EFFECTIVENESS OF RETARGETED DIRECT MAILING: WHEN DOES IT WORK?

Saeid Vafainia ESCP Business School Els Breugelmans KU Leuven Tammo Bijmolt University of Groningen

Cite as:

Vafainia Saeid, Breugelmans Els, Bijmolt Tammo (2021), EFFECTIVENESS OF RETARGETED DIRECT MAILING: WHEN DOES IT WORK?. *Proceedings of the European Marketing Academy*, 50th, (104605)

Paper from the EMAC Regional 2021 Conference, Warsaw, September 22-24, 2021



EFFECTIVENESS OF RETARGETED DIRECT MAILING: WHEN DOES IT WORK?

Abstract

Retailers nowadays use direct mailings tailored to customer's purchase recency in order to convince them to repurchase. This paper aims to investigates whether such retargeted direct mailings are more effective in impacting customer purchase behavior than non-targeted direct mailings, using an empirical a quasi-experimental setting. We found that retargeted direct mails are only effective in increasing the purchase likelihood of customer, while not successful in increasing their spending. Plus, the effectiveness of retargeted direct mailings depends on customer characteristics and retargeted direct mailing's type. The results of the study provide valuable insights for managers when allocating the direct mailing budget.

Keywords

Direct mailing, Retargeting, Customer retention

INTRODUCTION

Marketers continue to use direct mail (DM) in the recent years, even in the digital age (DMA 2018). This could be due to the improvements in collecting relevant consumer data on customer purchase history, demographics and geographics and the shift toward retargeted direct mail (RDM). RDM is to use the information from past consumers behaviors and send out tailored DMs to reactivate customers and entice them to come back to store and repurchase (Forbes, 2020). The use of RDM has resulted in increase in effectiveness of DM according to business presses. The Forbes, for instance, reported that over 84% of consumers would be more likely to open a piece of DM if DM is tailored to their needs (Forbes, 2017).

Although business press predicts that RDMs have a higher relative performance in comparison with traditional DMs because they are tailored to customer's purchase recency (e.g., Forbes 2017), yet, there is little academic evidence on the effectiveness of the RDM, compared to traditional DMs. Therefore, in this study, we aim to empirically investigate the effect of the RDM on actual customer purchase behavior and whether its effectiveness depends on customer and RDM characteristics. To examine the effectiveness of RDM, we use a large-scale dataset from a direct mail agency in the Netherlands.

PURPOSE

The purpose of this paper is to quantify the impact of RDM efforts on customer actual purchases. In particular, we address the following research questions:

- 1. What is the impact of RDM on customer purchase behavior, namely purchase incidence and purchase amount?
- 2. For which groups of customers, in terms of behavioral and demographic characteristics (e.g., customer demographics, relationship duration with the retailer and communication history), is RDM more effective?
- 3. Which type of RDM campaigns are more effective, namely transaction-oriented RDM versus relationship-oriented DM?

CONCEPTUAL FRAMEWORK

The main difference between traditional DMs and RDMs is in their timing. Firms use a RDM to retarget the individual customers based on individual's purchase recency, and by doing this, they try to prevent customers from becoming inactive. Hence, RDMs are expected to be more relevant and persuasive compared to the traditional DMs, where DMs are sent to all customer, no matter how long ago an individual customer has made a purchase. Therefore, we anticipate that the RDMs to have a higher relative performance in comparison with traditional DMs in terms of customer response. Despite the increased popularity of retargeted direct mail, yet, there is little academic evidence on the effectiveness of the RDM. The current literature on direct mailings effectiveness has investigated customer response to traditional DMs (e.g., van Diepen, Donkers, and Franses 2009; Feld et al. 2013; Vafainia, Breugelmans, and Bijmolt 2019), however, it remains silent on the impact of RDM on customer purchase behavior. The extant literature on targeted price promotions effectiveness also highlights the incremental benefits of targeted promotional offers (Zhang and Wedel 2009; Ansari and Mela 2003). Thus, the first objective of this study is to empirically examine the effectiveness of RDMs compared to traditional DMs, which is missing in the existing direct marketing literature.

The impact of RDM may also depend on individual customer characteristics (Lewis, Whitler, and Hoegg 2013). In particular, previous studies in relationship marketing literature have shown that response to marketing interventions is highly heterogeneous based on customer differences in relationship history (such as relationship duration), communication history (how recently and frequently customers have received DMs) and socio-demographics (age and

gender) (Rust and Verhoef 2005; Neslin et al. 2013). Therefore, the second objective of this study is to investigate whether customer characteristics can moderate the impact of RDM on customer's purchase behavior.

In addition, the direct marketing literature distinguishes between marketing communications that directly stimulate product or service sales and those that focus on the maintenance and development of customer relationships (Gázquez-Abad, Canniére, and Martínez-López 2011). In a similar manner, the RDMs can have two different purposes: i) RDMs with a transaction-oriented purpose, focusing on triggering customer to take an action and then rewarding customers (i.e., when the firm uses a financial incentive to trigger customer response) or, ii) relationship-oriented RDMs that focus on the maintenance and development of customer relationships (i.e., when the retailer uses non-financial incentive to strengthen the relationship with a firm, like a thank you letter). It is largely unknown whether these results are generalizable to context or RDMs. Therefore, our third objective is this research is to understand whether the type of RDMs (transaction- oriented versus relationship-oriented) moderate the effect of RDM on customer purchase behavior. Figure 1 summarizes our conceptual framework.

Figure 1- Conceptual framework



METHODOLOGY

Data

We address our research questions using a unique customer-level dataset for 10 optical retailers in the Netherlands across eight years (2011-2018). These optical retailers are independent and do not belong to large chains. Five out of 10 retailers participated in the RDM program, while the rest did not. Both of these two groups of the retailers are very similar in terms of customer base and location. For the five retailers who participate in RDM, RDM are sent to all the customers depending on their last purchase recency, during a purchase recency period of maximum four years, with the goal of inviting the customer to re-purchase. So, during this period of 4 years, a customer will receive several transaction-oriented and relationship-oriented, where in this DMs the retailer tries to re-activate the customers.

We track purchase behavior, customer characteristics and DM communication history of customers who have valid information on age, gender and registration date. These constraints leave us with 17,064 customers in the RDM treatment group (5 retailers that participate in RDM) and 15,601 in the control group (5 retailers that do not participate in RDM).

Propensity Score Estimation and Matching

In order to retrieve the effect of RDM, it is important to disentangle RDM effect from other extraneous effects or trends. To do so, we adopt a quasi-experimental design approach using propensity score matching to identify non-RDM receivers similar to RDM-receivers, along their observed characteristics (for a similar approach, see Datta, Knox, and Bronnenberg (2018)). We match customers in the RDM group to a similar customer in the control group, based on individual customer demographics (e.g., age, gender), behavioral measures (e.g., initialization period spending, purchase frequency and recency, customer duration of relationship with the retailer, frequency and recency other traditional direct mailings sent to customer besides RDM), Mahalanobis distance algorithm with replacement. We use an initialization period of one year (2011) to construct our hold-our period variables (Narang and Shankar 2019).

As shown in Figure 2, matching improves the percentage balance of propensity scores, making the matched treated and control groups comparable. This is important evidence that matching results in a valid control group. The matching procedure yields 15,677 treated and 15,677 matched control users.



Figure 2. Distribution of Propensity Scores Before and After Matching

Treatment Effect

To estimate the effect of RDM, we compare the purchase outcomes for customers who receive RDM compared to the customers in the control groups, who do not receive RDM. The outcome variables in our research are customer purchase incidence as well as purchase amount in each quarter during the estimation period (2012-2018), where purchase incidence equals to one if the customer *i* makes a purchase in quarter t^{I} and purchase amount is customer's spending amount² in quarter *t*.

Given that purchase amount only exists if a customer has made a purchase, we need to address the potential bias in the regression parameters in the purchase amount equation. To account for this selection bias, we employ the Heckman selection model (Heckman 1979), which has found other applications in marketing literature (e.g., Ying, Feinberg, and Wedel, 2006). We model the purchase amount, conditional on customer's purchase incidence as follows:

¹ The reason for choosing quarter as our time unit is that customers at optical retailers do not purchase glasses or lenses every day or even every month.

² We take the logarithm of the spending to reduce the skewness (e.g., Ataman et al. 2010).

(1) Purchase_Incidence_{it} = $\beta_0 + \beta_1 RDM_T reat_{it} +$

```
(\sum_{char=1}^{char=5} \beta_{2,char} Consumer_{Characteristics_{it}}) + (\sum_{dummy=1}^{dummy=14} \beta_{7,dummy} Year / \beta_{7,dummy})
```

 $Season_{dummy}) + \in_{it}$

We model the purchase amount conditional on the occurrence of purchase as follows:

(2) $Spending_{it} = \beta_0 + \beta_1 RDM_T reat_{it} + (\sum_{char=1}^{char=5} \beta_{2,char} Consumer_C haracteristics_{it}) + \beta_1 RDM_T reat_{it} + (\sum_{char=1}^{char=5} \beta_{2,char} Consumer_C haracteristics_{it}) + \beta_1 RDM_T reat_{it} + (\sum_{char=1}^{char=5} \beta_{2,char} Consumer_C haracteristics_{it}) + \beta_1 RDM_T reat_{it} + (\sum_{char=1}^{char=5} \beta_{2,char} Consumer_C haracteristics_{it}) + \beta_1 RDM_T reat_{it} + (\sum_{char=1}^{char=5} \beta_{2,char} Consumer_C haracteristics_{it}) + \beta_1 RDM_T reat_{it} + (\sum_{char=1}^{char=5} \beta_{2,char} Consumer_C haracteristics_{it}) + \beta_1 RDM_T reat_{it} + (\sum_{char=1}^{char=5} \beta_{2,char} Consumer_C haracteristics_{it}) + \beta_1 RDM_T reat_{it} + (\sum_{char=1}^{char=5} \beta_{2,char} Consumer_C haracteristics_{it}) + \beta_1 RDM_T reat_{it} + (\sum_{char=1}^{char=5} \beta_{2,char} Consumer_C haracteristics_{it}) + \beta_1 RDM_T reat_{it} + (\sum_{char=1}^{char=5} \beta_{2,char} Consumer_C haracteristics_{it}) + \beta_1 RDM_T reat_{it} + (\sum_{char=1}^{char=5} \beta_{2,char} Consumer_C haracteristics_{it}) + \beta_1 RDM_T reat_{it} + (\sum_{char=1}^{char=5} \beta_{2,char} Consumer_C haracteristics_{it}) + \beta_1 RDM_T reat_{it} + (\sum_{char=1}^{char=5} \beta_{2,char} Consumer_C haracteristics_{it}) + \beta_1 RDM_T reat_{it} + (\sum_{char=1}^{char=5} \beta_{2,char} Consumer_C haracteristics_{it}) + \beta_1 RDM_T reat_{it} + (\sum_{char=1}^{char=5} \beta_{2,char} Consumer_C haracteristics_{it}) + \beta_1 RDM_T reat_{it} + (\sum_{char=1}^{char=5} \beta_{2,char} Consumer_C haracteristics_{it}) + \beta_1 RDM_T reat_{it} + (\sum_{char=1}^{char=5} \beta_{2,char} Consumer_C haracteristics_{it}) + \beta_1 RDM_T reat_{it} + (\sum_{char=1}^{char=5} \beta_{2,char} Consumer_C haracteristics_{it}) + \beta_1 RDM_T reat_{it} + (\sum_{char=1}^{char=5} \beta_{2,char} Consumer_C haracteristics_{it}) + \beta_1 RDM_T reat_{it} + (\sum_{char=1}^{char=5} \beta_{2,char} Consumer_C haracteristics_{it}) + \beta_1 RDM_T reat_{it} + (\sum_{char=1}^{char=5} \beta_{2,char} Consumer_C haracteristics_{it}) + \beta_1 RDM_T reat_{it} + \beta_1 RDM_T reat_{$

 $(\sum_{dummy=1}^{dummy=14} \beta_{7,dummy} Year/Season_{dummy}) + \epsilon_{it}$ if Purchase_Incidence_{it} = 1

where i is the individual, t is the quarter, RDM_Treat is a dummy variable denoting whether the customer is in the treatment group. We also control for the customer characteristics that we explained in the data section.

We measure the heterogeneity in treatment effects to examine the potential moderation effect of customer characteristics as well as RDM type (transaction-oriented vs. relationshiporiented), by estimating the Model 1 and 2, where we interact these moderator variables with the RDM_Treat variable.

RESULTS

We present the results of main RDM treatment effect (estimated model 1 and 2 without the interaction terms) as well as the moderators (estimated model 1 and 2 including interactions with the moderators) in Table 1 and Table 2, accordingly. Results in Table 1 show a positive and significant impact of RDM on customer purchase incidence (β =.11, p<.01). However, the RDM is not successful in increasing the customer purchase amount (β =.01, p>.1). This shows that although RDM are effective in triggering customer to come to store and make a purchase, while they do not affect customer purchase amount.

In addition, we observe that there exists heterogeneity in the RDM treatment effects. In particular, the negative significant coefficient of the transaction-oriented RDMs $(\beta_{RDM*transaction_{pi}} = -.07, p<.01; \beta_{RDM*transaction_{spending}} = -.11)$ indicates that a relationship-oriented RDM has a higher impact on purchase outcomes than a RDM transactionoriented RDM. This is in line with the finding of where they found that relational mailings yielded a higher value than current promotional mailings (Gázquez-Abad, Canniére, and Martínez-López 2011). We also see that the effect of RDM on purchase outcomes varies across customers. Most notably, the impact of RDM is higher on customer who receive more frequently the traditional direct mailings $(\beta_{\text{RDM*Frequency}DM pi} =$.13, p<.01; $\beta_{\text{RDM*Frequency}DM_spending}$ = .14). In addition, a customer of higher age seems to be less responsive RDMs ($\beta_{RDM*age pi}$ = -.003, p<.01).

Variables	(log) Spending	Purchase incidence	
RDM treatment	0.01	0.11***	
Age	0.02***	-0.01***	
Gender	-0.10***	0.07***	
Customer duration	0.02***	0.001*	
Frequency_DM	0.41***	-0.17***	
Recency_DM	0.01***	0.00***	
Season_dummy			
2	-0.12***	-0.02***	
3	-0.12***	-0.06***	
4	-0.06***	-0.04***	
Year_dummy			
2012	-0.07***	-0.09***	
2013	-0.16***	-0.18***	
2014	-0.37***	-0.19***	
2015	-0.31***	-0.21***	
2016	-0.34***	-0.18***	
2017	-0.44***	-0.25***	
2018	-0.55***	-0.32***	
Constant	4.17***	-0.67***	

Table 1- Impact of RDM Treatment on Customer Purchase Outcomes

p < .1 = *, p < .05 = ** and p < .01 = ***

Table 2- Assessing Potential Moderators of the RDM treatment effect

Variables		(Log) Spending	Purchase Incidence
Interaction RDM type	RDM treatment *Transaction-oriented	-0.11***	-0.07***
Interaction Customer characteristics	RDM treatment *Age	-0.001	-0.003***
	RDM treatment *Gender	-0.008	-0.009
	RDM treatment *Customer duration	-0.07***	0.01***
	RDM treatment *Frequency_DM	0.14*	0.13***
	RDM treatment *Recency_DM	0.02***	-0.08***

p < .1 = *, p < .05 = ** and p < .01 = *** The independent variables are the interaction effects to capture heterogeneous treatment effects

CONCLUSION

The key contribution of this paper is that we quantify the impact of RDM efforts on customer actual purchase outcomes, namely, purchase incidence and spending and how its effectiveness depends on customer characteristics and RDM type. An interesting finding is that the RDMs are only effective in increasing the purchase likelihood of customer, while not successful in increasing their spending.

In addition, with this paper, we extend the current direct mailing literature by showing that relationship-oriented RDMs have a higher impact on customer's purchase outcomes, compared with transaction-oriented RDMs.

PRACTICAL IMPLICATIONS

The results of the study will provide valuable insights for managers when allocating their direct marketing budget. First, our results suggests that it pays off to send out RDM to customers, with the goal of triggering customers to make a purchase and avoid potential permanent churning. In addition, our results challenge the common practice of retailers to target customers with the transaction-oriented communications, as we found that relationship-oriented RDMs are more effective in terms of impacting purchase outcomes. Finally, our results highlight the importance of targeting customers based on (behavioral) customer characteristics, as we found that customers who received more traditional DM in the past are more likely to respond to RDMs.

SOCIAL IMPLICATIONS

In this study, showed that the RDMs are more effective for certain customers, then the retailers can optimize the DM campaigns and avoid sending them to all the customers, using less papers to print that are thrown away.

RESEARCH LIMITATION

One limitation of this study is that we rely on natural variation in the data between the retailers that participate in RDM and the ones that do not join. Thus, controlled randomized field experiments could provide future researchers with unique opportunities for testing specific RDM-related manipulations.

REFRENCES

- Ansari, Asim and Carl F Mela (2003), "E-customization," *Journal of marketing research*, 40 (2), 131–45.
- Bleier, Alexander and Maik Eisenbeiss (2015), "The importance of trust for personalized online advertising," *Journal of Retailing*, 91 (3), 390–409.
- Datta, Hannes, George Knox, and Bart J Bronnenberg (2018), "Changing their tune: How consumers' adoption of online streaming affects music consumption and discovery," *Marketing Science*, 37 (1), 5–21.
- van Diepen, Merel, Bas Donkers, and Philip Hans Franses (2009), "Does irritation induced by charitable direct mailings reduce donations?," *International Journal of Research in Marketing*, 26 (3), 180–88.
- DMA (2018), Statistical Fact Book: The Ultimate Source for Data-Driven Marketing Insight, DMA.
- Feld, Sebastian, Heiko Frenzen, Manfred Krafft, Kay Peters, and Peter C. Verhoef (2013), "The Effects of Mailing Design Characteristics on Direct Mail Campaign Performance," *International Journal of Research in Marketing*, 30 (2), 143–59.
- Forbes (2017), "Print Media Isn't Dead, It's Just Moved," *Forbes*, [available at https://www.forbes.com/sites/freddiedawson/2016/01/31/print-media-isnt-dead-its-just-moved].
- Gázquez-Abad, Juan Carlos, Marie Hélène De Canniére, and Francisco J. Martínez-López (2011), "Dynamics of Customer Response to Promotional and Relational Direct Mailings from an Apparel Retailer: The Moderating Role of Relationship Strength," *Journal of Retailing*, 87 (2), 166–81.
- Heckman, James J (1979), "Sample selection bias as a specification error," *Econometrica: Journal of the econometric society*, 153–61.
- Lewis, Michael, Kimberly A. Whitler, and Jo Andrea Hoegg (2013), "Customer relationship stage and the use of picture-dominant versus text-dominant advertising: A field study," *Journal of Retailing*, 89 (3), 263–80.
- Narang, Unnati and Venkatesh Shankar (2019), "Mobile app introduction and online and offline purchases and product returns," *Marketing Science*, 38 (5), 756–72.
- Neslin, Scott, Gail Ayala Taylor, Kimberly D. Grantham, and Kimberly R. McNeil (2013), "Overcoming the 'Recency Trap' in Customer Relationship Management," *Journal of the Academy of Marketing Science*, 41 (3), 320–37.
- Rust, Roland T. and Peter C. Verhoef (2005), "Optimizing the Marketing Interventions Mix in Intermediate-Term CRM," *Marketing Science*, 24 (3), 477–89.
- Vafainia, Saeid, Els Breugelmans, and Tammo Bijmolt (2019), "Calling Customers to Take Action: The Impact of Incentive and Customer Characteristics on Direct Mailing Effectiveness," *Journal of Interactive Marketing*, 45, 62–80.
- Ying, Yuanping, Fred Feinberg, and Michel Wedel (2006), "Leveraging missing ratings to improve online recommendation systems," *Journal of marketing research*, 43 (3), 355–65.