# The Impact of Retargeted Direct Mailings on Consumer Response – A Quantitative Research

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## Abstract (English)

Despite the digital age, direct mailings (DM) are (again) of high importance for managers and marketers to attract consumers and alter their behaviour. Specifically, retargeted direct mailings (RDM) are currently receiving the utmost attention in professional practice. Widely accessible technologies to collect valuable consumer data on behavioural and attitudinal aspects allow for tailoring campaigns to (re)activate customers with the goal of triggering a purchase and maximizing their lifetime value.

This thesis studies the effectiveness of RDM on customer purchase behaviour, i.e., purchase and spending decision, and how this effect is moderated by customer relationship characteristics (purchase frequency and relationship duration) as well as communicated incentive type (discount vs. premium vs. none). For this purpose, panel data on individual purchase behaviour from 7,839 customers across 12 optical retailers in the Netherlands over 8 years is analysed.

The results show that while RDMs, in general, significantly alter purchase likelihood and spending amount, this positive effect is diminished for customers with higher purchase frequencies. Moreover, RDMs have a higher positive effect on customers with higher relationship durations with their retailers. Furthermore, communicating an incentive eliminates the original positive impact of RDMs without incentive while the size of the impact does not significantly differ between discounts and premiums.

These results confirm that customers respond heterogeneously to RDM campaigns and that especially the customer life cycle stage is a decisive factor. It provides guidance for managers and marketers on which metrics to track, whom to target, and how to design their RDM communications.

*Keywords: Retail, purchase incidence, purchase spending, retargeted direct mailing, customer relationship characteristics, incentives*

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## Abstract (Portuguese)

A *retargeted* publicidade endereçada (RPE) está actualmente a receber a maior atenção na prática profissional, uma vez que as tecnologias amplamente acessíveis para recolher dados dos consumidores sobre aspectos comportamentais e atitudinais permitem adaptar as campanhas para (re)activar os clientes com o objectivo de desencadear uma compra e maximizar o seu valor ao longo da vida.

Esta tese estuda a eficácia da *RPE* no comportamento de compra do cliente, ou seja, na decisão de compra e de despesa, e a forma como este efeito é moderado pelas características da relação com o cliente (frequência de compra e duração da relação), bem como pelo tipo de incentivo comunicado (desconto vs. prémio vs. nenhum). Para este efeito, são analisados dados de painel sobre o comportamento de compra individual de 7.839 clientes de 12 retalhistas de produtos ópticos nos Países Baixos ao longo de 8 anos.

Os resultados mostram que, embora os *RPE* em geral alterem significativamente a probabilidade de compra e o montante das despesas, este efeito positivo é reduzido para os clientes com maior frequência de compra. Além disso, os *RPE* têm um efeito maior para os clientes com uma relação mais duradoura com o seu retalhista. Além disso, a comunicação de um incentivo elimina o impacto positivo inicial das *RPE*, enquanto a dimensão do impacto não difere significativamente entre descontos e prémios.

Estes resultados confirmam que os clientes respondem de forma heterogénea ao *RPE* e que, em especial, a fase do ciclo de vida do cliente é um factor decisivo.



*Palavras-chave: Retalho, incidência de compras, despesas de compras, retargeted publicidade endereçada, características da relação com o cliente, incentivos*


Título: O Impacto de Retargeted Publicidade Endereçada na Resposta dos Consumidores - uma Investigação Quantitativa

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# 1. Introduction

Digitalisation and the advances and technologies that come with it have provided us with seemingly endless tools and methods to communicate and interact with each other. Especially in the area of marketing, where access, connection, and relation to the consumers in times of maximum competition are of utmost importance, new paths have been paved. However, what may be surprising to many, traditional direct mailing (DM) is still a frequently used tool in the world of direct marketing. DM can be defined as one-on-one communication that reaches the consumer by post (Kotler et al., 2009). In order to stand out among consumers, who are constantly being approached on various channels by various brands, retailers are moving towards more personalized and targeted direct marketing.

While the earliest use of (personalized) direct marketing letters was reportedly in 1870 (Ross, 1992), the global DM advertising market was expected to reach $61.14 billion in 2021, representing a yearly growth of almost 5% (The Business Research Company, 2021). This positive development can, among other things, be attributed to the increasing effectiveness, which certainly also benefits from the latest technology trends. Recently, researchers proved the effectiveness of DM itself while, at the same time, also showing the positive synergy between DM and (online) display advertising (Lesscher et al. 2021). Moreover, a 2018 DMA (Data & Marketing Association) report shows that the response rate for DM is the highest compared to email and social media (ANA, 2018), reaching an average of 9% in 2020 (Robinson, 2021).

With access to consumer data from various sources, be it from online as well as offline interactions, marketers are now moving away from mass (direct) mailings toward more targeted DM. Instead of sending out vast amounts of letters to the maximum possible audience, the focus now lies on delivering more personalized content at the right time to a selected target group or even an individually targeted customer (McMeekin, 2019). Going further, through retargeted DM (RDM), marketers aim at addressing already known individuals, i.e., previous customers. As a special form of personalized direct marketing (Bleier & Eisenbeiss, 2015), information gathered from past purchases can be utilized to tailor the DM campaign and (re)activate existing customers. This allows marketers to leverage existing customer relationships with the goal of increasing customer lifetime and value.

In fact, there is evidence that consumers would rather open a piece of DM if it is personalized to their needs (Gould, 2017). While there is a selection of research that examines the effect and success factors of personalized and retargeted communication in the digital marketing world, i.e., for online ads like banners (e.g., Sahni et al. 2019, Bleier & Eisenbeiss, 2015; Van Doorn & Hoekstra, 2013; Lambrecht & Tucker, 2013), there is hardly any academic work on the effectiveness of (postal) RDM. Therefore, the present study focuses specifically on RDM as a form of direct marketing.

Considering DM as an overarching construct, there is a large number of studies on this topic. Previous studies investigated the impact of DM campaigns in general on indicators like consumer trust (De Wulf & Odekerken-Schröder, 2003), consumers' perceived relationship investment (De Wulf et al., 2001), purchase likelihood (Naik & Piersma, 2002; Simpson & Mortimore, 2015), and customer share development (Verhoef, 2003). Moreover, there are empirical studies that analyse the moderating role of certain design characteristics, like letter length (Feld et al., 2013) and envelope lettering/design (James & Li, 1993; De Wulf et al., 2000). Other works examine the (optimal) frequency of DM activities (Jonker et al., 2006; Arora & Stoner, 1992; Venkatesan & Kumar, 2004), and a range of researchers investigate the role of personalized DM (Source, 2006; Institute of Information Management, 2001; Broudy & Romano, 1999; Morris-Lee, 2002). Finally, a few authors explore the effect of the content of DM, i.e., the communication of incentives, on consumer response (Bawa & Shoemaker, 1987; Arora & Stoner, 1992; Vafainia et al., 2019).

It is conceivable that synergies among DM and RDM exist and certain results are transferable or generalizable to the specific case of RDM. Nevertheless, the distinctive features of retargeting should not be neglected. One reason retargeting is such an important tool these days is that it leverages existing relationships and thus investments already made in these relationships – from both, retailers and customers. It follows the empirically proven hypothesis that retaining existing customers is usually more profitable for firms than acquiring new ones (e.g., Duncan & Ouwersloot, 2008; Gupta et al., 2004).

Given the nature of this relationship, a degree of trust has been established, and information about the client as an individual as well as about their past purchases should be available. The goal of retailers and marketers is then to exploit this information in the most effective way (Lewis et al., 2013). A challenge arises as consumers' response to direct marketing efforts is found to be highly heterogeneous due to the moderating effects of relationship history and characteristics (Rust & Verhoef, 2005; Gázquez-Abad et al., 2011; Elsner et al., 2004). This means that the effectiveness of RDMs may depend on the individual stage of the life cycle a customer finds him- or herself in (Lewis et al., 2013). Two important forces for this purpose are purchase frequency and relationship duration (Kumar et al., 2006). For instance, there are arguments that loyal customers making purchases on a regular basis are less responsive to marketing efforts (Reinchheld, 1996). At the same time, the communicated content plays an important role as customers in different relationship stages have different interests or needs (Rust & Verhoef 2005; Gázquez-Abad 2011). It is, therefore, necessary to explore which customer life cycle moderators play a significant role in shaping consumer behaviour and how they work.

Few academics have investigated the moderating role of these customer relationship characteristics in the context of direct marketing and therefore call for further research (Rust & Verhoef, 2005; Gázquez-Abad et al., 2011). However, in the area of RDM, there is no work on this perspective at all. In essence, this means that the present study is the first to investigate the effectiveness of RDM, given the role of customer relationship characteristics.

This paper precisely addresses these identified research gaps by studying the following research questions: What is the impact of retargeted direct mail communication on consumer response, i.e., on purchase incidence and spending amount? How is the impact of a retargeted direct mail communication on consumer response moderated by a customer's life cycle characteristics, i.e., purchase frequency and relationship duration? How is the impact of a retargeted direct mail communication on consumer response moderated by the communicated content, i.e., incentives?

By answering those research questions, this study gives empirical insights into the effectiveness of RDM and the associated decisions on timing with respect to the customer life cycle stage and content design. This paper provides a significant academic contribution as it responds to the concrete request of researching the moderating effects of customer (relationship) characteristics on customer response to direct marketing and mailing (Rust & Verhoef, 2005; Gázquez-Abad et al., 2011). In this light, it specifically fills the research gap on the impact of offline RDM, which has hardly been addressed so far and thus complements the existing literature on the respective digital online efforts. It will help to understand whether new customer acquisition and customer retention require different approaches and strategies and further why this is needed.

The presented findings will help retailers and marketers to optimize their direct marketing strategy and effectively design their RDM campaigns to keep customers active and evoke consumer response. It will additionally help to understand why customers might react differently to RDMs given their individual lifecycle stages and characteristics, and given different content strategies. This research can specifically support the most efficient allocation of a marketing budget by serving as a first guidance on deciding who and when to target and which message to communicate to enhance purchase probability and revenue ultimately.

## 2. Structure of the Study

The present study is structured as follows. First, it introduces some basic concepts to understand the topic and context. This involves a review of existing literature on the impact of (retargeted) direct mail, customer life cycle characteristics, and incentives. This forms the basis for developing the hypotheses to answer the proposed research questions. In the main part of the paper, the research design is described, and the empirical results are presented and discussed. From this, the conclusion, as well as academic and managerial implications, are formed. Ultimately, the limitations of the work are presented, and directions for future research are pointed out.

## 3. Literature Review

### 3.1. Direct Marketing

#### 3.1.1. Direct Mail

DM is a form of direct marketing which aims to create one-on-one relationships with consumers through non-public messages (Kotler et al., 2009). By specifically and selectively targeting individuals, it allows for flexible and personalized communication (Kotler et al., 2009). Typically, DM material is sent out unprompted to consumers with the goal of ultimately selling products or services to them (Chang & Marimoto, 2003), thus stimulating a response in the form of a purchase decision through interactive communication (Ekhlassi et al., 2012). Therefore, a DM piece often entails a call to action in the form of a special offer or specific information that is relevant to a consumer at a certain moment (Rust & Verhoef, 2005).

Within the sphere of individual-level communication, Venkatesan & Kumar (2004) consider DM as a rather standardized mode of communication. They find that its impact on consumer response is smaller compared to rich modes of communication, like personal selling. However, as it enables flexible and personalized communication, it distinguishes itself from traditional mass marketing (Kotler et al., 2009).

In order for any DM campaign to be successful, i.e., evoke a behavioural response, the delivered message needs to address or align with the consumer's wants and needs (Gould, 1987). Thus, its success is dependent on the communication elements (e.g., design), the content (e.g., offer, incentive), and the timing (Nash, 1984).

Besides academic research, there are several real-life case studies that showcase the impact and efficiency of DM campaigns. One example is a study conducted by USPS, a US mail processing and delivery service, that finds DM creates more attention and stronger emotional response as consumers find it more memorable and desirable compared to a digital approach (USPS Delivers, 2019). Similarly, the UK Royal Mail concludes that postal mail creates a more genuine relationship between customers and firms, proving effectiveness (Marketreach, 2015). Nordstrom, a US-based specialized fashion retailer, faced decreasing sales after eliminating paper notes within their loyalty program and attributes this observation to the positive influence of physical direct communication (Thomson Reuters Streetview, 2019).

Naik & Piersma (2002) demonstrate that DM campaigns positively influence consumer response by creating a positive attitude towards the sender, which then increases the consumer's likelihood to make a purchase. Referring to *Reciprocal Action Theory*, Godfrey et al. (2011) determine how direct marketing positively impacts customers' decisions to (re)purchase. "Reciprocity means that people reward kind actions and punish unkind ones. [It] takes into account that people evaluate the kindness of an action […] also by the intention underlying this action" (Falk & Fischbacher, 2006, p. 293). Following this theory, consumers value investments made by the firm by approaching them and nurturing the relationship through the DM piece. This strengthens the consumer's trust (De Wulf & Odekerken-Schröder, 2003) and creates a sense of obligation and commitment to respond to this *kind* action with another *kind* action, i.e., a purchase (Godfrey et al., 2011).

As mentioned, DM pieces are typically sent to consumers unsolicited, i.e., without the consumer's concrete desire to receive the material (Chang & Marimoto, 2003). Based on the nature of this, there is a general risk that the recipient misunderstands the communication as a means of persuasion and manipulation (Godfrey et al., 2011). In line with Brehm's (1966) *Reactance Theory*, consumers might feel that their free will or behaviour is threatened, which might cause them to actively ignore the message and, taking it further, intentionally behave conversely (Fitzsimons & Lehmann, 2004; Miron & Brehm, 2006).

As a form of direct marketing, DM directly reaches consumers in their homes and, thus, their private space. Consumers might perceive these efforts as intrusive or disruptive and respond to them with annoyance or anger (Ekhlassi et al., 2012; Venkatesan & Kumar, 2004; Evans et al., 2001). A too-frequent reception of DM pieces might evoke irritation and, in turn, cancel out the initially positive effect (Naik & Piersma, 2002; Jonker et al., 2006; Roberts & Berger, 1999). Thus, the success of a DM (and in general marketing) campaign depends on an ideal level of communication (Godfrey et al., 2011).

### 3.1.2. Retargeted Direct Mail

The concept of retargeting, remarketing, or behavioural retargeting "targets people who are likely to know about the product" or the brand (Sahni et al., 2019, p. 401). Currently, retargeting is mainly associated with online advertising as online tracking technologies enable firms to clearly identify users who previously visited their website without making a purchase and trace their past search and navigation behaviour. Based on this knowledge, marketers can systematically target those consumers addressing their needs or interests through online advertisements or e-mail (Sahni et al., 2019). This focus is also reflected in the academic literature on the topic.

It can be concluded that retargeting is a special form of personalized direct marketing (Bleier & Eisenbeiss, 2015). Already in the 1990s, Milne and Gordon (1994) urged decision-makers to use consumers' attitudinal characteristics in addition to demographic and behavioural factors in order to optimize their DM efforts. Generally, there is empirical evidence that personalized (digital) advertising positively influences consumer response, i.e., Ansari & Mela (2003) explored that personalized email marketing increased click-through rates by 62%. Furthermore, following the *Elaboration Likelihood Model* which serves as a general framework to understand "the basic processes underlying the effectiveness of persuasive communications" (Petty & Cacioppo, 1986, p. 125), Micheaux (2011) determines that a higher level of personal relevance and personalization of the content of direct email advertising leads to higher response rates of consumers. The model is built on the theory that there are two distinct paths to persuasion depending on the recipient's motivation and ability to process the presented content (Petty & Cacioppo, 1986). If consumers are characterized by high levels of motivation and ability, for instance, because they are already interested in the topic or product and they have enough time to make a decision, they thoroughly evaluate the decision at hand. This process is called the *central route* to persuasion (Petty & Cacioppo, 1986). If, however, consumers face lower levels of motivation and ability, for instance, because it is less important to them or they do not have sufficient time, they can be persuaded to make the decision by the *peripheral route*, i.e., with less detailed and more superficial content (Petty & Cacioppo, 1986). It follows that attitudes or decisions formed through the *central route* are likely to be stronger, more internalized, and consistent. Therefore, in the case of direct email advertising, personalization has a positive impact as “personally relevant advertising motivates participants to elaborate on message content, leading to stronger and more durable positive attitude changes” (Micheaux, 2011, p. 47).

In line with those conclusions, De Wulf et al. (2001) explore that DM campaigns positively influence consumers’ perceptions of the firm’s investment in the relationship when the communicated content is aligned with their needs, i.e., when a certain level of personalization is given. Consumer attitudes and responses to (highly) personalized messages depend on the perceived utility that they experience as they subconsciously follow a “utility maximization principle” (White et al., 2008, p. 48). They make a trade-off between sharing their personal information to being specifically targeted by personalized advertising and experiencing the benefits of receiving relevant and useful content (White et al., 2008).

Although retargeting, in particular, is a common marketing method these days (Helft & Vega, 2010; Peterson, 2013; Sengupta, 2013), there is only a moderate number of academic research and empirical work on the topic and its effects (Bleier & Eisenbeiss, 2015). Studying the impact of retargeting in an online setting of a retailer for home improvement products, Sahni et al. (2019) conclude that “retargeting increases the likelihood of the users returning to the website and engaging more by visiting the website more frequently” (p. 417). Considering the effect of timing, there is evidence that the positive impact of retargeting decreases the more time elapses since the first website visit (Sahni et al., 2019). Furthermore, they do not observe a negative moderating effect of the frequency of retargeted advertisement on consumer response (Sahni et al., 2019), as was partly the case with direct mail (see Chapter 3.1.1 Direct Mail). On the contrary, they find that the positive effect of the retargeted campaign even increases when consumers are targeted in the first two weeks after their first website visit (Sahni et al., 2019). Lambrecht & Tucker (2013) study the circumstances under which online retargeting efforts perform better compared to generic online advertising of a travel website, i.e., lead to a purchase. They observe that retargeting outperforms mass advertising when consumers have a clear(er) picture of what they are looking for, i.e., they already have a selected set of alternatives in mind, as in this stage, they are more open and responsive to concrete information and details

(Lambrecht & Tucker, 2013). In a more general setting where consumers are just exploring, however, generic or mass online advertising is found to be more effective. It should be noted that Lambrecht & Tucker (2013) define generic advertising as a form of retargeting in the sense that it targets consumers who previously visited the website with generic content, e.g., the brand's logo. One theory that may explain the underlying psychological phenomenon leading to the effectiveness of retargeting is the *Mere Exposure Effect* (Fishman, 2020). This effect describes how "mere repeated exposure of the individual to a stimulus object enhances his attitude toward it" (Zajonc, 1968, p. 1). In other words, this means that the more people are confronted with something, e.g., a product or a brand, the more they like it and (unintentionally) develop a positive attitude toward it. In the case of retargeting, consumers are exposed to products and brands that they already know due to shown interest, e.g., by visiting the website, or they are already customers of. This brings the marketed product, as well as the brand, back into the consciousness of the individual, increases familiarity and salience, and ultimately drives the consumer toward a purchase decision.

As retargeting is an instrument built upon detailed knowledge about consumers and their interests and preferences, it brings the risk of the consumer feeling closely observed and manipulated (King & Jessen, 2010; Tucker, 2012; White et al., 2008). Bleier & Eisenbeiss (2015) conclude that the effect of online retargeting on consumer response is determined by the level of trust a consumer perceives towards a retailer. When trust in the retailer is higher, retargeted online ads increase click-through-rates (Bleier & Eisenbeiss, 2015). On the contrary, with lower levels of trust towards the retailer, retargeted online ads prompt negative responses in the form of decreasing click-through rates as it fosters consumer reactance (Bleier & Eisenbeiss, 2015).

Although the online channel allows for an almost holistic collection and combination of data points and consequently enables real-time targeting and response, retargeting is not limited to the digital world. Firms operating (in) offline channels, like physical retailers, may also use the methodology. Specifically, the case of RDM as a sub-category of DM offers a more personalized approach to contacting consumers by DM using information collected on their individual past purchase behaviour and interactions with the firm. It is considered a unique form of advertising as, instead of trying to attract a new audience, it aims at re-engaging and re-activating current or inactive customers (Hecht, 2021).

However, there is no academic literature on the concept of RDM and its impact on consumer response. As explained in Chapter 1 Introduction, this paper aims at addressing exactly this research gap. It is expected that due to the nature of a physical mailing piece, the RDM receives the recipient's undivided attention, in contrast to an online retargeting campaign which often only takes up a fraction of a website (Bleier & Eisenbeiss, 2015; Lambrecht & Tucker, 2013). Given that the recipients of the campaign are not strangers but rather current or former customers of the marketed firm, it is assumed that following the *Mere Exposure Effect* theory, the consumer's sentiment towards the brand and the advertised product enhances and a positive attitude is being formed. As RDM is a form of personalized DM, it is designed to address consumers' needs and provide them with relevant information and content. In light of the *Elaboration Likelihood Model*, this is expected to nurture consumers' attempts to maximize their experienced utility and strengthen their positive attitude. Ultimately, it showcases the firm's investment and effort in the mutual relationship and creates a sense of responsibility on the consumer side to return the latter in the form of a *reciprocal* action, i.e., a purchase. Although there are some risks of provoking a negative consumer response, the favourable effects are expected to outweigh potential negative reactions, for instance due to feelings of manipulation or intrusiveness. Thus, the following hypotheses are formed based on the elaborated literature and findings on the impact of DM, personalized direct marketing, and online retargeting:

H1a: Retargeted direct mail communication has a significant and positive impact on purchase incidence.

H1b: Retargeted direct mail communication has a significant and positive impact on spending amount.

## 3.2. Customer Relationship Management

### 3.2.1. Definition & Importance

Reinartz et al. (2004) define customer relationship management (CRM) as a "systematic process to manage customer relationship initiation, maintenance, and termination across all customer contact points in order to maximize the value of the relationship portfolio." To do so, they stress the importance of analysing customers by collecting information on their behaviour and needs. This enables marketers to target and nurture each customer relationship with respect to its value and maturity (Reinartz et al., 2004). Swift (2001) further points out that the CRM approach, besides understanding customer behaviour, is also about influencing the latter through meaningful communications. Additionally, Kotler et al. (2009) expand the definition by including the customer's perspective and define the generation of "customer satisfaction through superior value" creation as the means to practice CRM successfully. This highlights the two-way nature of the customer-firm relationship and the resulting goal of building loyalty that benefits both parties (Berger & Nasr, 1998; Buttle, 1999; Walton & Xu, 2005). However, it must be noted that there is no universal explanation or definition of the concept of CRM (Wilson et al., 2002).

There is the general assumption that such loyalty, i.e., a long-lasting customer relationship, is desirable and valuable for a company (Dawkins & Reichheld, 1990). Reasonings for this belief are, for example, that loyal customers tend to purchase at higher frequencies and serve as ambassadors through word of mouth (Ahmad & Buttle, 2001). Thus, Rust & Zahorik (1993) argue that retention rate positively influences market share, which is ultimately positively linked to profits. Further, Buttle (1999) reasons that the main driver for practicing CRM is its capability to create higher shareholder value in the long term. Moreover, with the advances of and access to the internet and technology, as we know it today, the world has evolved into a global, unified marketplace which makes the buyer-seller-relationship a decisive purchase factor (Strategic Direction, 2002).

### 3.2.2. Customer Life Cycle

Customer-firm relationships pass through different phases or stages. These stages that the customer goes through when considering, purchasing, and finally using a product or service are referred to as the customer life cycle (CLC). However, there is no consensus in academia on the division, i.e., the number of separate phases or their labels. Reinartz et al. (2004) divide the CLC into three phases: *relationship initiation, maintenance,* and *termination*. While Rousseau et al. (1998) also commit to three phases, they refer to these as *building, stability,* and *dissolution.* Both approaches are built on the activities undertaken during the CLC. Dwyer et al. (1987), in turn, divide the CLC into five stages, namely, *awareness, exploration, expansion, commitment,* and *dissolution.* Kotler (1997) follows a different approach and defines the CLC stages based on the role of the customer in the relationship: *suspect, prospect, first-time customer, repeat customer, client, advocate, member,* and *partner*.

The notion on which all these approaches are grounded is that the characteristics of the customer-firm relationship, e.g., strength and trust, vary over time and evolve with the CLC stages. Consequently, consumer needs and, thus also, communication goals are strongly linked to and dependent on the latter (Kotler et al., 2009). For this reason, CRM processes and marketing methods should be aligned with the CLC stages (Santouridis & Tsachtani, 2015; Lewis, 2006). More precisely, Neslin & Shankar (2009) stress the importance of matching the applied channel to the CLC stage for CRM in general and highlight the research gap thereof. This means that different communication channels achieve different results depending on the individual's CLC stage. Along with this, the communicated content also appeals differently to consumers in distinct CLC stages.

However, several authors criticize that marketing research and also practice still mainly focus on new customer acquisition instead of customer retention (e.g., Kotler et al., 2009; Ahmad & Buttle, 2001) although the latter is found to usually be more profitable for firms (Duncan & Ouwersloot, 2008; Dawkins & Reichheld, 1990; Reichheld & Sasser, 1990). In fact, there is evidence that a 1% retention rate increase can lead to a 5% increase in firm value (Gupta et al., 2004).

### 3.2.3. Customer Lifetime Value

A customer's value for a firm can be measured through the Customer Lifetime Value (CLV). CLV can be defined as the total revenues generated by an individual customer over time, i.e., over the whole duration of the relationship or CLC (Kotler et al., 2009):

$$CLV = average\ purchase\ value * purchase\ frequency * lifespan$$

$$CLV = (average\ number\ of\ products\ purchased * average\ product\ price) \\ * purchase\ frequency * lifespan$$

(Lilien et al., 2013)

Looking at the CLV formula presented above, one can identify two levers to enhance the individual CLV that can be influenced through RDMs and thus focus on customer retention. The first goal of an RDM is to trigger a purchase, i.e., to activate purchase incidence, increasing purchase frequency. Then, following the purchase decision itself, the revenue is made up of the number of products purchased and the respective prices. While prices are clearly not decided on the customer side, the second goal of an RDM is to influence the amount spent by the customer by either leading the individual to purchase a higher number of products or a higher-priced product, or even both. Therefore, these two variables were chosen as the outcome variables of this study.

As soon as the CLV exceeds the costs of attracting, selling, and servicing the individual entailed by the firm, the customer can be considered profitable (Kotler et al., 2009). Consequently, only some customers will become profitable and thus valuable for the firm (Kotler et al., 2009). Therefore, firms and their marketers are interested in targeting those individuals with the highest profitability potential and simultaneously optimizing their marketing efforts to leverage the CLV (Reinartz & Kumar, 2003). At the same time, the variables representing the CLV formula may ultimately influence how those marketing efforts affect the CLV.

Consumers' response to direct marketing efforts is highly heterogeneous due to the moderating effects of relationship history and characteristics (Rust & Verhoef, 2005; Gázquez-Abad et al., 2011; Elsner et al., 2004). Kumar et al. (2006) study the impact of customer relationship characteristics on the CLV and find that both relationship duration and purchase frequency are positively related to CLV. For this reason, this paper examines the moderating effect of precisely those two variables. Purchase frequency can be defined as the number of times a customer purchases within a given timeframe. Relationship duration represents the time since the first purchase with the firm, i.e., the time since the start of the customer-firm relationship.

There are arguments that loyal customers tend to purchase on a regular basis which might make them less responsive to marketing and advertising as they have already established a preference and do not wait for promotions or incentives before making a purchase (Reinchheld, 1996).

On the other hand, Bauer (1988) confirms the general observation in direct marketing that "multi buyers are more likely to purchase again than single buyers" (p.18), which implies that customers characterized by a higher purchase frequency are more responsive to DM and thus more likely to make another purchase. The psychological reasoning behind consumers proactively reducing their set of brand and product choices and thus increasing purchase frequency is that "they want to simplify their buying and consuming tasks, simplify information processing, reduce perceived risks, and maintain cognitive consistency and a state of psychological comfort" (Sheth & Parvatlyar, 1995, p. 255). Extending this observation to the specific case of RDM, it is conceivable that the effect may even be amplified, since RDMs are built precisely on the customer-firm relationship, which is supposedly even stronger for frequent customers. While classical DM approaches consumers with quite generic content, RDM offers the possibility to target consumers by instrumentalizing their past purchase behaviour. This happens, for instance, by highlighting exactly those products that a customer bought frequently, to ultimately capitalize on the relationship or customer stage he or she finds him- or herself in.

Although there are opposing arguments for both sides, it is expected that:

H2a: The impact of retargeted direct mail communication on purchase incidence is higher for customers with higher purchase frequency.

H2b: The impact of retargeted direct mail communication on spending amount is higher for customers with higher purchase frequency.

Considering relationship duration, Rust & Verhoef (2005) conclude that a higher or longer duration has a negative impact on consumer response to DM. In line with Reinchheld (1996), an underlying argument can be that the longer a firm is in the consumer's set of preferences and the longer the consumer is thus familiar with it, the clearer the consumer's preferences are established and the less he or she can be steered by external influences.

However, Verhoef et al. (2002) argue that a longer relationship duration increases consumers' confidence about and belief in the firm due to increasing intimacy and feelings of attachment. On the contrary, customers whose relationship and experience with the firm is very new and recent are likely to not have established a strong commitment and attachment towards the firm (yet). Therefore, the positive attitude resulting from a higher relationship duration is expected to be projected onto the RDM and makes the respective consumer more responsive to the latter.

Moreover, Reinartz & Kumar (2003) prove that there is a positive relation between relationship duration and spending amount. Customers with a higher commitment represented in a higher relationship duration tend to seek relationship expansion and enhancement, which is reflected in a higher purchase amount (Bendaupi & Berri, 1997).

Therefore, it is hypothesized that:

H3a: The impact of retargeted direct mail communication on purchase incidence is higher for customers with a higher relationship duration.

H3b: The impact of retargeted direct mail communication on purchase spending is higher for customers with a higher relationship duration.

## 3.3. Incentives

### 3.3.1. Incentives Overall

With the goal of encouraging direct consumer response, marketing activities often make use of promotional tools (Peattie & Charter, 1994; Kotler, 2009). Therefore, it is common that DM campaigns entail a sort of incentive (Verhoef, 2003) to influence consumers and alter their purchase behaviour (Rust & Verhoef, 2005). This type of DM is called a *call-to-action* (CTA) DM. The integrated incentive can be interpreted as a reward for the customers who follow the CTA and, for instance, make a purchase. Thus, the present paper focuses on CTA DM with a transaction orientation.

Generally, the *Usage Dominance Theory* proposes that "prior purchases of a brand diminish response to promotions that follow because personal usage dominates external information during purchase decisions" (Bridges et al., 2006, p. 296). This suggests that consumers who already experienced a brand or a product through a purchase and/or use are less responsive to promotional activities and more led by non-monetary factors (Heilman et al., 2000; Kopalle & Lehmann, 1995). Given the nature of RDMs, the recipients of the marketing campaigns are current or former customers which implies that they are already familiar with the brand and at least one of its products or services. Subsequently, this would mean that RDMs containing an incentive should be expected to either not be effective or to be only moderately effective.

On the contrary, an existing relationship between customer and firm can generate and foster a positive attitude toward the firm, given that the consumer perceives the previous experience(s) as positive (Oskamp & Schultz, 2005). This positive attitude then stimulates a positive response to the promotional activity. A supporting theory for this argument is the *Elaboration Likelihood Model*. As consumers are already acquainted with the marketed firm, they are (subconsciously) more open to processing the promotional information following the *central (or cognitive) route* to persuasion (Petty & Cacioppo, 1986) and thus form a stronger response to the latter (Brides et al., 2006).

Overall, there is little academic literature on the impact of CTA DM on consumer response (Vafainia et al., 2019). Gázquez-Abad et al. (2011) study how customers respond to promotional DM and find mixed results in this case. While the short-term effects on purchase incidence and expenditure are found to be positive, the long-term effects can vary and even cause an opposite effect (Gázquez-Abad et al., 2011), as customers might create a negative attitude when being sent a high number of CTA DM pieces over time (Van Diepen et al., 2009). Here, again, *Reactance Theory* comes into play, arguing that consumers might perceive a CTA DM as a means to manipulate or control them specifically because of the integrated incentive (Simonson et al., 1994).

Arora & Stoner (1992) show that the response rate to DM campaigns is higher when an incentive is communicated. Vafainia et al. (2019) find that CTA DM positively impacts consumer response in terms of purchase incidence. One potential explanation for these observations stems from the *Reciprocal Action Theory*, which is explained in more detail in Chapter 3.1.1. Direct Mail. Consumers might interpret the offered incentive as an "extra effort and resource investment" (Vafainia et al., 2019, p. 64) and develop a stronger desire to respond to the *kind* action by following the CTA.

Due to the recency of the academic findings (Vafainia et al., 2019), the results of this work are expected to be similar, and the following hypotheses are created:

H4a: The impact of retargeted direct mail communication on purchase incidence is higher when an incentive is communicated compared to no incentive.

H4b: The impact of retargeted direct mail communication on purchase spending is higher when an incentive is communicated compared to no incentive

There are different types of incentives that follow different psychological mechanisms and processes to influence consumer response (Palazon & Delgado-Ballester, 2013). One significant factor is the way that incentives are framed which can cause consumers to value deals differently that are of objectively equal worth (Sinha & Smith, 2000). Two common types are discussed in the following.

### 3.3.2. Discount

A discount can be classified as a monetary incentive and comes in the form of a price reduction or percentage off the regular retail price (Vafainia et al., 2019). As discounts are presented in the same metric as the price of the product or service, i.e., monetary, consumers tend to perceive it as a reduced loss (Diamond & Campbell, 1989).

A study by Bawa & Shoemaker (1987) shows that DM coupons have a positive impact on purchase rates in the short term. Distinguishing between consumer types, they observe that the effect is stronger for consumers who have already purchased the promoted brand before, while loyal customers of competitive brands are not as responsive (Bawa & Shoemaker, 1987). In this paper, DM coupons are interpreted as discounts as redemption of such a coupon enables a price reduction of the specifically promoted product. A similar conclusion is derived by Kahn & Louie (1990). Applying these results to the case of RDM, it can be inferred that communicating discounts via the RDM piece should positively impact consumer response as it targets individuals who have already purchased from the firm before.

### 3.3.3. Premium

Alternatively, an incentive can come in the form of a premium. "A premium is a product or a service offered free or at a relatively low price in return for the purchase of one or many products or services. It may or may not belong to the same product category as the product or service that is purchased" (D'Astous & Jacob, 2002, p. 1270). Examples are free gifts or giveaways when purchasing a particular product. This incentive type is considered a non-monetary incentive (Vafainia et al., 2019) and is usually presented in a different metric than the product or service it is coupled with. This influences consumers to perceive it as a gain (Diamond & Campbell, 1989).

The overall effect of a premium is found to be dependent on consumer perceptions. When consumers consider the offered premium unattractive, and they have yet to form their own preferences, the premium does not increase purchase likelihood and creates confusion and suspicious feelings (Simonson et al., 1994). Yet, if the premium is perceived as useful and valuable, it provokes a positive consumer response (Simonson et al., 1994). In line with these findings, D'Astous & Jacob (2002) conclude that "the greater the [consumer's] interest [in the premium offered], the more a consumer appreciate[s] the offer and the less she/he perceive[s] manipulation intent [on the side of the firm]" (p. 1282). Since the present case concerns RDM, it addresses consumers who have already been in contact with the firm and have expressed a particular need and preference for its respective product(s). The communicated premiums, in turn, are directly linked to the firm's products and services. It is therefore expected that recipients of the RDMs classify the communicated premium as valuable and, consequently, the likelihood of a positive response increases.

There is evidence that the positive impact on purchase incidence as well as spending amount is smaller for premiums than for equivalent price cuts (= discount) (Foubert et al., 2018). A potential reason for this finding is that a premium might be seen as less tangible and valuable because the monetary value is not directly evident. From the consumer's perspective this could cause a feeling of manipulation and lead to a state of reactance (Miron & Brehm, 2006). On the contrary, comparing both incentive types, Vafainia et al. (2019) conclude that communicating non-monetary incentives, i.e., premiums, in a DM campaign has a stronger positive impact on purchase incidence than offering monetary incentives, i.e., discounts. This finding could be related to the finding of Diamond & Sanyal (1990), who demonstrate that consumers prefer incentives they encode as gains compared to incentives they encode as reduced losses.

Thus, it is expected that these observations also hold true in the specific case of RDM, and the following hypotheses are formed:

H5a: The impact of retargeted direct mail communication on purchase incidence is higher when a premium is communicated compared to a discount.

H5b: The impact of retargeted direct mail communication on purchase spending is higher when a premium is communicated compared to a discount.

## 3.4. Conceptual Framework

The following figure visualizes the described relations between the variables and associates the established hypotheses. It serves as a guide to understand the research approach of this paper. The variables indicated are discussed in the following chapter.

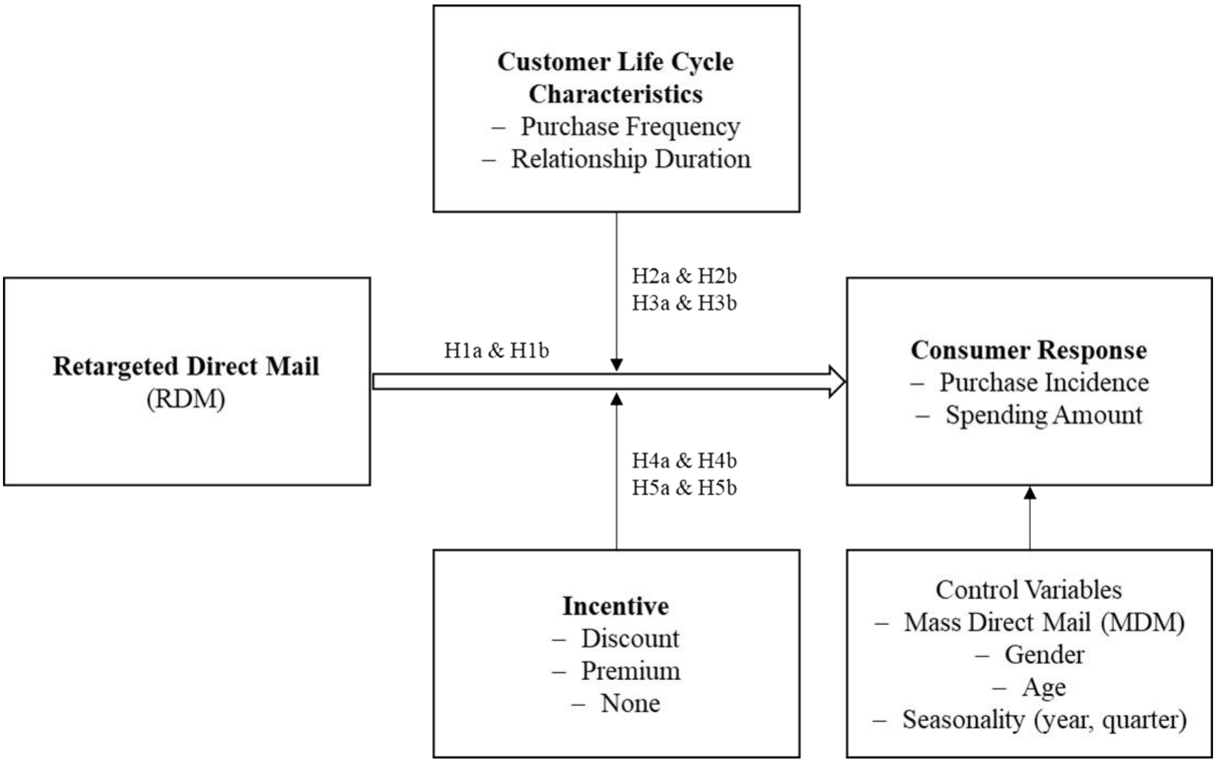



*Figure 1: Conceptual Framework*

# 4. Research Design

## 4.1. Data Description

This study is conducted within the context of optical retailers in the Netherlands. A customer-level data set from 12 optical retailer stores over 8 years (2011 to 2018) is being studied to investigate the proposed research question and address the formulated hypotheses. These optical retailers are independent and do not belong to large chains. A part of those retailers participates in an RDM program. To this end, they implement RDM communications in their marketing strategy during the observation period. Retailers of both groups, i.e., participating and not participating in the RDM program, are very similar in size, customer base, and location. A marketing consultancy firm coordinates the customer databases for these retailers and provided the data for this project.

The original dataset contains information on customer characteristics, purchase behaviour, and RDM communication history of in total 7,839 unique customers on a quarterly basis. Every observation represents a customer *i* in a quarter *t*. Customers in the dataset are uniquely linked to one retailer. Thus, every purchase is made and every communication is received from the same retailer. A special characteristic of this industry is that customers do not purchase on a highly regular basis as they do with fast-moving consumer goods. Moreover, customers are highly involved in those purchase decisions (Grewal et al., 2004). The commonly sold products of such optical retailers are glasses and lenses, which customers replace or repurchase less often. In line with this, the studied retailers usually send their DM on a quarterly basis, as well.

The observation period starts in the first quarter of 2011 and ends in the fourth quarter of 2018 and covers actual customers, i.e., individuals who have purchased with the respective optical retailer before. This means that customers first represented in the dataset have either already been customers before 2011 or have made their first purchase within the given period. In other words, all observed purchase incidences within the dataset represent at least the second purchase of that customer *i* from the respective retailer. At the same time, this means that the customers are not equally often represented in the dataset, i.e. the number of observations per customer varies (ranging from 1 to 29 observations per customer).

### 4.1.1. Dependent Variables

The main contribution of this work is to study the (moderated) impact of RDM on consumer response. The latter is translated into two outcome variables: *purchase_incidence* and *spending* *amount*. Both variables are being tracked on a quarterly basis during the estimation period. *Purchase_incidence* is documented as a dummy variable, i.e., it takes on the value of 1 if a given customer *i* made a purchase in a given quarter *t* or 0 otherwise. *Spending_amount*, on the contrary, is a discrete variable and represents the monetary (€) amount spent by a given customer *i* for the respective purchase incidence in a given quarter *t*. The variable refers to an entire purchase and does not take into account the quantity or prices of the products, i.e., it can be a single item or a larger purchase.

### 4.1.2. Independent Variables

<u>Retargeted Direct Mail (RDM)</u>

The main explanatory variable of this research is RDM. The optical retailers first start sending out RDMs after a customer is registered in their database, i.e., after a customer made his or her first purchase with them. Those RDMs are then sent to customers depending on their purchase recency during purchase recency of maximum four years. Thus, it can be interpreted as a CLC related DM. The goal is to (re)attract existing customers and influence their purchase behaviour by either triggering the purchase decision itself and/or by inducing them to spend a higher amount of money with their next purchase. Whether or not a customer *i* received a RDM in a given quarter *t* is indicated by the dummy variable *RDM*. It takes on the value 1 if an RDM is sent out and 0 otherwise. In analogy, RDM = 1 means a customer *i* received a RDM in quarter *t*. Every customer can, at most, receive one RDM per quarter.

<u>Customer Life Cycle (CLC) Characteristics</u>

*Relationship_duration* measures the number of quarters since a customer *i* has been registered in the respective retailer's database. Thus, it is also equal to the number of quarters since the first purchase.

To derive the *purchase_frequency* variable the *purchase_incidence* of the past four quarters (= last year) is taken into account. For each customer *i* in quarter *t*, the *purchase_incidence* of *t-4*, *t-3, t-2,* and *t-1* are being discounted by weighing it with a decay parameter of 0.75 and ultimately summed up (Van Diepen et al., 2009). With this, a more recent purchase is attributed more importance than a purchase made one year ago.

Incentive

For every RDM sent out, it is specified if and which type of incentive was communicated. Generally, the variable *RDM*_incentive indicates if the RDM included an incentive (= 1) or not (= 0). Further, the two possible incentive types are discount or premium, represented by the variables *RDM_discount* and *RDM_premium*. *RDM_discount = 1* indicates that the RDM sent out to customer *i* in quarter *t* provides the customer with a monetary reward in the form of a price discount. *RDM_premium = 1*, instead, indicates that the RDM sent out to customer *i* in quarter *t* provides the customer with a non-monetary reward, like a free collection item, an artwork, or a free sun cream. Following the logic of dummy variables, incentive type "none" is represented if both dummy variables take on a value of 0. In this case, the RDM sent out to customer *i* in quarter *t* invites him or her to visit the store and/or make a purchase but does not promise any reward linked to it. It can be considered a CTA DM without incentive.

### 4.1.3. Control Variables

Control variables are included to control for effects that are outside the scope of the retailers' power or not part of the subject of this study.

One of these is seasonality, to account for differences between quarters and years. Appropriate dummy variables are incorporated for this purpose.

As not all of the studied optical retailers in the dataset took part in the RDM program, the variable *treated* controls for effects on the retailer level and potential target selection techniques or criteria. It is a dummy variable that takes on the value 1 (for all observation periods) if customer *i* belongs to a participating retailer and has thus received at least one RDM during the observation period, and 0 otherwise.

Besides the studied RDM activities, the optical retailers in the dataset also regularly sent out mass DM (MDM), which are independent of the CLC stage and communicate the same content to every recipient. The content is mostly very generic and has a different purpose than the RDM, as for instance, providing basic information about the retailer (e.g., changes in opening hours). As such MDMs are not in the focus of this study their effect needs to be controlled for. For this purpose, the variable *MDM* is utilized. Similarly, to the RDM variable, it is a dummy variable that takes on the value 1 if customer *i* received a MDM in a given quarter *t* and 0 otherwise.

Ultimately, the variables *age* and *gender* are integrated to control for the effects of those basic customer demographics. *Age* measures the customer *i's* age in years at the given quarter *t*. The dummy variable *gender* takes on the value 1 if the respective customer *i* identifies as male and 0 for female customers.

## 4.2. Data Cleaning and Preparation

As shortly mentioned before, the original dataset contains information on 7,839 unique customers. The sample covers in total 179,110 observations measured on a quarterly basis from 2011 to 2018.

Customers aged below 18 years at a given observation period were filtered out to exclude children. Moreover, observations with ages over 90 years were removed, as well. It is assumed that these are results of IT systems that have not been updated or also cases in which the family continues to use the client status of a relative (in the original dataset, age ranged up to 119 years). Additionally, customers with the gender code “O” were excluded as it represents either missing information or individuals who did not wish to provide this piece of information. The goal is to have valid and interpretable information to be able to operationalize the independent variables.

Next, potential outliers were investigated. For this purpose, boxplots were created for all numerical variables (see figures 2 to 4). Additionally, z-scores were calculated, and a cut-off threshold of 4 was chosen to detect outliers but not be too conservative as outliers can contain valuable information. In addition, manual checks were carried out to make individual decisions in some cases. As a result, 1,671 observations were removed based on the outlier detection of the variables *purchase_spending*, *relationship_duration,* and *purchase_frequency.*

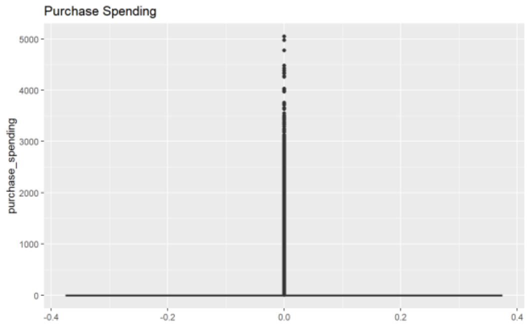



*Figure 2: Boxplot Purchase_Spending*

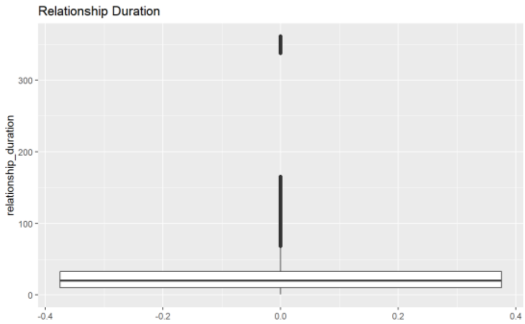



*Figure 3: Boxplot Relationship_Duration*

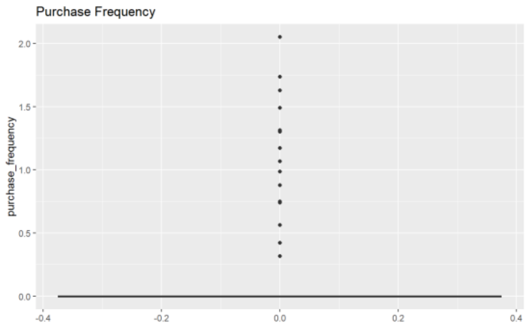



*Figure 4: Boxplot Purchase_Frequency*

## 4.3. Descriptive Statistics

Performing the data cleaning process, leaves a total of 166,275 observations that cover 7,494 unique customers. Out of the twelve retailers featured in the sample, the “smallest” retailer serves 1 customer and the “biggest” retailer serves 1,145 customers. 1,203 customer IDs are not assigned to a retailer which is likely to be due to a system’s error.

When visualizing the (aggregated) time series of the dependent variables *purchase_incidence* and *purchase_spending* an increasing trend between 2011 and 2018 is observable (see figures 5 and 6). A possible (partial) explanation can be found in the number of *shopids* (= shop ID that uniquely identifies a retailer) featured in the dataset (see figure 7). From Q2 2016 to Q3 2016, the number of documented retailers has increased from 10 to 11. However, the number of *customerids* (= customer ID that uniquely identifies a customer) documented in the system has steadily increased over the whole observation period (see figure 7). No extraordinary changes (for example in line with the *shopids*) can be observed here.

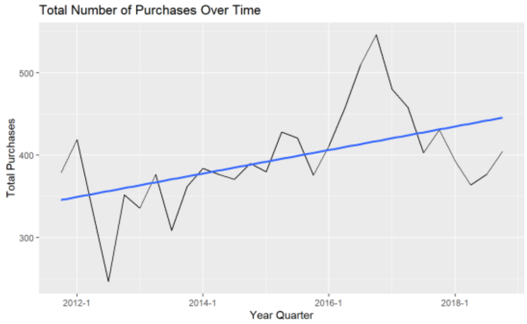



*Figure 5: Total Purchases Over Time*

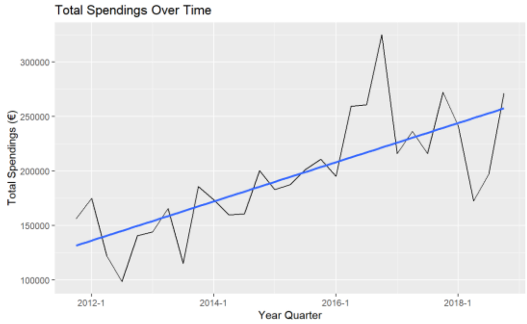



*Figure 6: Total Spendings Over Time*

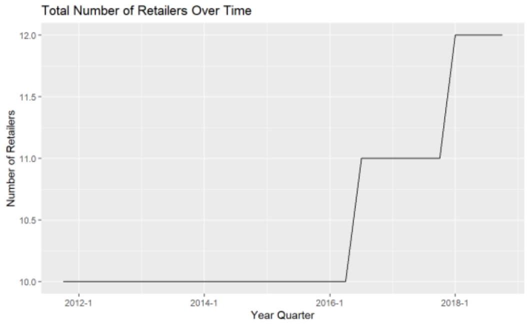



*Figure 7: Total Number of Retailers Over Time*

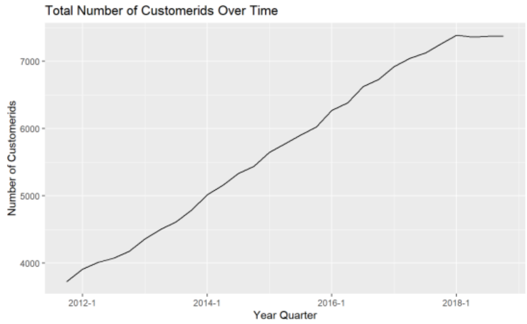



*Figure 8: Total Number of Customer IDs Over Time*

With respect to purchase incidence, the maximum number of purchases made by a single customer is 15 and the minimum number 0. The average customer makes a total of 1.5 purchases during the observation period.

Aggregating the spendings per customer over the whole observation period, the maximum amount spent is 10,860 (€) and the minimum amount 0 (€). On average, a customer spends in total 753 (€) at the respective retailer over the whole observation period.

Considering the main variable of interest, *RDM,* 50% of the retailers which corresponds to six shops participated in the RDM program. In total 12,086 RDMs were sent out over the whole period. About 33% of those RDMs included a discount, 9% included a premium, and the remaining 58% came without an incentive. With the dataset containing observations from 2011 to 2018, the first RDMs were sent out in Q4 of 2012 (see figure 9).

Looking at the whole observation period, the maximum number of RDMs received by a single customer is 13. On average, a customer in the final sample receives 1.6 RDMs during the observation period.

To get a first insight into the main research question, the time series of the purchases and respective spendings of the six retailers participating in the RDM program are illustrated in figures 10 and 11. When graphically comparing the development of the total number of RDMs sent out (see figure 9) and the respective development of purchases and spendings (see figures 10 and 11) it is notable that retailers started sending out RDMs in the second half of 2012 after purchases and spendings reached a substantial low in the first half of 2012. It may well be that the RDM initiative contributed to the subsequent rise in performance. A similar argument could be applied to the development around the 2016 period. While purchases decreased again strongly towards the end of 2015, RDMs have been increasingly sent out in Q1 2016. After that, a clear peak in purchases and spendings can then be observed in the second half of 2016. These initial visual observations confirm the hypothesis that RDMs have a positive influence on *purchase_incidence* and *purchase_spending*.

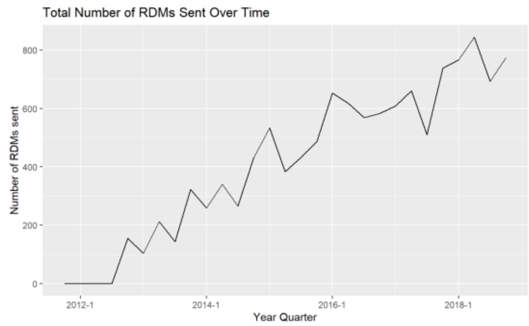



*Figure 9: Total Number of RDMs sent Over Time*

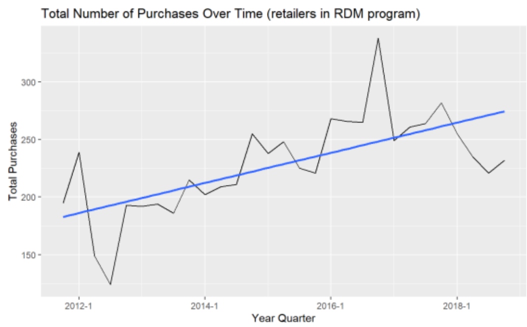



*Figure 10: Total Purchases Over Time of Retailers Participating in RDM program*

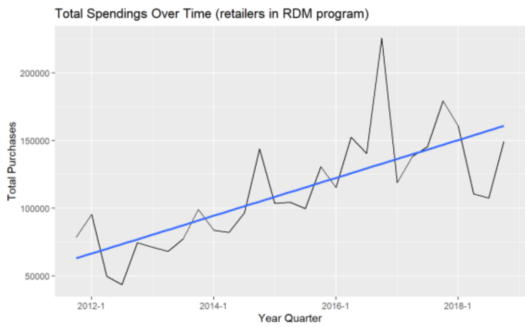



*Figure 11: Total Spendings Over Time of Retailers Participating in RDM program*

Finally, table 1 provides an overview of the variables used in this study and its descriptive statistics based on the final dataset.

*Table 1: Description and Descriptive Statistics of Variables*

| | Variable | Description | Mean | SD | Min. | Max. |
|---|---|---|---|---|---|---|
| Dependent variables | purchase_incidence | Dummy variable indicating whether customer makes a purchase in quarter t | 0.069 | 0.253 | 0 | 1 |
| | purchase_spending | Value (in €) of purchase made in quarter t | 33.931 | 189 | 0 | 5,05 |
| Independent variables | RDM | Dummy variable indicating whether customer receives RDM in quarter t | 0.073 | 0.260 | 0 | 1 |
| | relationship_duration | Number of quarters since the first purchase/registration of customer i in the retailer's database | 24.803 | 20.063 | 0 | 110 |
| | purchase_frequency | Weighted frequency of purchases in the last 4 quarters | 0.131 | 0.281 | 0 | 1.312 |
| | RDM_incentive | Dummy variable indicating whether customer receives RDM with an incentive in quarter t (either discount or premium) | 0.030 | 0.172 | 0 | 1 |
| | RDM_discount | Dummy variable indicating whether customer receives RDM with a discount in quarter t | 0.024 | 0.154 | 0 | 1 |
| | RDM_premium | Dummy variable indicating whether customer receives RDM with a premium in quarter t | 0.006 | 0.078 | 0 | 1 |
| Control variables | MDM | Dummy variable indicating whether customer receives MDM in quarter t | 0.099 | 0.299 | 0 | 1 |
| | gender | Indicator for customer *i*'s gender (1 = male, 0 = female) | 0.468 | 0.499 | 0 | 1 |
| | age | Age of customer *i* in years in quarter t | 54.006 | 17.023 | 18 | 90 |
| | treated | Dummy variable indicating whether customer belongs to the group of retailers joining the RDM program (= receives at least 1 RDM) | 0.499 | 0.500 | 0 | 1 |
| | year | Dummy for year | | | 2011 | 2018 |
| | quarter | Dummy for quarter | | | 1 | 4 |

## 4.4. Model Design / Formulation

The goal of this study is to understand the impact of RDM on purchase behaviour, i.e., *purchase_incidence* and *purchase_spending*. Given that the underlying data comes in the form of panel data, a plm (= panel linear model) model was chosen for analysis. Thus an individual *i's* purchase decision (*purchase_incidence*) and behaviour (*purchase_spending*) in period t, t = 1, …, T are being modelled using a plm regression with individual-specific random effects. The intention is to capture unobserved heterogeneity across consumers beyond the featured customer properties of the control variables (*gender* and *age*) (Van Diepen et al., 2009).

As *purchase_incidence* is a dummy variable, the applied models follow a binomial logic. This means that the estimated outcome is the estimated probability of an individual *i* making a purchase in quarter *t*. For this reason, a probit regression is applied to predict the likelihood of the outcome. With *purchase_spending* being a continuous variable, the respective models estimate the monetary spending amount (€) of an individual *i* in quarter *t*.

Several, different models are being built to test the previously elaborated hypotheses.

## 4.5. Model Assumptions

In the case of (multiple) linear regressions, there are a few important assumptions that must be fulfilled in order to obtain statistically consistent and valid results. These are examined and discussed below in the light of the present models.

### 4.5.1. Non-Linearity

*Purchase_spending*, as one of the two outcome variables this study focuses on, is modelled using a linear regression model. One of the main assumptions of multiple linear regression analysis is a linear relationship between the dependent variable and every independent variable (Woolridge, 2015). In the case of binary independent variables (like *RDM, MDM, RDM_incentive, RDM_discount, RDM_premium, treated, gender, age* and all year and quarter variables) this condition is always met. It is therefore relevant to assess the relationship between *purchase_spending* and the three continuous independent variables *purchase_frequency, relationship_duration* and *age*, respectively. For this purpose, scatterplots that include a trendline are generated. As the underlying dataset is quite imbalanced, i.e., 93% of observations report a purchase spending of 0, the data is being stratified by *purchase_spending* > 0 to be able to reveal any patterns and identify the nature of the relationship between the predictors and the outcome variable. Looking at figures 12 to 14 it can be confirmed that there are linear relationships in all cases and that the assumption of linearity is thereby fulfilled.

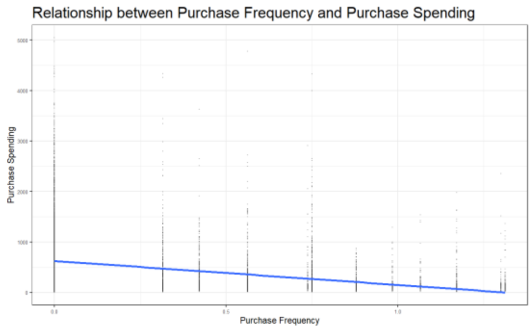



*Figure 12: Scatter Plot Purchase Frequency vs. Purchase Spending*

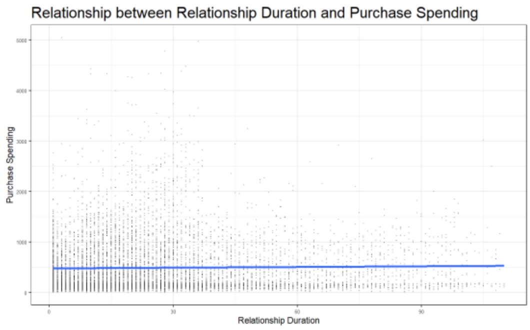



*Figure 13: Scatter Plot Relationship Duration vs. Purchase Spending*

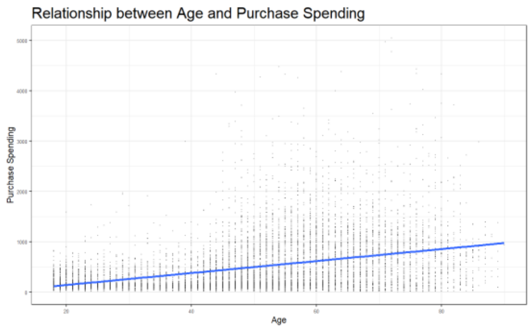



*Figure 14: Scatter Plot Age vs. Purchase Spending*

### 4.5.2. Multicollinearity

Multicollinearity means that at least two of the explanatory variables used in a regression model are moderately to highly correlated with each other (Daoud, 2017). Therefore, the model is not able to properly "distinguish between the effect of one variable and the effect of another" (Siegel, 2016, p. 540). As a consequence, the individual coefficients of the explanatory variables are more likely to be considered insignificant due to inflated standard errors although they should be significant (Daoud, 2017).

To identify potential multicollinearity issues it makes sense to investigate the correlations between the explanatory variables used in the models (see table 2). Shrestha (2020) defines the threshold to identify potential multicollinearity at |0.8|. In fact, there is high correlation between *RDM_*incentive and *RDM_discount* which is logical as the *RDM_incentive* variable is computed based on *RDM_discount* and *RDM_premium*. As those two variables will not be used within the same model, it does not pose a problem and further multicollinearity is unlikely to exist. It can be concluded that the independent or explanatory variables are sufficiently independent from each other and this assumption is satisfied.

*Table 2: Correlation Matrix of Explanatory Variables (excl. year and quarter variables)*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 RDM | 1 | | | | | | | | | |
| 2 relationship_duration | 0.044111465 | 1 | | | | | | | | |
| 3 purchase_frequency | 0.041132231 | 0.45662307 | 1 | | | | | | | |
| 4 RDM_incentive | 0.632400514 | 0.017532688 | 0.02103832 | 1 | | | | | | |
| 5 RDM_discount | 0.562927238 | 0.020790860 | 0.02870683 | 0.890143549 | 1 | | | | | |
| 6 RDM_premium | 0.281166342 | -0.002395594 | -0.01026338 | 0.444601698 | 0.012406372 | 1 | | | | |
| 7 MDM | 0.084438464 | 0.075121777 | -0.09774593 | 0.050495340 | 0.036814037 | 0.038439404 | 1 | | | |
| 8 gender | -0.009824876 | -0.014631863 | -0.04176015 | -0.005851214 | -0.005525476 | -0.001978226 | -0.01163613 | 1 | | |
| 9 age | -0.021183366 | 0.105748268 | -0.10838309 | -0.013135612 | -0.012809098 | -0.003645382 | 0.04587139 | 0.019957105 | 1 | |
| 10 treated | 0.280691903 | 0.181406823 | 0.06864852 | 0.177509704 | 0.158009118 | 0.078921116 | 0.09053528 | -0.005898165 | -0.020433945 | 1 |

### 4.5.3. Heteroskedasticity

Another assumption for multiple linear regression is homoskedasticity which implies that the error terms (disturbances) are homoscedastic. In other words, this means that the variance of the residuals are consistent across different values of the explanatory variables. A violation of this assumption can be found in heteroskedasticity which can lead to biased estimated standard errors and thus biased coefficients and inferences. (Breusch & Pagan, 1979)

To check for heteroskedasticity all models were examined by the Breusch-Pagan-Test (Breusch & Pagan, 1979). In every case, significance was found at the 1% level indicating that the models were heteroskedastic. To counteract the violation of this assumption, robust standard errors were applied to each model.

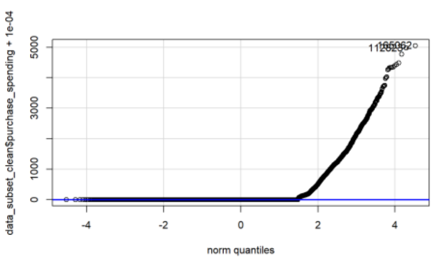
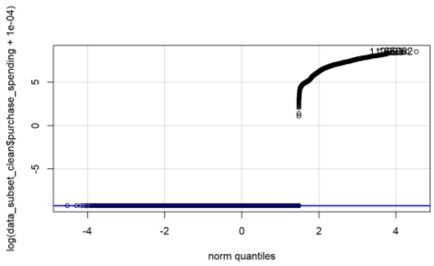
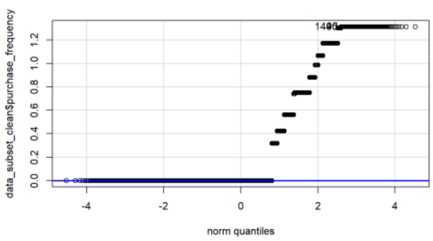
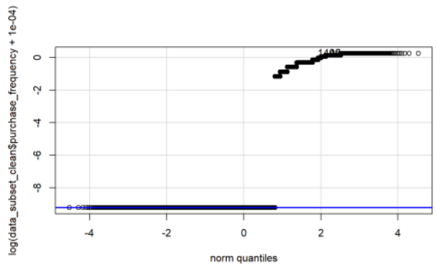
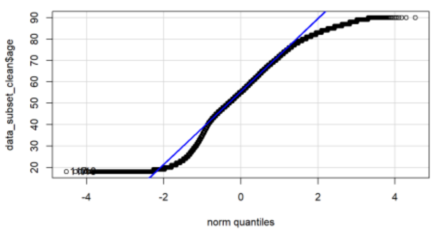
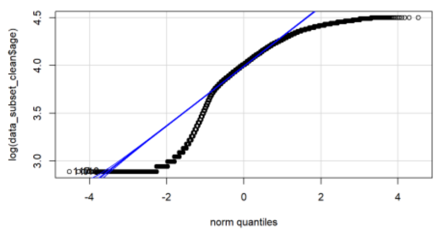
### 4.5.4. Autocorrelation

Moreover, the validity of the regression model is based on the error terms being independent of each other. In the case of autocorrelation (or serial correlation) errors are correlated across time, i.e., successive errors are dependent on each other (Durbin & Watson, 1992). This could mean that the sample used is not random. Especially in the case of panel data, this could be a problem. To check for autocorrelation the Breusch-Godfrey/Wooldridge test for serial correlation in panel models was applied. In every case, significance was found at the 1% level indicating that autocorrelation is present. To counteract the violation of this assumption, robust standard errors were applied to each model.

### 4.5.5. Nonnormality

Normality means that the residuals are normally (identically) distributed. Conversely, "violation of the normality assumption may lead to the use of suboptimal estimators, invalid inferential statements and to inaccurate conclusions" (Jarque & Bera, 1987, p. 164). To detect nonnormality the Kolmogorov Smirnov test (Massey, 1951) was performed as it allows to be applied to large sample sizes while the Shapiro Wilk test is not useful for sample sizes larger than 5,000. The p-values were found to be extremely small which implies that nonnormality exists. In addition, QQ plots (= quantile-quantile plots) can be used to provide a graphical analysis (see table 3). Here, it also becomes clear that the variables do not follow a normal distribution. Two potential solutions to counteract the issue are to exclude outliers or transform the (dependent) variable(s). The first approach was already conducted as explained in Chapter 4.2 Data Cleaning and Preparation. Therefore, the variables were log-transformed[1]. However, it was found that this measure does not cause any improvement as the Kolmogorov Smirnov test still detects nonnormality. Looking at the QQ plots it seems that the distribution has moved even further away from a normal distribution (see table 3). Therefore, it was decided to continue with the non-transformed variables as the sample size is quite large and it is assumed that the application of robust standard errors help to counteract this issue.

*Table 3: QQ Plots of Numerical Variables Before and After Log-Transformation*

| Variable | Before log-transformation | After log-transformation |
|---|---|---|
| *purchase_spending* |  |  |
| *purchase_frequency* |  |  |
| *age* |  |  |

[1] for *spending_amount = 0* 0.0001 was added to be able to perform the log transformation

### 4.5.6. Endogeneity

The exogeneity assumption requires that the explanatory variables are exogeneous which means that they are uncorrelated with the error term (and vice versa) (Woolridge, 2015). A violation of this assumption could be due to unobserved or omitted variables and results in endogeneity. In the present case, for instance, the variable *RDM*, indicating a retailer's decision to send a respective customer *i* a RDM communication in quarter *t*, might be a result of a specific target selection technique. So it could therefore be that metrics which are subject to this selection technique and which are not factored in the regression models (and thus part of the error term) are correlated with *RDM* and lead to an overestimation of the direct effect of *RDM* on the outcome variables. In fact, the Hausman test showed that endogeneity is likely to be present in the models of this study. To control for this endogeneity it would make sense to apply instrumental variables estimators as the Two Stage Least Squares (TSLS) (Woolridge, 2015). For complexity reasons, this procedure is not adopted in the present study. However, it is conceivable to follow the example of Vafainia et al. (2019) in a subsequent stage.

# 5. Results

In principle, five probit models are built, each of which is applied to estimate the two outcome variables *purchase_incidence* and *purchase_spending,* respectively. It follows that in total 10 probit models are created to predict customer purchase behaviour and to test the stated hypotheses. This way, the different impacts (i.e., coefficients) of customer relationship characteristics and incentive types can be tested and compared.

Model 1 (a and b) measures the overall impact of *RDM* on purchase behaviour irrespective of customer relationship characteristics or incentive type and is used to test H1 (a and b). Models 2 and 3 (a and b) include customer relationship characteristics (i.e., *purchase_frequency* and *relationship_duration*) to test their moderating effects on RDM in line with H2 and H3 (a and b). Model 4 (a and b) estimates the moderating effect of incentives on RDM using a dummy variable to test H4 (a and b). Finally, model 5 (a and b) separates the moderating effect of incentives to compare the effect of discount and premium to test H5 (a and b).

## 5.1. Overall Results

Table 3 provides an overview of the estimation results with *purchase_incidence* being the outcome variable. In analogy, table 4 provides an overview of the estimation results with *purchase_spending* being the outcome variable. The effects of the explanatory variables on both, *purchase_incidence* and *purchase_spending*, are all significant (except for the interaction effect of *RDM * purchase_frequency* on *purchase_incidence* and *relationship_duration* on *spending_amount*). Moreover, in both cases they follow the same direction, i.e., have the same sign.

*Table 4: Model Estimation Results – Dependent Variable:* ***purchase_incidence***

| Variables | Model 1a | | Model 2a | | Model 3a | | Model 4a | | Model 5a | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Coef | SE | Coef | SE | Coef | SE | Coef | SE | Coef | SE |
| Intercept | 0.0158*** | 0.007 | 0.163*** | 0.007 | 0.159*** | 0.007 | 0.158*** | 0.007 | 0.158*** | 0.007 |
| RDM | 0.045*** | 0.003 | 0.048*** | 0.003 | 0.036*** | 0.005 | 0.079*** | 0.004 | 0.079*** | 0.004 |
| purchase_frequency | | | -0.082*** | 0.004 | | | | | | |
| RDM * purchase_frequency | | | -0.010 | 0.014 | | | | | | |
| relationship_duration | | | | | 0.0002*** | 0.0001 | | | | |
| RDM * relationship_duration | | | | | 0.0004** | 0.0001 | | | | |
| RDM_incentive | | | | | | | -0.082*** | 0.005 | | |
| RDM_discount | | | | | | | | | -0.082*** | 0.005 |
| RDM_premium | | | | | | | | | -0.080*** | 0.008 |
| MDM | 0.008*** | 0.002 | 0.001 | 0.002 | 0.005** | 0.002 | 0.008*** | 0.002 | 0.008*** | 0.002 |
| age | -0.001*** | 0.0001 | -0.001*** | 0.0001 | -0.001*** | 0.0001 | -0.001*** | 0.0001 | -0.001*** | 0.0001 |
| gender | -0.012*** | 0.002 | -0.014*** | 0.003 | -0.012*** | 0.002 | -0.012*** | 0.002 | -0.012*** | 0.002 |
| treated | 0.014*** | 0.002 | 0.017*** | 0.003 | 0.012*** | 0.002 | 0.014*** | 0.002 | 0.014*** | 0.002 |
| 2012 | -0.017*** | 0.005 | -0.006 | 0.005 | -0.018*** | 0.005 | -0.017*** | 0.005 | -0.017*** | 0.005 |
| 2013 | -0.023*** | 0.005 | -0.010 | 0.005 | -0.025*** | 0.005 | -0.023*** | 0.005 | -0.023*** | 0.005 |
| 2014 | -0.027*** | 0.005 | -0.014*** | 0.005 | -0.030*** | 0.005 | -0.027*** | 0.005 | -0.027*** | 0.005 |
| 2015 | -0.031*** | 0.005 | -0.018*** | 0.005 | -0.035*** | 0.005 | -0.031*** | 0.005 | -0.031*** | 0.005 |
| 2016 | -0.027*** | 0.005 | -0.014*** | 0.005 | -0.031*** | 0.005 | -0.027*** | 0.005 | -0.027*** | 0.005 |
| 2017 | -0.040*** | 0.005 | -0.025*** | 0.005 | -0.044*** | 0.005 | -0.040*** | 0.005 | -0.040*** | 0.005 |
| 2018 | -0.050*** | 0.005 | -0.038** | 0.005 | -0.056*** | 0.005 | -0.050*** | 0.005 | -0.050*** | 0.005 |
| quarter2 | -0.002 | 0.002 | -0.001 | 0.002 | -0.002 | 0.002 | -0.002 | 0.002 | -0.002 | 0.002 |
| quarter3 | -0.006*** | 0.002 | -0.006*** | 0.002 | -0.007*** | 0.002 | -0.006*** | 0.002 | -0.006*** | 0.002 |
| quarter4 | -0.004** | 0.002 | -0.003* | 0.002 | -0.005** | 0.002 | -0.004** | 0.002 | -0.004** | 0.002 |

*p<0.1 (two-sided)
**p<0.05 (two-sided)
***p<0.01 (two-sided)

*Table 5: Model Estimation Results - Dependent Variable:* ***purchase_spending***

| Variables | Model 1b | | Model 2b | | Model 3b | | Model 4b | | Model 5b | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Coef | SE | Coef | SE | Coef | SE | Coef | SE | Coef | SE |
| Intercept | 18.422*** | 3.458 | 20.145*** | 3.497 | 18.264*** | 3.469 | 18.480*** | 3.465 | 18.479*** | 3.464 |
| RDM | 32.087*** | 2.579 | 36.529*** | 3.079 | 24.471*** | 3.751 | 59.277*** | 3.852 | 59.278*** | 3.852 |
| purchase_frequency | | | -22.983*** | 1.768 | | | | | | |
| RDM * purchase_frequency | | | -22.914*** | 6.204 | | | | | | |
| relationship_duration | | | | | 0.010 | 0.025 | | | | |
| RDM * relationship_duration | | | | | 0.307*** | 0.111 | | | | |
| RDM_incentive | | | | | | | -65.359*** | 3.295 | | |
| RDM_discount | | | | | | | | | -65.669*** | 4.429 |
| RDM_premium | | | | | | | | | -64.128*** | 6.130 |
| MDM | 11.081*** | 2.073 | 8.507*** | 2.083 | 14.261*** | 2.102 | 10.842*** | 2.071 | 10.833*** | 2.072 |
| age | 0.330*** | 0.026 | 0.287*** | 0.028 | 0.322*** | 0.026 | 0.330*** | 0.026 | 0.330*** | 0.026 |
| gender | -4.790*** | 1.066 | -5.369*** | 1.125 | -4.732*** | 1.065 | -4.783*** | 1.066 | -4.784*** | 1.066 |
| treated | 5.285*** | 1.083 | 6.214*** | 1.140 | 4.885*** | 1.104 | 5.319*** | 1.083 | 5.319*** | 1.083 |
| 2012 | -4.504 | 3.161 | -1.308 | 3.155 | -4.280 | 3.163 | -4.277 | 3.162 | -4.276 | 3.162 |
| 2013 | -4.867 | 3.173 | -1.353 | 3.206 | -4.267 | 3.181 | -5.070 | 3.175 | -5.072 | 3.175 |
| 2014 | -5.749* | 3.134 | -2.205 | 3.163 | -5.165 | 3.138 | -5.455* | 3.135 | -5.458* | 3.135 |
| 2015 | -6.176** | 3.103 | -2.605 | 3.135 | -5.650* | 3.120 | -6.131** | 3.103 | -6.129** | 3.103 |
| 2016 | -0.152 | 3.187 | 3.347 | 3.215 | 0.126 | 3.124 | -0.158 | 3.188 | -0.156 | 3.188 |
| 2017 | -8.150*** | 3.083 | -4.116 | 3.111 | -8.373 | 3.106 | -8.185*** | 3.082 | -8.179 | 3.082 |
| 2018 | -12.352*** | 3.121 | -8.929*** | 3.143 | -12.797*** | 3.161 | -12.133*** | 3.120 | -12.133*** | 3.120 |
| quarter2 | -1.332 | 1.289 | -1.202 | 1.281 | -1.338 | 1.290 | -1.588 | 1.302 | -1.587 | 1.302 |
| quarter3 | -1.923 | 1.297 | -2.022 | 1.290 | -1.676 | 1.299 | -2.174* | 1.311 | -2.175* | 1.311 |
| quarter4 | 3.089** | 1.381 | 3.557*** | 1.377 | 2.633* | 1.382 | 3.078** | 1.391 | 3.080* | 1.391 |

*p<0.1 (two-sided)
**p<0.05 (two-sided)
***p<0.01 (two-sided)

For demonstration reasons, two additional models were estimated to predict *purchase_incidence* and *spending_amount* with the help of all explanatory variables presented in this study (and control variables). Not surprisingly, the results are in line and confirm the separate models' results.

*Table 6: Model Estimation Results - all explanatory variables*

| Variables | Model *purchase_incidence* | | Model *purchase_spending* | |
|---|---|---|---|---|
| | Coef | SE | Coef | SE |
| Intercept | **0.164*** ** | 0.007 | **22.308*** ** | 3.598 |
| RDM | **0.074*** ** | 0.006 | **56.832*** ** | 4.790 |
| purchase_frequency | **-0.069*** ** | 0.004 | **-58.584*** ** | 2.141 |
| RDM * purchase_frequency | -0.016 | 0.014 | **-28.666*** ** | 6.705 |
| relationship_duration | **0.0003*** ** | 0.0001 | **0.049* ** | 0.028 |
| RDM * relationship_duration | **0.0003** ** | 0.0001 | **0.329*** ** | 0.112 |
| RDM_discount | **-0.081*** ** | 0.005 | **-64.369*** ** | 4.331 |
| RDM_premium | **-0.085*** ** | 0.008 | **-69.703*** ** | 6.160 |
| MDM | 0.0004 | 0.002 | **8.854*** ** | 2.104 |
| age | **-0.001*** ** | 0.0001 | **0.213*** ** | 0.031 |
| gender | **-0.014*** ** | 0.002 | **-6.100*** ** | 1.216 |
| treated | **0.015*** ** | 0.002 | **6.984*** ** | 1.248 |
| 2012 | -0.008 | 0.005 | 3.962 | 3.133 |
| 2013 | **-0.014*** ** | 0.005 | 4.457 | 3.241 |
| 2014 | **-0.019*** ** | 0.005 | 4.004 | 3.201 |
| 2015 | **-0.024*** ** | 0.005 | 3.163 | 3.177 |
| 2016 | **-0.021*** ** | 0.005 | **8.573*** ** | 3.278 |
| 2017 | **-0.033*** ** | 0.005 | 1.028 | 3.163 |
| 2018 | **-0.046*** ** | 0.005 | -4.739 | 3.215 |
| quarter2 | -0.002 | 0.002 | -1.314 | 1.282 |
| quarter3 | **-0.007*** ** | 0.002 | -2.123 | 1.295 |
| quarter4 | **-0.004** ** | 0.002 | **3.491*** ** | 1.379 |

*p<0.1 (two-sided)
**p<0.05 (two-sided)
***p<0.01 (two-sided)

Looking at the performance metrics for all presented models in table 6 reveals that the explanatory power of all models is very low. This, however, is not surprising. Complex outcome variables, as in this case purchase decision and spending, are dependent on a huge variety of internal and external factors and cannot be predicted by such a limited amount of explanatory variables. The F statistic shows that in every case, the joint significance of the variables used is given at a 1% level which confirms that the models are still useful as there is a significant relationship between the explanatory variables and the outcome variable.

*Table 7: Model Performance Metrics*

| Model | R2 | Adjusted R2 | F |
|---|---|---|---|
| Model 1a | 0.005 | 0.005 | 908.203*** |
| Model 1b | 0.004 | 0.003 | 594.797*** |
| Model 2a | 0.012 | 0.012 | 2,045.281*** |
| Model 2b | 0.005 | 0.005 | 804.230*** |
| Model 3a | 0.007 | 0.007 | 1,106.103*** |
| Model 3b | 0.003 | 0.003 | 543.413*** |
| Model 4a | 0.008 | 0.007 | 1,259.871*** |
| Model 4b | 0.006 | 0.006 | 957.274*** |
| Model 5a | 0.008 | 0.007 | 1,259.943*** |
| Model 5b | 0.006 | 0.006 | 957.325*** |
| | | | |
| Model all *purchase_incidence* | 0.013 | 0.013 | 2,162.401*** |
| Model all *spending_amount* | 0.011 | 0.011 | 1,906.920*** |

*p<0.1 (two-sided)
**p<0.05 (two-sided)
***p<0.01 (two-sided)

## 5.2. Hypotheses Tests

### 5.2.1. Main Effect of RDMs

H1a and H1b consider the overall impact of RDM on customer purchase behaviour, i.e., purchase decision and spending amount. To test those hypotheses, models 1a and 1b are considered which both include a dummy variable indicating the receipt of a RDM communication. For both dependent variables, the coefficient of *RDM* is positive and significant (for $p < 0.01$) which means that receiving a RDM communication, in general, positively influences a customer's purchase likelihood and spending amount. Concretely, receiving a RDM increases purchase likelihood, on average, by 4.5% and purchase spending by ~ 32 (€) (ceteris paribus). Consequently, H1a and H1b are supported. The finding is valid for all models.

### 5.2.2. Moderating Effect of Customer Relationship Characteristics

As one of the main contributions of this study is to analyse the effectiveness of RDM communication given varying CLC stages and thus relationship characteristics, H2a and H2b consider *purchase_frequency* as a moderator impacting the relationship between RDM and purchase behaviour. Model 2a and 2b estimate the moderating effect by including an interaction term between *RDM* and *purchase_frequency*. The coefficient of the latter is found to be negative in both models. However, in model 2a which predicts *purchase_incidence* it is not significant. Thus, H2a cannot be supported. Yet, model 2b estimates a significant negative impact (for $p < 0.01$). Keeping all other factors constant, an increase of *purchase_frequency* by 1 unit additionally decreases estimated average spending by ~ 23 (€) for customers who receive a RDM compared to customers who do not receive a RDM, ceteris paribus. This means that the positive impact of RDM on spending amount is eliminated for customers with higher purchase frequency (ceteris paribus). As it was expected to find a positive moderating effect, H2b cannot be supported.

Analogously, model 3a and 3b measure the moderating impact of *relationship_duration* on the relationship between RDM and customer purchase behaviour. The coefficient of the interaction term between *RDM* and *relationship duration* is positive and significant in both models (for $p < 0.05$ in model for *purchase_incidence* and for $p < 0.01$ in model for *purchase_spending*). This means that the positive (sole) effect of receiving a RDM on the likelihood of a customer deciding to make a purchase and on the amount spent increases with an increasing relationship duration, i.e., for individuals who have been customers at the respective retailer for a longer time. Keeping all other factors constant, when relationship duration for customers targeted by a RDM increases by 1 unit (= 1 quarter), purchase likelihood, on average, increases by 0.04% and spending amount by ~ 0.4 (€), compared to customers who do not receive the RDM. It follows that H3a and H3b are supported.

### 5.2.3. Moderating Role of Incentives

To investigate the moderating effect of communicating an incentive in a RDM models 3a and 4b can be considered. The dummy variable *RDM_incentive* can be interpreted as an interaction variable indicating whether a RDM involved an incentive or not as it is always linked to the *RDM* variable. In both models, the coefficient is negative and significant (for $p < 0.01$) meaning that including an incentive when sending out a RDM decreases the initial positive impact of RDM on both the customer's likelihood to purchase and the spending compared to not communicating any incentive. In other words, a RDM with incentive decreases a customer's purchase likelihood and spending, as the positive effect of a RDM in general (= without incentive) is eliminated. For customers receiving a RDM, the purchase likelihood, on average, decreases by ~ 8% and the expected spending by ~ 65 (€) when an incentive is communicated (ceteris paribus). This finding is contradictory to the initial expectation and H4a and H4b cannot be supported.

Further considering the type of incentive, models 5a and 5b replace the overall incentive variable by two dummy variables *RDM_discount* and *RDM_premium* which, again, can be interpreted as interaction variables between RDM and incentive type. In line with the previous finding, the coefficients in both models are negative and significant (for $p < 0.01$). Further considering the size of the coefficients, it can be drawn that a RDM that either communicates a discount or a premium even decreases purchase likelihood and spending as the negative effect of both incentives eliminate the initial positive effect of the RDM. Including a discount, on average, decreases purchase likelihood by 8.2% and spending amount by ~ 66 (€) for customers receiving a RDM (ceteris paribus). Analogously, including a premium, decreases purchase likelihood by 8% and spending amount by ~ 64 (€) for customers receiving a RDM (ceteris paribus). Moreover, looking at the 95% confidence intervals for both coefficients (which are overlapping) it can be concluded that their respective impacts are not significantly different from each other. Consequently, H5a and H5b are not supported.

## 5.3. Effect of Control Variables

Controlling for the impact of MDMs reveals that receiving a MDM positively impacts purchase likelihood and spending amount, as the coefficients are positive and significant (for $p < 0.01$) in all models (except in model 2a). Concretely, receiving a MDM, on average, increases purchase likelihood by between 5% and 8% and spending amount by ~ 8.5 (€) to 14 (€), ceteris paribus.

Moreover, looking at the *age* variable confirms its role as a control variable as it is found to be significant (for $p < 0.01$) in all models. While the estimated relationship between *age* and *purchase_incidence* is negative, i.e., with every year older the purchase probability decreases by 0.1% (ceteris paribus), it is positive between *age* and *purchase_spending* indicating that customers of higher age spend more money at their optical retailer (between ~ 0.29 and 0.33 (€) for every additional year, ceteris paribus).

*Gender* is statistically significant (for $p < 0.01$) in all models and is predicted to have a negative impact on both *purchase_incidence* and *purchase_spending*. This means that for men (gender = 1) the baseline purchase likelihood is ~ 1.2% lower and spending amounts are ~ 5 (€) lower compared to women, ceteris paribus.

Furthermore, the *treated* variable which indicates whether a customer belongs to a retailer that participates in the RDM program and thus receives at least one RDM communication during the whole observation period is positive and significant (for $p < 0.01$) for all models. On average and keeping all other factors constant, customers of a participating retailer have a 1.2% to 1.7% higher purchase likelihood and spend between 5 (€) and 6 (€) more than customers of retailers not participating in the program. This shows that controlling for this retailer-level information and separating the effect is important.

Interestingly, year and quarter dummies are not consistently significant throughout all models. While, for example, quarter 2 is not significant in any model, all other year and quarter variables are significant for the models with the dependent variable *purchase_incidence*. The year dummies 2012, 2013, and 2016 are not significant in the models with the dependent variable *purchase_spending*. However, as most of the year and quarter dummies are significant, it can be concluded that it is important to control for those time effects to prevent potential omitted variable bias.

## 5.4. Theoretical Discussion

The motivation behind this study was to investigate and quantify the impact of RDMs given specific CLC characteristics and incentive types. For this reason, three main research questions were addressed. Table 5 summarizes the ten hypotheses that guided this study and the respective results. These findings will now be discussed in the following section.

*Table 8: Summary of Hypotheses and Results*

| Variable | Hypothesis | Effect on | Anticipated Sign | Result |
|---|---|---|---|---|
| RDM | H1a | purchase_incidence | + | Supported |
| RDM | H1b | spending_amount | + | Supported |
| purchase_frequency | H2a | purchase_incidence | + / - | Not supported (not significant) |
| purchase_frequency | H2b | spending_amount | + / - | Supported (-) |
| relationship_duration | H3a | purchase_incidence | + / - | Supported (-) |
| relationship_duration | H3b | spending_amount | + / - | Supported (-) |
| RDM_incentive | H4a | purchase_incidence | + | Not supported (effect reversed) |
| RDM_incentive | H4b | spending_amount | + | Not supported (effect reversed) |
| RDM_discount and RDM_premium | H5a | purchase_incidence | + | Not supported (effect reversed) |
| RDM_discount and RDM_premium | H5b | spending_amount | + | Not supported (effect reversed) |

The first research question this study aimed to address is: "*What is the impact of retargeted direct mail communication on consumer response, i.e., on purchase incidence and spending amount?*". It was found that RDM has a positive impact on both purchase incidence and spending amount, meaning that it increases the probability of the customer making a purchase as well as the monetary amount spent for that purchase. This is in line with the previously formed expectations. The unique dataset underlying this study comes from an optical retailing context. On the one hand, this implies that the relevant products purchased, e.g., glasses and contact lenses, are durable goods. On the other hand, these products are mostly (medically) necessary and of utilitarian nature. Consequently, consumers usually have a more defined need in mind and an intrinsic interest in the product (category), which makes them more open and responsive to concrete information (Lambrecht & Tucker, 2013; Petty & Cacioppo, 1986). As the RDM targets existing customers with relevant information (e.g., based on past purchases), it encourages the recipients to elaborate more thoroughly on the message, strengthens their positive attitude, and ultimately provokes a (bigger) purchase (Micheaux, 2011). As the RDM piece physically reaches customers at their homes (by mail), it receives the recipient's undivided attention at the moment of opening (Bleier & Eisenbeiss, 2015; Lambrecht & Tucker, 2013). Moreover, being repeatedly exposed to a familiar brand or retailer increases salience even further and enhances the customer's positive attitude (Fishman, 2020).

Going further, the second research question was set to answer: "*How is the impact of a retargeted direct mail communication on consumer response moderated by a customer's life cycle characteristics, i.e., purchase frequency and relationship duration?"*. The results prove that customers respond heterogeneously to RDMs which complements previous literature findings (Rust & Verhoef, 2005; Gázquez-Abad et al., 2011; Elsner et al., 2004). Customers who purchase more frequently are found to be less responsive to RDMs. While the negative effect on purchase incidence is not significant, receiving an RDM significantly decreases spending amount when purchase frequency is higher. A possible explanation for this effect is that regular customers (who purchase at higher frequency) have already developed a clear picture of the retailer as well as clear preferences, which makes them less influenceable by external influences like marketing materials (Reinchheld, 1996). However, with respect to relationship duration, the positive effect of RDM on consumer response increases with a higher duration. This finding indicates that a longer relationship between customer and retailer results in feelings of intimacy and attachment (Verhoef et al., 2002) due to increased familiarity and also increased investments (i.e., time, money, effort) from both parties. As a consequence, consumers project their positive attitude on the RDM and react positively. This result confirms previous empirical findings of a positive relationship between relationship duration and spending amount from Bendaupi & Berri (1997) and Reinartz & Kumar (2003)

Lastly, this study was designed to investigate the third research question: "*How is the impact of a retargeted direct mail communication on consumer response moderated by the communicated content, i.e., incentives?"*. Contrary to the stated expectations, the study reveals that an RDM with an incentive actually has an overall negative impact on consumer response. Hereby, the type of incentive communicated, i.e., discount or premium, makes no (significant) difference. This is contradictory to the recent findings of Vafainia et al. (2019), who estimate a positive relationship between CTA DM and purchase incidence as customers appreciate the effort and investment made by their retailer and want to reciprocate it by making a new purchase (Vafainia et al., 2019; Arora & Stoner, 1992). However, it confirms Gázquez-Abad et al.s'(

2011) conclusion that relational mailings are generally (= irrespective of the time of sending) more effective than promotional CTA mailings. One reason for the present negative impact can be found in *Usage Dominance Theory*. When receiving the RDM piece, customers are already familiar with the sending retailer as they have already made at least one purchase. This experience makes them less responsive to such incentives as their personal opinion outweighs external information or influences (Bridges et al., 2006). Going one step further, it is conceivable that consumers feel patronized or manipulated and consciously decide to behave conversely, which would explain the negative impact (Simonson et al., 1994). While this study was not concerned with the value of the incentive nor the incentivized product type and brand, the amount or value of the incentive may not exceed the "threshold" that stimulates a consumer purchase decision (Gupta & Cooper, 1992). At the same time, it could also indicate a saturation effect which implies that too high incentives are not effective at influencing consumer behaviour (Gupta & Cooper, 1992). Additionally, in the case of the studied RDM program, the type of content or incentive might not be individually adapted to the receiving customers or might have been made under incorrect beliefs. The common assumption that customers characterized by a high churn risk are also more sensitive and responsive to incentives is found not to be valid (Ascarza, 2018). Therefore, it is possible that the "wrong" customers were targeted with the "wrong" incentives, which ultimately led to a reverse effect. Ultimately, it is also conceivable that consumers are generally saturated with or even tired of being targeted with generic incentives, like price discounts or premiums. Instead, they may rather seek emotional connections to the brand or retailer and are more likely to respond to campaigns with "personalized messages designed to resonate with the emotional motivators that drive behavior at each stage of the customer journey" (Magids et al., 2015, p. 73). Although there is no detailed information about the content of the RDMs without incentive, it could well be that the personalized content is formed on a more emotional level, which could explain the higher effectiveness compared to incentives.

# 6. Conclusion

With about 2,3000 opticians in the Netherlands and a steady upward trend, the optical retail environment is highly competitive (Retail Insiders, 2023). This observation can certainly be extended to other retail industries or countries/regions. Therefore, it is essential for competing companies to, on the one hand, win customers but then, on the other hand, maintain existing customer relationships and maximize the CLV (Kotler et al., 2009; Ahmad & Buttle, 2001). In addition, consumers are permanently targeted directly and indirectly through various online and offline channels, which makes it all the more difficult to stand out and reach the individual in a memorable and actionable way. It is, therefore, not surprising that such a traditional and supposedly outdated method as postal DM is still (or again) frequently used (The Business Research Company, 2021). Specifically, to nurture or reactivate existing customer relationships, marketers make use of RDMs which are built and personalized based on information from, for example, past purchases (Bleier & Eisenbeiss, 2015). For this reason, marketers, retail managers, and academics are interested in how such RDM campaigns provoke purchase behaviour and, consequently, how to best design and time them.

## 6.1. Academic Implications

Existing research and studies investigate the impact of DM campaigns in general (e.g., De Wulf & Odekerken-Schröder, 2003; Naik & Piersma, 2002; Simpson & Mortimore, 2015; Verhoef, 2003), considering certain design and content characteristics (e.g., Feld et al., 2013; Bawa & Shoemaker, 1987; Arora & Stoner, 1992; Vafainia et al., 2019), or even timing (e.g., Jonker et al., 2006; Venkatesan & Kumar, 2004). Moreover, there are publications addressing personalized DM (e.g., De Wulf et al., 2001; Morris-Lee, 2002), which in some aspects, might be transferable to retargeting. When it comes to the specific effectiveness and impact of retargeting, however, the author of this paper is not aware of any work that considers or studies the case of physical RDMs, as a number of researchers only explore retargeting in online settings (e.g., Sahni et al., 2019; Bleier & Eisenbeiss, 2015; Lambrecht & Tucker, 2013).

What can be concluded from all these papers and studies is that the performance of DMs and RDMs cannot be considered in isolation. Consumers receiving those materials respond differently and heterogeneously. For this reason, it is crucial to take into account customer (relationship) characteristics as a moderating force. This paper fills precisely the academic research gap on the effectiveness of (physical) RDMs while following the clear call to integrate the moderating role of customer relationship characteristics (Rust & Verhoef, 2005; Gázquez-Abad et al., 2011). It thus offers academics first insights into the mechanism of RDMs given certain content decisions, i.e., incentive types and customer relationship characteristics, i.e., length of the customer-firm relationship (*relationship_duration*) and purchase frequency (*purchase_frequency*). Future studies can then build upon these findings. Especially the findings on RDMs, including an incentive, were surprising and contrary to previous studies and literature. This should stimulate deeper and further research, especially against the challenging findings of Ascarza (2018). In this light, it could also be highly interesting to investigate the combined moderating roles of CLC characteristics and incentive types and explore, for instance, whether more frequent buyers respond differently to RDMs with incentives compared to less frequent buyers or whether customers with a longer relationship to the firm are more attracted to RDMs with relational content.

## 6.2. Managerial Implications

Expenditures in global DM advertising are steadily increasing (The Business Research Company, 2021). Specifically, in the case of consumer durables, as covered in this study, those investments reach high levels (Gázquez-Abad et al., 2011). Marketers and retailers must therefore make informed and forward-looking decisions about the allocation of their budgets and investments to maximize outcome and return. In this context, it is important not only how to reach the customers (i.e., through RDMs) but also who, when, and which message to communicate (i.e., incentive) (Ascarza, 2018). The findings from this study provide valuable insights and guidance for managers to form their strategies and make those decisions.

First, it is shown that targeting customers with RDMs pays off in terms of enhancing purchase likelihood and ultimate spending. Moreover, it is more effective than sending out generic MDMs, which implies that retailers should place a greater emphasis on tracking their customer interactions and personalizing their communications accordingly.

Second, there is evidence that there is heterogeneity in how customers respond to such campaigns. Considering and incorporating customer relationship history measures into the targeting strategy significantly impacts effectiveness in terms of purchase likelihood and spending amount. More concretely, targeting customers with lower purchase frequencies increases estimated purchase spending. Additionally, retailers should focus on targeting customers with higher relationship duration as it raises purchase likelihood and spending. To achieve the best possible outcome, retailers should therefore try to identify customers that meet these criteria and prioritize them when designing their marketing campaigns.

Third, when it comes to the content of the RDMs, it was found that incentives of any type, be it a discount or a premium, actually eliminate the positive effect of an RDM on purchase likelihood and spending. This would imply that retailers should step away from offering gifts or monetary discounts and rather focus on, for instance, relationship-building content, like thank-you letters or CTA messages, like inviting customers to visit a store or make a new purchase without any specified reward. However, it must be noted that these insights are very contradictory to the original expectations and should be taken with caution (see Chapter 6.3. Limitations and Future Research).

At a higher level, the results prove that tracking customers, not only with respect to basic information like demographics but with a dedicated focus on purchase and relationship history, empowers retailers to effectively design and manage their RDM strategies to foster purchase likelihood and revenues ultimately. This, on the one hand, requires the definition of tracking metrics and KPIs and, on the other hand, the technical implementation of a reliable (CRM) system.

## 6.3. Limitations and Future Research

Given that this study is based on data from a large group of optical retailers located in the Netherlands, it is conceivable that the results are not generalizable to neither another industry nor another region. Even within the context of consumer durables, which optical products like glasses or lenses belong to, there might be differences in the resulting effects for durables characterized by high purchase frequency or low involvement (compared to low purchase frequency and high involvement in the present case). Therefore, it would make sense to replicate this study in different settings (i.e., other industries for consumer durable products or other geographical areas).

Another limitation is that consumer response to the RDM is solely measured as purchase incidence and spending amount and therefore does not consider the full behavioural response. It would make sense to explore further variables to measure, for instance, whether consumers decide to purchase in higher quantities, more expensive products, or completely different types of products. Additionally, it could be interesting to break down the consumer response to the RDM and explore the different response stages, like opening and keeping rates (Feld et al., 2013).

Future studies could consider further RDM characteristics like the timing (e.g., the period between last purchase and receipt of RDM) or the frequency of receiving RDMs (following a similar logic as *purchase_frequency*), as well as more nuanced content decisions (e.g., the value of premium or discount offered). This would provide retailers with even more precise and actionable guidance.

When it comes to the relationship characteristics used in this study (i.e., *purchase_frequency* and *relationship_duration*) it is not possible to make a valid conclusion about the stage of the

CLC the individual is in. It would be interesting and valuable to differentiate between active and inactive customers (i.e., customers in the process of leaving) and investigate whether they respond significantly differently to an RDM (Ascarza, 2018). This would give retailers the opportunity to react even more nuancedly, refine their strategy, and target the right customers with the right approach.

The next limitation of this study is that it does not specify the time horizon of consumer response. It is thinkable that there is a lag between receiving the RDM and positive consumer response. This means that a purchase might happen in the same but also in later periods of receiving the RDM. Therefore, it would make sense to differentiate between short- and long-term effects and explore potential differences or even contradictions. In analogy, future researchers could implement simulations to evaluate potential saturation effects (e.g., for *purchase_frequency* and *relationship_duration* or control variables like *age* in the present case or incentive value) (Vafainia et al., 2019). These insights would then allow retailers to create an even deeper level of personalization.

Looking at the underlying dataset, the next limitation is due to imbalance. The final sample covers 11,476 observations with *purchase_incidence = 1* (and thus *purchase_spending > 0*). Therefore, only 7% of observations represent the feature space of interest which makes it highly imbalanced. While it constitutes a reflection of reality, from a statistical perspective, it may lead to biased results (in favour of the overrepresented class, which would be *purchase_incidence = 0*). To counteract this problem, it would make sense to apply other types of distributions of the dependent variables when modelling a subsequent study.

A reason for this issue is that the data represents actual transaction data that was not collected with the purpose of theory testing. Therefore, all observations, such as consumer response as well as the retailers' decisions to participate in the RDM program and (when and how) to send out RDMs, are due to natural variation. To derive more valid results, randomized field experiments could allow for testing specific RDM-related manipulations and disentangle the causal effects.

Finally, considering the discussed model assumptions, exogeneity is not given. As already explained in that section (see Chapter 4.5.6. Endogeneity), further research should start with identifying potential instrumental variables, for instance, through literature research but also through interviews with the participating retailers and then incorporating them for a control function approach.

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# Appendix

## Model Estimation Results without Robust Standard Errors

### A: Model Estimation Results - Dependent Variable: *purchase_incidence*

| Variables | Model 1a | | Model 2a | | Model 3a | | Model 4a | | Model 5a | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Coef | SE | Coef | SE | Coef | SE | Coef | SE | Coef | SE |
| Intercept | 0.158*** | 0.007 | 0.163*** | 0.007 | 0.159*** | 0.006 | 0.158*** | 0.007 | 0.158*** | 0.007 |
| RDM | 0.045*** | 0.002 | 0.048*** | 0.003 | 0.036*** | 0.004 | 0.079*** | 0.003 | 0.079*** | 0.003 |
| purchase_frequency | | | -0.082*** | 0.003 | | | | | | |
| RDM * purchase_frequency | | | -0.010 | 0.007 | | | | | | |
| relationship_duration | | | | | 0.0002*** | 0.0001 | | | | |
| RDM * relationship_duration | | | | | 0.0004*** | 0.0001 | | | | |
| RDM_incentive | | | | | | | -0.082*** | 0.004 | | |
| RDM_discount | | | | | | | | | -0.082*** | 0.005 |
| RDM_premium | | | | | | | | | -0.080*** | 0.008 |
| MDM | 0.008*** | 0.002 | 0.001 | 0.002 | 0.005** | 0.002 | 0.008*** | 0.002 | 0.008*** | 0.002 |
| age | -0.001*** | 0.0001 | -0.001*** | 0.0001 | -0.001*** | 0.0001 | -0.001 | 0.0001 | -0.001*** | 0.0001 |
| gender | -0.012*** | 0.004 | -0.014*** | 0.003 | -0.012*** | 0.002 | -0.012*** | 0.004 | -0.012*** | 0.004 |
| treated | 0.014*** | 0.004 | 0.017*** | 0.003 | 0.012*** | 0.003 | 0.014*** | 0.004 | 0.014*** | 0.004 |
| 2012 | -0.017*** | 0.004 | -0.006 | 0.004 | -0.018*** | 0.004 | -0.017*** | 0.004 | -0.017*** | 0.004 |
| 2013 | -0.023*** | 0.004 | -0.010** | 0.004 | -0.025*** | 0.004 | -0.023*** | 0.004 | -0.023*** | 0.004 |
| 2014 | -0.027*** | 0.004 | -0.014*** | 0.004 | -0.030*** | 0.004 | -0.027*** | 0.004 | -0.027*** | 0.004 |
| 2015 | -0.031*** | 0.004 | -0.018*** | 0.004 | -0.035*** | 0.004 | -0.031*** | 0.004 | -0.031*** | 0.004 |
| 2016 | -0.027*** | 0.004 | -0.014*** | 0.004 | -0.031*** | 0.004 | -0.027*** | 0.004 | -0.027*** | 0.004 |
| 2017 | -0.040*** | 0.004 | -0.025*** | 0.004 | -0.044*** | 0.005 | -0.040*** | 0.004 | -0.040*** | 0.004 |
| 2018 | -0.050*** | 0.004 | -0.038*** | 0.004 | -0.056*** | 0.005 | -0.050*** | 0.004 | -0.050*** | 0.004 |
| quarter2 | -0.002 | 0.002 | -0.001 | 0.002 | -0.002 | 0.002 | -0.002 | 0.002 | -0.002 | 0.002 |
| quarter3 | -0.006*** | 0.002 | -0.006*** | 0.002 | -0.007*** | 0.002 | -0.006*** | 0.002 | -0.006*** | 0.002 |
| quarter4 | -0.004*** | 0.002 | -0.004* | 0.002 | -0.005*** | 0.002 | -0.004 | 0.002 | -0.004 | 0.002 |

*p<0.1 (two-sided)
**p<0.05 (two-sided)
***p<0.01 (two-sided)

### B: Model Estimation Results – Dependent Variable: *purchase_spending*

| Variables | Model 1b | | Model 2b | | Model 3b | | Model 4b | | Model 5b | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Coef | SE | Coef | SE | Coef | SE | Coef | SE | Coef | SE |
| Intercept | 18.422*** | 3.942 | 20.145*** | 3.942 | 18.264*** | 4.997 | 18.480*** | 3.934 | 18.479*** | 3.934 |
| RDM | 32.087*** | 1.901 | 36.529*** | 2.141 | 24.471*** | 2.894 | 59.277*** | 2.378 | 59.278*** | 2.378 |
| purchase_frequency | | | -22.983*** | 1.879 | | | | | | |
| RDM * purchase_frequency | | | -22.914*** | 5.746 | | | | | | |
| relationship_duration | | | | | 0.010 | 0.057 | | | | |
| RDM * relationship_duration | | | | | 0.307*** | 0.075 | | | | |
| RDM_incentive | | | | | | | -65.359*** | 3.442 | | |
| RDM_discount | | | | | | | | | -65.669*** | 3.686 |
| RDM_premium | | | | | | | | | -64.128*** | 6.259 |
| MDM | 11.081*** | 1.663 | 8.507*** | 1.672 | 14.261*** | 1.670 | 10.842*** | 1.661 | 10.833*** | 1.662 |
| age | 0.330*** | 0.036 | 0.287*** | 0.036 | 0.322*** | 0.065 | 0.330*** | 0.036 | 0.330*** | 0.036 |
| gender | -4.790*** | 1.239 | -5.369*** | 1.241 | -4.732** | 2.220 | -4.783*** | 1.234 | -4.784*** | 1.234 |
| treated | 5.285*** | 1.270 | 6.214*** | 1.273 | 4.885** | 2.277 | 5.139*** | 1.265 | 5.139*** | 1.265 |
| 2012 | -4.504 | 3.470 | -1.308 | 3.477 | -4.280 | 3.438 | -4.277 | 3.466 | -4.276 | 3.466 |
| 2013 | -4.867 | 3.437 | 1-353 | 3.447 | -4.267 | 3.427 | -5.070 | 3.434 | -5.072 | 3.434 |
| 2014 | -5.749* | 3.408 | -2.205 | 3.417 | -5.165 | 3.431 | -5.455 | 3.405 | -5.458 | 3.405 |
| 2015 | -6.176* | 3.391 | -2.605 | 3.400 | -5.650 | 3.458 | -6.131* | 3.387 | -6.129* | 3.387 |
| 2016 | -0.152 | 3.372 | 3.347 | 3.381 | 0.126 | 3.495 | -0.159 | 3.369 | -0.156 | 3.369 |
| 2017 | -8.150** | 3.372 | -4.116 | 3.384 | -8.373*** | 3.106 | -8.185** | 3.369 | -8.179** | 3.369 |
| 2018 | -12.352*** | 3.375 | -8.929*** | 3.383 | -12.797*** | 3.648 | -12.133*** | 3.372 | -12.133*** | 3.372 |
| quarter2 | -1.332 | 1.317 | -1.202 | 1.316 | -1.338 | 1.303 | -1.588 | 1.316 | -1.587 | 1.316 |
| quarter3 | -1.923 | 1.318 | -2.022 | 1.317 | -1.676 | 1.308 | -2.174* | 1.316 | -2.175* | 1.316 |
| quarter4 | 3.089** | 1.324 | 3.557*** | 1.324 | 2.633** | 1.320 | 3.078** | 1.323 | 3.080** | 1.323 |

*p<0.1 (two-sided)
**p<0.05 (two-sided)
***p<0.01 (two-sided)