information. During this 'first round', the company obtains the leads, and then needs to determine the respondents that will be targeted in the 'second round', that is which of these respondents has a high probability of becoming a customer (lead qualification). By using the campaign to sell a new product to current customers, or by offering special services or advice to current customers, the campaign may maintain, and possibly deepen, customer relationships (Hoekstra, 1998, p. 87), (Roberts and Berger, 1999, p. 10).

It should be mentioned, though, that most direct marketing campaigns, especially in consumer markets, are concerned with sales of a product or service. The use of direct marketing to generate and qualify leads and maintain customer relationships is more applicable to business-to-business markets (Stone, 1994, p. 141).

## 3.2 Target Audience

A decision has to be made on the target audience, that is, who will be approached by the campaign? Should the campaign be targeted at current customers and/or at potentially new customers? The decision on who to approach is usually related to the goal of the campaign. Lead generation is targeted at potential new customers, whereas the maintenance of customer relationships is aimed at current customers. When a company has decided to approach either current and/or new customers, a quantitative analysis is usually performed to determine which segments of the customers may be profitable. The company can then decide to aim the campaign at a few or at all segments (see Section 4.2).

At this stage the target audience is defined in general terms: will we approach current or potential new customers (prospects)? The first group will be more profitable in the short run (as the response to a mailing sent to current customers is usually higher than the response to a mailing sent to new customers), whereas in the longer term it is important to obtain new customers (otherwise there will be only outflow of current customers but no inflow of new customers). This leads to a trade-off: which part of the total budget will be spent on acquiring new customers and which part on targeting current customers? Stanford et al. (1996) propose a linear programming method to determine the optimal allocation.

## 3.3 Media Selection

The next step in the preparation of the campaign is to determine the media that will be used in the campaign. The choice between the different media is influenced by the goal(s) of the campaign (creating product knowledge or selling the product), the budget, the target audience, available time, nature of the product (service) and position in the market (Hoekstra, 1998, p. 149). A distinction should be made between the direct media, like direct mail, direct non-mail (door-to-door in-print advertising), telephone and catalogs, and the more traditional mass-media, like television, radio, newspapers and magazines. The direct media are mainly used to sell a product or service, whereas the mass-media are primarily used to create awareness and knowledge, besides generating sales. Internet is a medium that could be used as a direct media, but is still often used as a mass media vehicle (Wind and Rangaswamy (2001)).

Direct mail is the most well-known and most used form of the different direct media. Direct mail is an addressed written commercial message. Direct non-mail is a non-addressed mailbox advertisement (with the possibility to response directly by mail, telephone or electronically). It is mostly door-to-door advertising, and the customer's ability to respond directly to the supplier makes it a form of direct media.

Direct mail has a number of advantages (Stone, 1994, p. 362):

- It is possible to target customers with substantial precision.

- It is personal and confidential.
- It is competitively secret.
- The message can be highly specific.
- A variety of formats and materials can be used.
- There are many opportunities to introduce novelties.

Direct mail is however not appropriate for all markets, or for all objectives, and it cannot be used in isolation to build a brand (image). Additionally, some customers are very sceptical of direct mail (Stone et al., 1995, p. 159). Therefore, a company should not only rely on direct mail to communicate with potential customers. Using for instance mass-media like billboards to increase awareness (and generate sales) can enhance the positive effect of the direct mail campaign (Hoekstra, 1998, p. 181). Also the telephone can be used to interact directly with consumers. This medium provides many insights into the satisfaction of the customers.

Direct non-mail has some of the advantages of direct mail, but its main advantage is that the costs per contact are lower. This is because one abstains from a detailed analysis of previous responses or alternative campaigns. However, the distribution of direct non-mail is less specific and the message is not personal. Direct non-mail is most useful when there are no addresses of possible prospects (= leads) available or when direct mail is too expensive (Hoekstra, 1998, p. 175).

Some of the advantages of the use of the telephone are that (i) it provides immediate feedback on the quality of the marketing program, (ii) it is a flexible medium (it is possible to respond immediately to questions of the customer), (iii) it provides incremental effectiveness when used in conjunction with other media, (iv) it provides a method of building and maintaining customer goodwill between sales and it provides opportunities for increased levels of customer service (Roberts and Berger, 1999, p. 331). A disadvantage is that if the campaign is to be effective, it has to be applied systematically, and this requires substantial investments. Also, the costs per contact are relatively high and it is perceived to be a very intrusive medium.

The mass media sources such as television allow for less selection of potential customers than direct media do. However, there is information available on the audiences of magazines, newspapers, television programs, radio, internet and billboard advertising, and these can be used to select the outlets that will most likely reach the target audience, see Danaher and Green (1997) for an application to direct response television and see Verhoef et al. (1998) for an application to direct response radio. The costs per contact for mass media sources are relatively low, but the effectiveness of the advertisements is also expected to be lower than direct (non-)mail. When used in a direct marketing context, mass media sources are mainly used to create awareness or they are used to support direct media. For example, a company can develop a direct mail campaign, that is preceded by an announcement in a newspaper. During the campaign, television commercials can be used to increase awareness about the campaign and the product (Hoekstra, 1998, p. 28).

Using internet as a direct marketing medium has gained much attention in recent years. Internet is mostly used as a mass media vehicle: the sites/emails are the same for each customer. Especially the use of untargeted emails is not appreciated by customers Mehta and Sividas (1995). The success of internet as a marketing medium remains mixed Parsons et al. (1998), but a body of research is emerging, that tries to improve the use of internet as a direct marketing medium (Wind and Rangaswamy (2001)).

## 3.4 Timing of the Campaign

A very important decision is when the campaign should be held. Ideally, one wants to approach each customer at the appropriate moment. For most practical circumstances this will be too expensive. Hence, in practice timing amounts to determining the best time of the year, season or week, see (Stone, 1994, p. 231). Usually the approach will be: given that we want to do a campaign at the present time, who should we approach? Most selection techniques, (discussed in Section 4.2.3) only have a short term horizon. They determine the individuals who are (now) most likely to respond, but the techniques do not take future mailings into account. Exceptions are the models by Gönül and Shi (1998) and Bitran and Mondschein (1996) which explicitly take long term actions into account[1].

The problem with modeling timing in direct marketing is that there are usually no data available to determine the optimal moment of sending a mailing. Only if there is enough variance in the time between two campaigns, it might be possible to look at optimal timing, see Allenby et al. (1999) for an application.

# 4 Operationalization of the Campaign

Next, the following issues have to be dealt with:

1. How is the content formatted?
2. Which individuals will be selected?
3. Will a test campaign be performed?

The company has to determine how the campaign will be presented and to which individuals the campaign will be targeted. If the company is not certain about the format of the campaign or about the individuals it wants to approach (or both), then one can decide to run a test. In the following subsections, each of these three steps will be discussed.

## 4.1 The format of the direct marketing campaign

There are no clear cut rules how the campaign should be presented. A test campaign (see Section 4.3) can be helpful to obtain information on the effectiveness of different formats. There are a number of elements that can be tested, that is, the physical elements of the product or service (the most attractive composition), and the additional elements of the product, like positioning, price, length of commitment and terms of payment. Other aspects that can be tested are the physical characteristics, the timing and the frequency of the campaign, see (Roberts and Berger, 1999, p. 203). After analyzing the impact

[1]However, the models also give no indication on the optimal timing of the mailing. Bitran and Mondschein (1996) only looks at the optimal yearly frequency and Gönül and Shi (1998) assumes the timing of the mailing is fixed and examines whether it is more profitable to sent a mailing to a specific individual or not.

of the different versions, it can be determined which version is most suitable to use in the actual campaign. The test campaign may also indicate that it is more profitable to approach different segments in different ways.

A number of studies consider determining the effect of differently formatted mailings (Bult et al. (1997) and Vriens et al. (1998)), and catalogs (Seaver and Simpson (1995)). The idea is that a number of characteristics of the mailing/catalog can be varied, resulting in a number of different versions. These versions are then sent to the customers, and by analyzing the response one can determine how the different factors influence response. The number of different versions depends on the number of characteristics that is investigated, and on the method used to determine the "design" of each version of the mailing. Bult et al. (1997) and Vriens et al. (1998) have used a fractional factorial design and Seaver and Simpson (1995) uses a Plackett-Burman design (see Plackett and Burman (1946)). These experimental designs ensure that the effects and interaction effects of different factors can be determined without having to examine every possible combination. The response model (see Section 4.2.3) can then be adjusted by adding dummy variables to capture differences in mailing design.

## 4.2 Selection of targets

In preparing the direct marketing campaign, the company has decided what the target audience should be. This has been done in general terms. Now the company has to determine the potential customers from the target audience it wants to approach. Usually this amounts to selecting the most profitable customers. These are determined using one (or more) selection techniques. In this section we will look at the various selection techniques that have been suggested in the literature.

The selection is usually determined using information on the (potential) customers. In this section we also look at the ways to obtain (or collect) this information.

### 4.2.1 Internal data

To determine segments of individuals to target, the company needs information about existing and/or potential new customers. Information about existing customers may be internally available from the customer database. The development and maintenance of a customer database is an important part of direct marketing. Some of the information about customers that the database could contain is name, address, telephone, date of entry in database, gender, date of birth, mailings send, response behavior, satisfaction, complaints and problems, dates of purchases, products/services bought, amount spent and bank account-number.

Although more and more companies are becoming aware of the importance of keeping an accurate and up-to-date database, information is often not recorded accurately. For instance, information about customers may be recorded by different departments, and it may oftentimes be difficult to link these different databases. On the other hand, different departments may record the same information, whereas other data is not recorded at all. Because direct marketing focuses on developing a long-term relationship between the customer and the company, the information in the database needs to be complete, accurate and up-to-date.

The potential pay-off of using purchase history information is examined by Rossi et al. (1996). They assess the information content of various information sets available for direct marketing purposes. They find that there is a tremendous potential for improving the profitability of direct marketing efforts by more fully utilizing household purchase histories. Even rather short purchase histories can produce a substantial net gain in revenue. This result implies that even modestly targeted marketing strategies are already profitable, and that these strategies will probably become more prevalent in the future.

### 4.2.2 Determining the selection using external data

To obtain information about potential new customers, the company usually has to rely on information from external sources. There are a number of companies that can provide information about potential customers at a low level of aggregation. A distinction should be made between zipcode segmentation systems (providing information at the level of the zipcode) and individual segmentation systems (providing information at the individual level). These systems use demographic and socio-economic information to distinguish a number of customer profiles. An example of such a profile would be young couples without children with an income above average, who live in the suburbs of larger cities and have an education above average. Other elements that can be a part of such a profile are the magazines that they read, and the products and services in which individuals have indicated to have an interest.

Companies can use this information to determine potentially new customers, for example by comparing this external information with the profile of current customers. In the Netherlands, the two most important developers of zipcode segmentation systems are Geo-Marktprofiel and MOSAIC, and the three individual level segmentation systems are the "Large Consumer Survey" (Grote Consumenten Enquete), Omnidata and Claritas. It is expected that individuals with a profile that matches the profile of current customers will be more interested in the products of the company.

A number of issues concerning the use of external data to acquire new customers are discussed by Lix et al. (1995). The first issue they discuss is the development of a scoring equation for linking external and internal lists. Next, a scoring equation is used to determine the probability of response. This equation is usually based on the purchase-related measures Recency of the last purchase, Frequency of purchases and Monetary value of the purchases (RFM). These measures are obviously not available for individuals on the external list who are not yet customers. The authors therefore propose to use information from the internal list to predict a score for the individuals on the external list. They use regression analysis and log-linear analysis to obtain a prediction of the scores.

At this stage (before the campaign has actually started), it is difficult to analyze information about (potential) new customers, that is, to determine the individuals who should be addressed in the campaign. In fact, there are no data available on the relationship between (the characteristics of) the respondents and their willingness to respond to this offer. One can decide to analyze previous campaigns in order to obtain some insight into this relationship, by determining the 'look-alikes' of the current customers, that is, the (potential) new customers with similar characteristics as those of the current customers. This is done using both internal data and external data. One then assumes that individuals who have bought products in the past are reasonable proxies for individuals who intend to buy in the future. One can also opt for a test campaign to analyze how the new customers will respond (see Section 4.3).

### 4.2.3 Determining the selection using internal data

There is usually more information available about individuals who have already responded to a direct marketing campaign in the past. If someone responded, there are, by definition, variables available describing the response to previous direct marketing campaign(s). These variables are often referred to as the RFM-variables (Recency, Frequency, Monetary Value, see Section 4.2.2) and they are considered to be the most important variables, as past behavior has proven to be a good predictor for future behavior. Often there are also some personal variables (such as an address) and perhaps even some socio-demographic variables (age, household size, (proxy of) income, etc) available. If these are not available, they can often be purchased from external providers.

The number of variables available per customer depends on the number of campaigns that have been targeted at the customer and the type of direct marketing campaigns that have been used, among others. The overall view is that more and more data will become available. This enables firms, which used to rely on mass communication (such as retailers), to start approaching customers at the individual level (see Rossi et al. (1996)).

The focus in the remainder of this section will be on selection techniques for direct mailings and catalogs. These are the two most important types of direct marketing campaigns that require individual selection.

The target selection techniques that are used in direct mail can be divided into two categories: the segmentation techniques and response modeling techniques. Segmentation techniques aim to divide individuals into groups (segments) using a number of explanatory variables, such that each segment is expected to be more or less homogeneous with respect to these variables and their (expected) response to a direct mail offer. When applied to target selection, response is often used as the dependent variable. RFM and socio-demographic variables are used as explanatory variables. The segments that have the highest probability to respond are then selected to receive a mailing. Usually the cut-off point is arbitrarily assigned. Hence there is no guarantee that the most profitable selection has been made.

In response modeling, a model is developed to predict the probability of response for an individual customer. Those who have the highest probability to respond are selected to receive a mailing or a catalog. The appropriate cut-off point is sometimes provided by the method itself, but often the user has to indicate it (for instance: select the top 25%). Hence, there is again no indication on the optimality of the selection.

Most recent literature on direct marketing deals with (target) selection issues. The next two subsections provide an overview of the most relevant selection techniques.

### Segmentation

The goal of segmentation is to determine groups or segments of customers that are as homogeneous as possible within segments with respect to response behavior and as heterogeneous as possible between segments (Wedel and Kamakura, 2000, p. 3).

The most often used segmentation techniques are cluster analysis such as Automatic Interaction Detection (AID), Chi-square Automatic Interaction Detection (CHAID) and Classification and Regression Trees (CART). These last three methods result in a decision tree, where at each node there is a division. The groups are ultimately described as a combination of variables (group 1 has variable 1 smaller than $x$, variable 2 between $y$ and $z$, etc). Magidson (1988) recommends not to use AID, as this method only allows binary splits. CART and CHAID do not seem to differ much in performance, but CART is preferred when there are a large number of (continuous) variables, and one should opt for CHAID when there are many categorical variables (Haughton and Oulabi (1993), Trasher (1991)).

In practice, segmentation is often performed by calculating the RFM-score and dividing the total list into groups in a rather ad hoc way, see Levin and Zahavi (1996) for an example of such a method. Theoretically, this cannot be viewed as being a real segmentation as there is no objective determination of the cut-off points between the segments.

Although Markov models are not really segmentation tools, they have been applied to target selection. Markov models distinguish between a number of states that individuals go through. In direct mailing, these states are usually defined by the RFM-criteria: how long has it been since the last response, how often has been responded in the past and how much has been donated in the past? Hence, in this case, a state will consist of three dimensions. The states are individually exclusive and collectively exhaustive, that is each individual $i$ can be assigned to exactly one state at each time $t$.

In this context, the goal of the Markov models is to determine a mailing strategy: how many mailings should be sent to people who are in a certain state? An extensive Markov model (that also takes inventory costs into account) is developed by Bitran and Mondschein (1996). The same Markov model can also be used to model the Lifetime Value of a customer (see Pfeifer and Carraway (2000) who only use recency and frequency to define a state).

Gönül and Shi (1998) combine a Markov model for the actions of the customers with the profit function of the firm. They also formulate utility functions for the customers and hence they are able to determine a mailing strategy that optimizes both customer utility and the firm's profits. However, they do not model monetary value as this would dramatically increase the number of states.

One of the advantages of the Markov model is that it can be used to determine the long term optimal strategy. Most response models (discussed in the next section) determine the (optimal) selection in a one period setting, while neglecting that subsequent mailings will be sent after the current one.

However, the state space of the models by Bitran and Mondschein (1996) and Gönül and Shi (1998) is large, making it difficult to estimate the model. Hence, in practical applications Monetary value is either excluded (Gönül and Shi (1998)) or modeled by a small number of values (Bitran and Mondschein (1996)).

### Response modeling

Individual scoring methods predict the probability of response per individual (although these predictions are usually again combined into clusters). Some of these techniques are:

- (multiple) regression;
- loglinear regression;
- (multiple) discriminant analysis;
- logit and probit models;
- neural networks;
- tobit model;

see (Hoekstra, 1998, p. 133), (Roberts and Berger, 1999, p. 94) and Franses (1998). Each of these models will be discussed in more detail below.

To discuss the models, we first introduce a general notation. Lets say a firm has a database consisting of $I$ individuals. The firm has sent mailings at time $1, 2, ..., T$. However, not everyone will have received each mailing. The variable $d_{i,t}$ is one if individual $i$ received a mailing at time $t$, and is zero otherwise. For each individual $i$ $(i = 1, ..., I)$ there are $K$ explanatory variables available: $x_{k,i,t}$ $(k = 1, ..., k,\ t = 1, ..., T)$. Let $r_{it}$ be equal to 1 if individual $i$ has responded to a mailing received at time $t$, and 0 otherwise. The revenue generated by individual $i$ if $i$ responded to the mailing at $t$ is $y_{it}$. Finally, let $M_t$ be the number of individuals who have received the mailing sent at time $t$ $(1, 2, ..., T)$ and let $N_t$ be the number of individuals who have responded to the mailing. Hence, by definition $N_t \leq M_t$.

The afore mentioned models will now be discussed using this notation.

### Multiple regression

One of the most basic models is the (multiple) regression model, see (Greene, 2000, p. 210). In direct marketing it is often used to model $y_{it}$ (revenues from the individuals who responded):

$$y_{it} = \beta_0 + \beta_1 x_{1,i,t} + \beta_2 x_{2,i,t} + ... + \beta_K x_{K,i,t} + \varepsilon_{it}, \tag{1}$$

with $\varepsilon_{it} \sim \mathrm{N}(0, \sigma^2)$ and for all $i$ and $t$ ($i = 1, ..., I$, $t = 1, ..., T$) where $r_{it} = 1$. It can be shown that this model is only valid if $N_t = M_t$, otherwise the estimators will be biased.

The model has also been applied to model $r_{it}$, see (Roberts and Berger, 1999, p. 96):

$$r_{it} = \beta_0 + \beta_1 x_{1,i,t} + \beta_2 x_{2,i,t} + ... + \beta_K x_{K,i,t} + \varepsilon_{it}, \tag{2}$$

(Roberts and Berger, 1999, p. 96) advocate the use of multiple regression to model response. They claim it can be used to forecast response probability. However, the multiple regression model is not suited to model binary data, see (Franses and Paap, 2001, p. 50). Also, there is no guarantee that the forecasted "response probabilities" will be between zero and one. Hence, multiple regression models should not be used to model response.

(Roberts and Berger, 1999, p. 100) acknowledge these drawbacks of multiple regression, but nonetheless recommend using it. Forecasting outside the unit interval is not seen as a problem, as individuals who are predicted to have a "response probability" smaller than zero should not receive a mailing and those who have a "response probability" larger than one should receive a mailing. However, the use of multiple regression has more drawbacks. First, the effect of explanatory variables is assumed to be linear. Suppose average past donation is an explanatory variable. Then an increase from, say \$10 to \$20 will have the same effect on response as an increase from \$90 to \$100. Second, there is also the problem that multiple regression will perform poorly when response percentage is low (or high).[2] As this is not uncommon in direct mailing, the use of multiple regression seems

[2]Berger and Magliozzi (1992) propose to circumvent this by artificially inflating the response rate in the sample ("salting" the data). There is no theoretical reason why this will improve performance (as the order of the individuals does not change). A more fundamental approach to deal with many zero observations is given by Cramer et al. (2000).

clearly inappropriate. (See also Magidson (1988), (Greene, 2000, p. 813), (Franses and Paap, 2001, p. 50)).

### Loglinear regression

The values of $y_{it}$ will not be normally distributed as there can be no negative donations. A possible correction would be to look at

$$\ln y_{it} = \beta_0 + \beta_1 x_{1,i,t} + \beta_2 x_{2,i,t} + ... + \beta_K x_{K,i,t} + \varepsilon_{it}, \tag{3}$$

with $\varepsilon_{it} \sim \mathrm{N}(0, \sigma^2)$ and for $i$ and $t$ ($i = 1, ..., I$, $t = 1, ..., T$) where $r_{it} = 1$. Again, however, the estimators will be biased if $N_t < M_t$ and the respondents are not a random sample for the total customer base.

### Multiple discriminant analysis

Multiple discriminant analysis is another popular method to determine those individuals who are most likely to respond. It is used to determine which variables discriminate between two or more groups. In direct marketing, the goal is to assess which variables drive response. However, when discriminant analysis is used to distinct two groups (respondents versus non-respondents), it is analogous to (multiple) regression, see (Lehmann et al., 1998, p. 659). Therefore, discriminant analysis is not a theoretically appropriate tool for response modeling (see also Magidson (1988)).

### Logit/probit

Logit and probit models are developed to model binary (1/0) processes. Hence, they are naturally suitable to model response (yes/no) to a direct mailing. The main difference between the two models is the way in which the disturbances $\varepsilon$ in the latent variable equations are distributed (see below). The logit model assumes they are logistically distributed, and the probit model assumes the disturbances are normally distributed.

The model assumes every individual $i$ has a certain (unobserved) tendency to respond $r^*_{it}$ to a mailing received at time $t$. This tendency is influenced by $x_{k,i,t}$ ($k = 1, ..., K$):

$$r^*_{it} = \beta_0 + \beta_1 x_{1,i,t} + \beta_2 x_{2,i,t} + ... + \beta_K x_{K,i,t} + \varepsilon_{it}. \tag{4}$$

for all $i$ and $t$ ($i = 1, ..., I$, $t = 1, ..., T$) where $d_{it} = 1$.

If the tendency $r_{it}^*$ is larger than zero, than individual $i$ will respond ($r_{it} = 1$), otherwise individual $i$ will not respond ($r_{it} = 0$):

$$r_{it} = \begin{cases} 1 & \text{if } r_{it}^* \geq 0 \\ 0 & \text{if } r_{it} < 0, \end{cases} \tag{5}$$

For the probit model $\varepsilon_{it} \sim \mathrm{N}(0, \sigma^2)$ and for the logit model $F(\varepsilon_{it}) = \frac{\exp(\varepsilon_{it})}{1+\exp(\varepsilon_{it})}$.

The formulation of the model above assumes there is no heterogeneity in response. Usually, this will not be the case. There might be, for instance, two groups: those who do not respond often, but when they do respond they spend a high amount and those who respond often, but only spend a low amount on each occasion. Therefore it is recommended to incorporate heterogeneity, see DeSarbo and Ramaswamy (1994) who have used a latent class formulation[3] of a probit model (which they call CRISP).

A drawback of the logit and probit models is that they only model response. A selection based on logit and probit will maximize response, but not revenues. Bult and Wansbeek (1995) have added a cutoff point to the logit model such that only those individuals will be selected for which profit is maximized. The individual response probability is multiplied with the estimate for revenue to obtain an estimate of total revenues. The profit function is defined as:

$$\pi_i = rR_i - c, \tag{6}$$

where $\pi_i$ is the (net) revenue for the firm generated by individual $i$, $r$ is the revenue from a positive reply (same across all customers), $c$ is the mailing cost and $R_i$ is a binary variable indicating response by individual $i$. Next, a selection is determined such that

[3] A latent class formulation is one of the methods that can be used when not all the household-specific variables that influence response behavior are observed, or when these variables are not able to explain all the individual differences in response behavior. In our case this would mean that we are not able to model response behavior correctly as there are differences between individuals in response behavior which cannot be taken into account. One way to take these individual differences into account is by making the parameter $\beta$ in equation 4 different across individuals ($\beta_i$). However, in most cases there are not enough observations to estimate such a model. In a latent class formulation, there are assumed to be $S$ classes. One or all of the parameters are class-specific. Each individual has a probability $p_s$ of belonging to class $s$, $s = 1, ..., S$.

marginal costs equal marginal revenues, and hence the selection will result in optimal revenues. However, their model has two important drawbacks. First, the model does not incorporate heterogeneity and second (and more important) revenues are assumed to be constant over individuals. Hence, the model will not maximize profits, as it is unrealistic to assume revenue ($y_{it}$) will be the same for all individuals.

Probit and logit models are usually estimated symmetric costs of misclassification: the same weight is given to incorrectly predicting a responder will be a non-responder, and vice versa. But in target selection the costs of misclassification are not symmetric. As the cost of sending a mailing at time $t$ ($c_t$) is usually low (relative to the revenue $y_{it}$ if individual $i$ responds), it will be more expensive to incorrectly predicting a responder will be a non-responder (cost $= y_{it}$) than the other way round (cost $= c_t$).

Examples of models that have used the asymmetric loss function are Bult (1993) and Bult and Wittink (1996). Bult (1993) used a semi-parametric version of a logit model. Bult and Wittink (1996) expand the asymmetric loss function by incorporating heterogeneity. A drawback of their model is that the different segments are determined a priori and revenue ($y_{it}$) is modeled as the average of last year.

The previous methods contain a separate estimation and selection stage. First, the parameters of the model describing consumers' reaction to a mailing have to be estimated before addresses for a future mailing are selected. Because these methods consider these two stages separately and thereby neglect estimation uncertainty, Muus et al. (1996) argue that these methods will lead to a suboptimal decision rule, and hence will not lead to optimal profits. Therefore, they derive an optimal Bayesian decision rule that follows from the firm's profit function and explicitly takes estimation uncertainty into account. The profit function is modeled as above, where $R_i$ is modeled as a probit and the total model is estimated using an asymmetric loss function. Although this model reduces parameter uncertainty, it has the same drawbacks as Bult and Wansbeek (1995): the model does not incorporate heterogeneity and revenues are assumed to be constant over individuals. Moreover, the model only shows an 0.8% improvement over the regular probit model.

Another problem in direct marketing is that there are usually hundreds of (potential) predictor variables available. Beforehand, it is difficult to determine which of these should be included in the analysis. A straightforward approach would be to use a method such as principal component analysis (Massy (1965)). Malthouse (1999) proposes to use a more controversial method called ridge regression (Hoerl and Kennard (1970)). The idea behind ridge regression is that one makes a trade-off by using a biased estimator with a smaller covariance matrix. Judge et al. (1985) indicates that under certain circumstances it might be worthwhile to make this trade-off[4]. Naik et al. (2000) propose to use a method called slice-regression, see Li (1991), and show that it outperforms the more standard principal component analysis.

A less formal approach for variable selection is used by Levin et al. (1995), who formulate a rule-based expert system to determine the best predictor variables.

### Tobit model

The tobit model is a natural extension of the probit model. It jointly models the response and the amount $y_{it}$ if $i$ responds. Response is modeled by a probit:

$$r^*_{it} = \beta_{1,0} + \beta_{1,1}x_{1,i,t} + \beta_{1,2}x_{2,i,t} + ... + \beta_{1,K}x_{K,i,t} + \varepsilon_{1,i,t}. \tag{7}$$

for all $i$ and $t$ $(i = 1, ..., I,\ t = 1, ..., T)$ where $d_{it} = 1$.

If the tendency $r^*_{it}$ is larger than zero, than individual $i$ will respond $(r_{it} = 1)$, otherwise individual $i$ will not respond $(r_{it} = 0)$:

$$y_{it} = \begin{cases} \beta_{2,0} + \beta_{2,1}x_{1,i,t} + \beta_{2,2}x_{2,i,t} + +... + \beta_{2,K}x_{K,i,t} + \varepsilon_{2,i,t} & \text{if } r^*_{it} \geq 0 \\ 0 & \text{if } r_{it} < 0. \end{cases} \tag{8}$$

with $\varepsilon_{1,i,t}$ and $\varepsilon_{2,i,t}$ normally distributed with covariance matrix $\Sigma = \begin{pmatrix} 1 & \sigma_{12} \\ \sigma_{12} & \sigma_{22} \end{pmatrix}$, so $(\varepsilon_{1,i,t}, \varepsilon_{2,i,t}) \sim \mathrm{N}(0, \Sigma)$.

[4]However, Malthouse (1999) does not present a strong case for the use of ridge regression in direct marketing. First, only the people who responded are modeled but the estimates are used to predict for both respondents and non-respondents. Second, the model is not compared to a good benchmark and third, the author claims improved performance but the results indicate otherwise.

The formulation above is called the tobit-2 model, as the parameters $\beta_{1,k}$ and $\beta_{2,k}$ are allowed to be different. In the tobit (or tobit-1) model, these are equal: $\beta_{1,k} = \beta_{2,k} \equiv \beta_k$. Levin and Zahavi (1998) found the performance for target selection of the tobit-1 model to be favorable over the logit model. Otter et al. (1997) have looked at the so-called two part model (see Duan et al. (1983)), which assumes no correlation between the two steps ($\sigma_{12} = 0$) and does not assume $\varepsilon_{2,i,t}$ is normally distributed. A disadvantage of these two applications is that they do not consider heterogeneity (see the argument in the section of logit and probit models). The two studies also did not fully explore the possibility that a tobit model provides an elegant selection rule that leads to an optimal selection.

### Artificial neural networks

An artificial neural network (ANN) is a non-linear model that consists of so-called nodes. A node can be seen as a function $G(.)$. Usually, there are a number of consecutive nodes: node $G_i(.)$ gets his input from $G_{i-1}(.)$ and gives his own output to node $G_{i+1}(.)$. The number of nodes is often referred to as the number of "hidden layers". The parameters of the nodes $G_i(.)$ are determined by backpropagation: the data (response variables $r_{it}$ and explanatory variables $x_{k,i,t}$) are fed through the network of nodes a number of times. Each time the parameters of the nodes are adjusted in order to minimize the sum of squared residuals. For notational purposes the explanatory variables are divided in two parts: $x^1_{k_1,i,t}$ and $x^2_{k_2,i,t}$, ($k_1 = 1, ..., K_1$, $k_2 = 1, ..., K_2$, with $K_1 + K_2 = K$, $i = 1, ..., I$, $t = t_{i,1}, t_{i,2}, ..., t_{i,T_i}$).

Usually ANN are represented using graphs, but it is possible to write an ANN in formulas. Using the notation by Franses (1998), an ANN model for log revenues becomes:

$$\ln y_{it} = \beta_0 + \beta_1 x^1_{1,i,t} + \beta_2 x^1_{2,i,t} + ... + \beta_k x^1_{k,i,t} + \sum_{q=1}^{Q} \lambda_q G(\gamma_{1q} x^2_{1,i,t} + \gamma_2 x^2_{2,i,t} + ... + \gamma_L x^2_{L,i,t} - \gamma_{0q}) + \varepsilon_{it}, \quad (9)$$

for all $i$ and $t$ ($i = 1, ..., I$, $t = 1, ..., T$) where $r_{it} = 1$. $G$ denotes the logistic activation function ($G(a) = \frac{1}{1+e^{-a}}$). The number of hidden layer units is given by the value of $Q$.

The results so far indicate that an ANN for response does not outperform a basic logit model (Zahavi and Levin (1997)), based on the out of sample percentage of correctly classified responders.

### Other methods

The method most used in practice is also the simplest. It concerns combining the individual values of Recency, Frequency and Monetary value (RFM) into an (one-dimensional) individual score. The weighting of the three dimensions is usually ad hoc, and interaction between the three dimensions is not considered, see Bauer (1988) for an example of such a method.

Another popular method it to assume each individual has a certain response probability $\pi_i$ which can be modeled by any chosen preferred distribution. A commonly used distribution is the beta distribution, see Colombo and Jiang (1999), Rao and Steckel (1995), Buchanan and Morrison (1988), which has the following distribution function:

$$f(\pi_i) = \frac{1}{B(a_i, b_i)} \pi_i^{a_i - 1} (1 - \pi_i)^{b_i - 1}, \tag{10}$$

where $\pi_i$ is the probability of response by individual $i$ $(0 \leq \pi_i \leq 1)$ and $B(a_i, b_i)$ is the beta function

$$B(a_i, b_i) = \int_0^1 t^{a_i - 1}(1 - t)^{b_i - 1} dt \tag{11}$$

and $a_i$, $b_i$ and $\pi_i$ are parameters, which have to be estimated. This method is discussed further in Section 5.1.

Most models select those individuals who are most likely to respond. As indicated above, a Tobit model can be used to provide an estimate of the expected revenue of an individual. An extension of this idea is the concept of lifetime value (LTV), where the decision to include a customer in the campaign is based on the expected revenues that this customer will generate for the firm during his/her lifetime as a customer (= the lifetime value or LTV). In a sense, the LTV is a proxy of the value of this customer to the company. Berger and Nasr (1998) describe (but do not compare) a number of mathematical methods for determining customer lifetime value.

Finally, when the response is integer valued, say for example, the firm is interested in the number of orders (from a catalog), then a Poisson regression model can be used (see Wedel et al. (1993)).

### 4.2.4 Discussion

Target selection is the most popular research topic in direct marketing. This section has illustrated that there are numerous models available to aid the direct marketeer in determining the customers who should receive a mailing.

However, most of the methods have a number of drawbacks. First (and foremost), almost all of the methods only consider response (yes/no). In practice, a direct marketer is more interested in maximizing profits and not in maximizing response. Some of the methods above do take revenue into account, but almost never as an intricate part of the model. Either revenue is assumed to be constant over individuals (Bult and Wansbeek (1995), Muus et al. (1996)), or is assumed to be equal to the past average (Bult and Wittink (1996)). As indicated, the tobit model provides an elegant framework to model response. However, only two restrictive formulations have been investigated: the regular tobit model (Levin and Zahavi (1998)) and the two-part model (Otter et al. (1997)).

The second drawback is that most of these methods do not take heterogeneity into account. It seems not very realistic that each individual will respond in the same way, and hence it would have improved face validity if the models had allowed for heterogeneity. Thirdly, the models do not take into account that mailings in the past were not sent randomly. This past mailing policy creates a non random sample where people who have received more mailings than others are over-represented.

## 4.3 Type of Campaign

An important question in the operationalization of the campaign is: do we perform a test campaign or do we start with the 'real' campaign? In a test, the campaign is performed on a selection of the total group of potential customers. The individuals included in the test can be selected randomly from the total population, but one can also decide to consider individuals belonging to certain segments. For instance, if a company wants to analyze whether there is a difference in response between one or double income households, both with a top level income, the company can send a mailing to individuals in both groups and compare the responses. If there is a difference in response in that double incomes respond more, and as this difference can be attributed mainly to the difference in the size of the household (because the other characteristics are comparable), the company can decide to approach mainly double income households. Also, managers often want to have an estimate of the response rate per segment. This is one of the criteria used to decide if the segment should be included in the final campaign. Often this estimate is obtained from a test on a random sample from the population.

Another goal might be to analyze the effects of different format(s) (see Section 4.1 and (Stone, 1994, p. 570)). As testing in direct marketing campaigns is mainly done in direct mail campaigns, this amounts to looking at the difference in response rate on different versions of the direct mail package. The test can help to determine which version is most appropriate for each segment (see Bult et al. (1997)). The results of the test mailing may also suggest that it is better not to send a mailing at all or to only one or a few segments.

The main issues in setting up a test are (1) how do we set it up? (who do we approach) and (2) how do we translate the outcomes to forecasts for the 'real' campaign (also called roll-out). Here, an interplay will have to take place between the input of managers and models (see Morwitz and Schmittlein (1998))

The size of a test mailing should not be too small (otherwise no reliable conclusions can be drawn) and not be too large (from a cost perspective). Jain (1995) (arbitrarily) suggests to use 2,500 individuals. However, there is no guarantee that this number will be sufficient. The appropriate number depends on the goal of the test (Hansotia (1990)). For example, if multiple versions of a mailing are to be tested, the test will require a larger size than if only one version is used.

If a test mailing has been performed, the response of the test mailing can be used to predict the response to the roll-out mailing. Firms often find that the predicted response of the roll-out is higher than the actual response. A number of methods have been suggested to adjust the test in order to obtain better forecasts (see Allenby and Blattberg (1987), Ehrman (1990*a*), Ehrman (1990*b*), Wang and Baker (1996), Jain (1995)).

Based on the empirical studies so far, we should mention one important issue here. Suppose a test mailing is performed. The problem often is that a test mailing is performed on a small sample of the entire list. Because the response to direct mail campaigns can be very low, the number of respondents (in absolute terms) can be small. This greatly influences the quality of the segmentation procedure, which is based on the response rate of the test mailing.

Besides predicting the response of the roll out campaign, the outcomes of the campaign can also be analyzed for other reasons. Bawa and Shoemaker (1987) analyze the effects of a direct mail coupon promotion and determine the characteristics of the households that use these coupons. The coupons can then be adjusted to appeal to those segments who are most likely to respond.

# 5 Campaign and Follow-up

The final part of the campaign consists of the actual campaign itself, and the following subsequent steps:

1. monotoring the response;
2. providing fulfilment;
3. monotoring profitability.

## 5.1 Response

Once the mailing has been sent, the company has to keep track of the response. This requires an accurate database, of which the contents must be updated when a response comes in. It is important to record if the response is informative or sales-oriented. This defines the quality of the response. A high quality response is characterized by a high percentage of sales. The incoming order should be processed quickly, and the reply to the response should be accurate. The time between an incoming order and an outgoing shipment should be as short as possible.

Using initial sales data to forecast total sales is a common topic in marketing (see for instance Bass (1969), Urban et al. (1990) and Sawhney and Eliashberg (1996)). One of the areas closely related to direct mail is the modeling of the response to mail surveys. In that area, a logistic model is commonly seen as the most appropriate model (Hill (1981), Parasuraman (1982)). Basu et al. (1995) have looked at modeling (aggregate) response to direct mailings by using a heterogeneous version of the exponential model. It outperforms the logistic model, and has a comparable performance as the Adbudg-model proposed by Little (1970).

Response can also be used to forecast the probability that a customer is or will become inactive. This can be done by analyzing the interpurchase times. If the time between two responses is increasing, this could indicate that a customer is becoming inactive. In marketing, different methods have been proposed to model interpurchase times. Schmittlein et al. (1987) and Schmittlein and Peterson (1994) have used an exponential distribution with an inverse gamma distribution of heterogeneity. Allenby et al. (1999) use a generalized gamma distribution, of which the exponential distribution is a special case. They model heterogeneity by using an inverse generalized gamma distribution.

Modeling interpurchase times in direct marketing is more difficult, as the interpurchase times depend on the actions of the firm. If an individual receives one mailing each year, and responds each time, the interpurchase time is quite large, but it gives no indication about the level of inactivity of the customer. However, the issue becomes different if we look at catalogs and assume customers will make purchases from old catalogs. Gönül et al. (2000) use hazard functions to determine the probability of a purchase in the next period, for the case when a catalog is sent and when it is not sent. This probability is used to determine the profit when the catalog is sent and when it is not sent. One of the drawbacks of this method is, however, that the amount spent is modeled as the average of past expenditures. This makes the calculation of the profit, and hence the determination of the mailing strategy, less convincing.

Another problem is: how many mailings do we send to a prospect (a potential new customer)? If he/she did not respond to the first mailing, do we sent another mailing, and possibly a third mailing? This problem has been analyzed by Rao and Steckel (1995), Ehrman and Funk (1997) and Pfeifer (1998), who use a beta logistic distribution to model the response probability $\pi_i$ of individual $i$ (see (10) and (11)). The probability of response $\pi_i$ is updated after each mailing, and these updated probabilities are used to determine whether the prospect should receive an additional mailing. The expected response probability, given $T$ mailings to which $i$ has not responded is in this model:

$$E(\pi_i|a_i, b_i, r_i = 0, T) = \frac{a_i}{a_i + b_i + T} \tag{12}$$

with $r_i$ is the number of responses by $i$. It is clear that $E(\pi_i|.)$ is declining in $T$.

Ehrman and Funk (1997) note that a large fraction of the population never reads direct mails, and therefore the beta logistic model needs to be adjusted. They propose to use a multivariate extension of the beta logistic model (the Dirichlet model) to model three outcomes: non response without reading, non response with reading and response. However, this model can not be estimated in practice as no information is available on whether someone has read the mailing or not. Therefore Pfeifer (1998) proposes to use a mixed beta logistic model, which does account for the possibility of non readers, but does not require information in the number of non-readers:

$$F(\pi_i) = q_i + (1 - q_i) \int_0^{\pi_i} \frac{1}{B(a_i', b_i')} x_i^{a_i'-1}(1 - x_i)^{b_i'-1} dx, \tag{13}$$

where $q_i$ is the probability that individual $i$ will never respond (= a non-reader) and $F(.)$ is the cumulative density function. Now the expected response probability becomes:

$$E(\pi_i|a_i, b_i, r_i = 0, T) = \frac{a_i'}{a_i' + b_i' + T} * \frac{(1 - q_i)NR_T}{q_i + (1 - q_i)NR_T} \tag{14}$$

where

$$NR_T = \frac{b_i'(b_i' + 1)...(b_i' + T - 1)}{(a_i' + b_i')(a_i' + b_i' + 1)...(a_i' + b_i' + T - 1)} \tag{15}$$

which is the probability a reader does not respond the $T$ successive mailings.

Expression (14) gives the updated estimated response probability given $i$ is a reader multiplied with the updated probability $i$ is a reader given that $i$ did not respond to the first $T$ mailings.

Using a (subjective) cut-off point, the direct mailer can now when a new prospect should not receive a new mailing.

## 5.2 Fulfilment

Fulfilment is defined as all the activities that occur once an order has been made or information has been requested. It deals with order-form issues, receiving orders, processing of orders, inventory policy, warehousing issues, customer service and planning and control (Roberts and Berger, 1999, p. 139). Fulfilment is an essential element of direct marketing because it is an important aspect in creating a relationship with the customer[5]. Although good fulfilment is no guarantee for a good relationship, bad fulfilment will almost surely lead to a bad relationship. Good fulfilment can become a competitive advantage. One of the important aspects of fulfilment is after-sales service, including handling of complaints and dealing with questions. It is found that there is a high correlation between the degree of success of a direct marketing campaigns and the quality of the after-sales service (Katzenstein and Sachs (1992)).

Good fulfilment is one way to deepen the relationship with the customer. (Stone et al., 1995, page 54) indicate that consumers seek:

- convenience and easy access to products and services
- appropriate contact and communication with the company
- 'special' priviliged status as a known customer - recognition of their history with the company
- effective and fast problem-solving

[5]Going into the details of (building a) relationship is beyond the scope of this paper. See Morgan and Hunt (1994) for an introduction into this area.

- appropriate anticipation of their needs
- a professional and friendly two way dialogue

To address these issues, the company needs to 'understand' its customers. From a database, the company can obtain information on the characteristics and the sales history of the customers. The company also wants to know if the customers are satisfied with the products they have bought, and what products they want to buy in the future. This information can be obtained by approaching individual customers, either through mail or by telephone. By showing interest in the satisfaction and future needs of the customers, and by offering them new products, the company can try to deepen the relationship with the customers.

Retailers can issue customer cards that give discounts on certain products. Producers can provide membership cards, giving the holders for instance the right to buy their products at lower than average retail prices. The advantages of these cards for the providers are that they constitute a 'relationship' with the customer (an indication of commitment of the customers to buy products from the provider), and that it is possible to keep track of the purchases of individual customers (which is often difficult for retailers and producers who do not deliver their goods directly to the customer), see (Hoekstra, 1998, p. 108).

As noted earlier, fulfilment is an important aspect of direct marketing. Good fulfilment encompasses accessable channels to handle complaints and questions (Morrow and Tankersley (1994)). Of course, the waiting time when using these channels should not be too long (Tom et al. (1997)). Another way to get information from the customers about their satisfaction with the company is through interviews with customers. Such interviews can be a valuable tool for providing insights into the purchase processes of customers (Woodside and Wilson (1995)).

As customers who buy a product from a catalog (or another direct medium) have not had the possibility to see the product beforehand in real-life, the purchase is more risky from the customers point of view. To lower this perceived risk, many direct marketing firms operate with generous return policies (a wide variety of warranty policies can be found in practice (Blischke and Murthy (1992))). In order to better handle returns, it is useful to have an (individual) prediction on the likelihood of a return (by a customer). This can be done using (split adjusted) hazard models (Hess and Mayhew (1997)). This enables the firm to identify customers who return purchased items more than expected, or determine items that are returned more often than expected. However, there might be some difficulty in obtaining the data to make predictions on returns. For new products, there are no data available on returns. Also, returns can be expected to depend on the quality of the products sold.

For a more detailed discussion on the different aspects of fulfilment see (Roberts and Berger, 1999, p. 138-159), (Hoekstra, 1998, p. 220-239) and (Nash, 1992, p. 449-519).

## 5.3 Evaluating and Measurement

A very important final step is to evaluate the campaign. First of all, a test can provide insight into the expected performance (and profitability) of a campaign. Next, a front-end analysis and a back-end analysis can help in monitoring the profitability. A front-end analysis measures the initial costs of and response to a direct marketing activity, and deals primarily with the costs of gathering new customers. Back-end analysis starts after the initial response, and deals with the potential revenues of a group of respondents after their personal data have been added to the database (Hoekstra, 1998, p. 284). Criteria in front-end analysis can be: costs (per thousand pieces of mailing), response per thousand, orders, costs per response and costs per order. Back-end analysis deals with sales, contribution-margin and profit. Here the following questions should be addressed: What was the quantity of the response? In other words: how many people responded? What was the quality of the response (were the respondents asking for information or did they buy the product)? It is also important to know who bought the product: do these individuals have distinguishing characteristics? How much did the respondents buy? Who did not buy the product? How do the results compare with prior expectations (see also Section 4.3)?

Of course, the campaign should also be monitored constantly *during* its execution, and when necessary, correcting steps should be taken. Usually the firm has a contingency plan to indicate what action should be taken when the results are not as expected. When for instance the intermediate response is very low, mass-media sources can be used to create extra awareness for the campaign.

# 6 Conclusion

A direct marketing campaign consists of a number of stages that can be divided into three parts: (1) setting up the framework of the campaign; (2) operationalisation of the campaign and (3) execution of the campaign and handling of the response. This survey paper has discussed each of these stages in detail, focusing on the (quantitative) research that has been done. Although there has been extensive research into the various aspects of a direct marketing campaign, there are still a number of issues that have not been dealt with sufficiently. Various future research topics were also discussed.

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