

Targeting Direct Marketing Campaigns
by a more differentiated View on Generated Sales
Rainer Olbrich and Benedikt Lindenbeck

Prof. Dr. Rainer Olbrich
University of Hagen
Faculty of Business Administration and Economics
Chair of Marketing
Universitätsstr. 11
58097 Hagen, Germany
Tel.: +49 2331 987 2541
E-Mail: lehrstuhl.marketing@fernuni-hagen.de

Benedikt Lindenbeck
Doctoral Student
University of Hagen
Faculty of Business Administration and Economics
Chair of Marketing
Universitätsstr. 11
58097 Hagen, Germany
Tel.: +49 2331 987 2482
E-Mail: benedikt.lindenbeck@fernuni-hagen.de

Abstract

Direct marketing is marked by an extensive academic interest and research, a big economic importance, and a high efficiency. The selection of customers or prospects to target plays an important role for the success of a direct marketing campaign. According to academic research, the generated sales seem to be a significant control factor for this selection process. Because of low response rates and high costs when using direct marketing, it seems necessary to investigate the controlling influence of this factor in a more differentiated way.

We divided the potentially addressed customers by their actually generated sales in different cohorts. By the use of a pretest, we identified the economic attractive cohorts according to their probably effectiveness and sorted them in descending order. On the basis of a Wilcoxon rank-sum test, we finally evaluated that contacting the customers in the order of these cohorts increases efficiency. We used a dataset from a German financial service provider for the empirical study. The data contain information about the real buying behavior and therefore the actually generated sales next to demographic characteristics of each person. Furthermore the data include information about performed direct marketing campaigns.

The results of this study show that the consideration of generated sales supports targeting direct marketing campaigns. The generated sales influence the customer selection by using a specific weight in each campaign. Therefore, the rating of this factor has to be implemented in a more differentiated way to improve the efficiency of direct marketing campaigns. According to these results, the customer selection can be enhanced and the campaign's success can be increased.

KeyWords

Customer selection; direct marketing; mailing campaigns; financial services; Wilcoxon rank-sum test (WRS)

Introduction and Objectives

As indicated by expanding academic interest and research in recent years (Feld et al. 2013; Lu et al. 2011), direct marketing offers promising possibilities for contacting customers and prospects in differentiated and personalized ways, leading to potentially better results than those achieved through other types of mass marketing (Guido et al. 2011). Expenditures for direct marketing instruments thus have remained at high levels in recent years; for example, in Germany, marketers spent 74.2 billion Euros in 2014 on direct marketing instruments, equivalent to 37% of the total expenditures in the marketing industry and 2.56% of Germany's national product (Deutsche Post AG 2015). The costs for these instruments include the design and production of differentiated, personalized advertising messages, along with the costs to dispatch those messages. Especially when the distribution is not digital, such costs are difficult to control. Because of their economic relevance, these physically distributed direct marketing instruments are the primary focus in this study.

Because any direct marketing campaign aims for economic success through its conception and application, it is necessary for each campaign to target profitable customers and prospects. The only targets who should be addressed also should be those with a high probability of a positive response (Asllani and Halstead 2011). Contacting these persons reduces the campaign's costs, by avoiding spreading losses. It also prevents the risk of annoying non-candidates, by preventing them from receiving inappropriate advertising messages. In turn,

the reduction in consumer annoyance or overload should improve their attitudes toward future messages.

The selection of appropriate customers or prospects also requires efficient targeting. That is, because targeting largely determines the success of a direct marketing campaign, the selection of the persons to target exerts a powerful influence on the campaign's success (Coussement et al. 2014; Lu et al. 2011). Various targeting methods have been proposed (Guido et al. 2011; Zahavi and Levin 1997), often based on intensive academic considerations. Yet direct marketing frequently achieves only low response rates, such that in some cases, even low single-digit response rates represent an apparent success in practice (Feld et al. 2013; Direct Marketing Association 2006; Bose and Chen 2009). Such low response rates suggest that the methods used for targeting in direct marketing campaigns offer substantial potential for optimization.

With this study, we propose a more efficient method to select the persons to be addressed by direct marketing. This expedited selection process offers a more differentiated view on the subsequently generated sales. Therefore, we start with our key research questions, then introduce a recency-frequency-monetary value (RFM) model for targeting direct marketing campaigns. This model already has been used widely in practice and in academic research (Zhang et al. 2015), and it has provided the basis for many algorithms developed in recent years (McCarty and Hastak 2007). With an empirical study, we identify whether the application of the RFM model leads to optimal results through targeting in direct marketing campaigns. Using a Wilcoxon rank-sum test, we also investigate whether the application of the RFM model results in a different selection than would be suggested by a pretest. We interpret and evaluate the resulting differences, with a focus on an economic perspective. The discussion of the results focuses on the appropriateness of using generated sales to select persons to address with direct marketing; we also note some limitations of this study and directions for further research.

Research Question

In this study, we propose that the process of selecting persons to target in direct marketing could be more efficient if it relied on a differentiated view of generated sales. Accordingly, we compare the performance of a selection based on a pretest against the results achieved when we apply an RFM model. In addition to its common usage, we prefer RFM because its factors have substantial relevance with respect to the selection of appropriate targets (McCarty and Hastak 2007; Fader et al. 2005b). In its basic form, RFM is a scoring model, such that a higher score represents a higher probability that an addressed target responds as expected. Therefore, addressing persons who earn higher scores should enhance the efficiency of the campaign. However, with respect to the amount of previously generated sales, this assumption does not appear true unconditionally, likely because this approach ignores several influential aspects. For example, saturation in a long-term relationship between a customer and the company featured in the direct marketing campaign is not addressed. Nor does this approach acknowledge that spending substantial amounts once might not lead to further purchases by the customer.

Therefore, we seek to investigate the influence of previously generated sales with a more differentiated view, in line with the following research question:

1. Does the consideration of previously generated sales, according to RFM, lead to an optimal selection of persons to address with direct marketing?

To answer this question, we need to compare the application of RFM against an alternative selection process. We consider selection based on a pretest as an alternative approach, considering the evidence in previous research that pretests are useful and necessary (Faulkner and Kennedy 2008). With respect to this comparison, we investigate the following research questions:

2. Does the selection of persons to address with a direct marketing campaign differ according to the use of RFM versus a pretest, with respect to previously generated sales?
3. Does a selection based on a pretest result in greater efficiency for a direct marketing campaign?

Conceptual Framework

Among the variety of methods adopted to target direct marketing campaigns, a thematic priority highlights the RFM model (Hu and Yeh 2014). This model is based on considerations of the transactions between customers and companies in the past. On the basis of this information, the modeler attempts to predict customers' future behavior and actions (Coussement et al. 2014). Because RFM is a score model, its application involves assigning every potentially addressable person a concrete score (Zhang et al. 2015). In its original form, the model consists of recency, frequency, and monetary value factors (Hughes 1994), which indicate when a customer bought a product or service last from the company, how often the customer has bought products or services, and the amount of the sales generated through this customer's purchases of products or services from the company (Fader et al. 2005a). Each factor gets quantified separately in an RFM application, and then the resulting values are multiplied by positive, subjective determined values to integrate previous experiences (Venkatesan et al. 2007). Finally, these values get multiplied or summed as a single score for each customer (McCarty and Hastak 2007). A higher resulting score implies that it is more worthwhile for the marketer to address this customer with a direct marketing campaign (Asllani and Halstead 2011; Cheng and Chen 2009). However, RFM is not always appropriate for predicting prospects' future actions, especially because the necessary information is not available for people who have not transacted with the company in the past. For this reason such prospects are not the focus for our elaboration in this article.

To examine potential issues with using the RFM model, we performed an empirical study with a data set from a German financial service provider. We investigate financial services precisely because of the peculiarities of this industry. First, customers tend to notice and attend to advertising messages in this industry (Peters et al. 2007). Second, financial service providers compete intensively, so they must engage in well-engineered marketing campaigns to attract the attention of their customers or prospects and achieve lucrative, long-ranging relationships. The data used in this study include information about the real buying behavior and actually generated sales, as well as the demographic characteristics of each person. They also feature information about two direct marketing campaigns performed in 2012 and 2013. In these campaigns, approximately 135,000 direct mail pieces were sent to customers. We investigate such direct mailings because they are a dominant instrument for direct marketing and account for most of the expenditures in this industry (Deutsche Post AG 2015; Feld et al. 2013).

In these two real-world campaigns, the addressed persons were not selected by their previously generated sales but rather by whether each person had already bought the advertised service or a substitute of it or not. In line with a key assumption of RFM, the probability of a positive response should be highest among those persons who have generated the greatest amount of sales in the past (Cheng and Chen 2009).

Method

To test these assumptions, we divided potentially addressed customers according to their previously generated sales. The resulting cohorts thus were sorted by the average value of generated sales, in descending order. We also executed a pretest based on randomly chosen members of each of the resulting cohorts. The outcome of the pretests served to determine an alternative order for the cohorts, that is, the sequence in which the cohorts should be organized according to their members' probability of issuing a positive response.

The results show that targeting customers according to the RFM model leads to unexpected results. As Figure 1 and Figure 2 reveal, the anticipated decreasing response rate among each additional contacted cohort did not occur for these campaigns. Furthermore, contacting the cohorts in the order derived from the performed pretest would entail a different order than the one suggested by RFM. For both campaigns, contacting the cohorts in the order suggested by the results of the pretest led to the expected decreasing response rate.

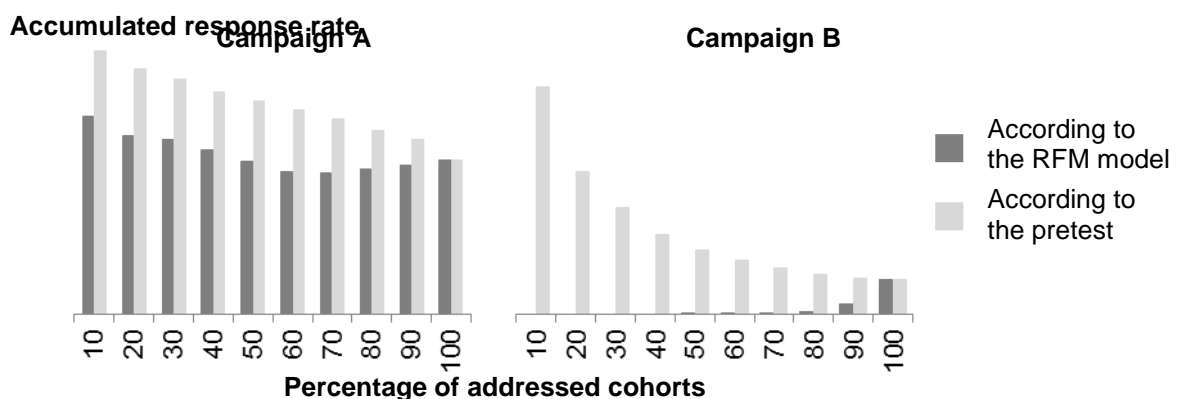


Figure 1 Accumulated response rates using RFM and pretest

Addressed cohort	1	2	3	4	5	6	7	8	9	10
Campaign A										
- RFM	1,528	1,222	1,306	1,028	,833	,667	1,028	1,361	1,417	1,000
- Pretest	2,037	1,759	1,667	1,389	1,389	1,204	1,111	,833	,741	,371
Campaign B										
- RFM	,000	,000	,000	,000	,010	,000	,020	,041	,211	,795
- Pretest	,671	,168	,101	,000	,000	,000	,000	,000	,000	,000

Figure 2 Response rates of each cohort in the order suggested by using RFM and pretest

Using a Wilcoxon rank-sum (WRS) test, we checked if the differences between the applications of the two methods were significant. We chose WRS primarily because of its ability to deal with available metrics but not normally distributed data. In addition, the WRS is widely used and well-established as a means to compare different distributions (Hossain et al. 2013;

Natarajan et al. 2012). It checks whether the distribution of the populations of two samples is identical (Mann and Whitney 1947). To do so, it substitutes actual numerical data, by ascending scores, to determine if the existing differences are significant (Wilcoxon 1945; Taheri and Hesamian 2013). Identical numerical values, so called ties, are tagged by their corresponding average ranks in this model (Gibbons and Chakraborti 2003). The application of the WRS thus enabled us to check the null hypothesis that both distributions were identical. According to the formula developed by Wilcoxon and generalized by Mann and Whitney, we determine if the null hypothesis is supported or rejected (Wilcoxon 1945; Mann and Whitney 1947).

Findings and Discussion

From the WRS, we learned that the distributions of response rates for both campaigns differ across the two methods. In Figure 3, we depict the percentage of addressed cohorts that exhibit significant differences. The order identified by the pretest was different than that suggested by RFM. With a view to Research Question 2, we thus verify that the selection of persons to address differs depending on whether we use previously generated sales according to RFM or a pretest.

Percentage of addressed cohorts	10	20	30	40	50	60	70	80	90	100
- Campaign A	-	x*	x*	x*	x*	x*	x*	x*	x*	-
- Campaign B	-	x*	x*	x*	x*	x*	x*	x*	-	-

* significant at the 0.05 level

Figure 3 Different distributions of response rates using RFM and pretest

Next, we compared the mean values in both campaigns, to evaluate whether the results differ from an economic perspective. Specifically, we compared the accumulated response rates of each performed campaign, as a percentage of addressed cohorts, using RFM and the applied pretest. As Figure 4 shows, the selection of potential targets according to the RFM model based on previously generated sales did not lead to optimal results. Instead, contacting the cohorts in the order identified by the pretest is economically more valuable. The accumulated benefit in percentage using a pretest compared to RFM model is shown on the ordinate. The respective benefit is unique to each campaign. For Research Question 3, we thus determine that the selection of persons based on a pretest leads to a more efficient direct marketing campaign.

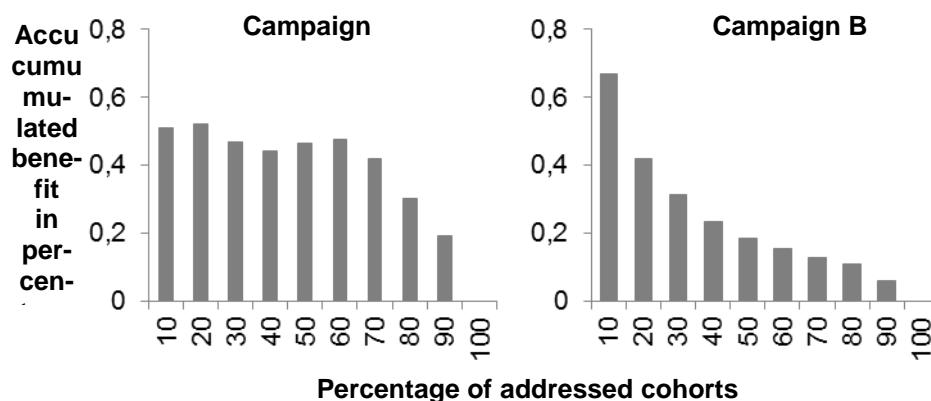


Figure 4 Benefit using pretest compared to RFM

The positive answers to Research Questions 2 and 3 lead us to address Research Question 1. That is, the consideration of previously generated sales, according to RFM, does not lead to

an optimal selection of persons that should be addressed by direct marketing. As existing criticism has suggested, we expected this result. The consideration of previously generated sales can influence the selection of potentially addressed persons positively though. Therefore, a preferable approach would divide the potentially addressed persons into different cohorts, according to their actually generated sales. The cohorts to be addressed should not reflect divisions according to the RFM model and not be selected exclusively by descending order of generated sales. Instead, to determine the order of these cohorts, marketers should execute a pretest. Then, this generally divergent order causes the generated sales to affect the selection process in a different way, because it becomes a consideration of the amount of generated sales. Previously generated sales influence the customer selection by a specific weight for each campaign. The rating of generated sales then can be implemented with greater differentiation, to improve the efficiency of direct marketing campaigns.

Conclusion

We have tested, on the basis of data from a German financial service provider, whether the consideration of generated sales affects targeting in direct marketing campaigns. To enable a comparison with established methods, we first checked whether the application of a common RFM model led to optimal results, with a concentration of generated sales and an assumption that the other RFM factors remained constant. Using generated sales, we investigated whether the application of RFM led to different results than a selection of addressable persons through means of a pretest. The Wilcoxon rank-sum test verified this prediction: The divergent selection, based on the pretest, led to economically better results, as verified by our comparison of the accumulated mean response rates in both campaigns. By verifying both aspects, we obtained a negative answer to the first research question. The consideration of previously generated sales, according to RFM, does not lead to the optimal selection of persons to address in direct marketing. The influence of generated sales on the targeting process must be more differentiated to enhance the customer selection process and increase the campaign's success.

Limitations and Further Research

Some restrictions are associated with this study. For example, by excluding monetary values and assuming the consistency of other factors, we might limit the effectiveness of the RFM model. Including all three recency, frequency, and monetary value factors might lead to better results for direct marketing campaigns. In addition, the data set we used contains information about only one industry. Therefore, the generalizability of the findings to other industries is questionable, though the financial industry also is meaningful, with a substantial economic impact. Finally, we neglected that different products were being advertised in both real-world campaigns. Integrating other, product-specific characteristics might enhance the selection of persons to address.

Additional research ideas follow from these limitations. Beyond considering other factors, researchers might integrate product-specific characteristics to determine how to target direct marketing campaigns. This inclusion might be especially beneficial for establishing long-term relationships between customers and the direct marketers, due to the economic potential of this relationship.

Managerial Implications

The outcomes of our study indicate that managers should divide persons they are considering addressing with a direct marketing campaign into cohorts, according to their actually, pre-

viously generated sales. This differentiation supports predictions of the likely response rates of each cohort. Targeting direct marketing campaigns exclusively on the basis of RFM is not optimal though. Identifying the order of cohorts to address with a pretest actually can lower the costs of the campaign and increase its chances of success.

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