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Calling Customers to Take Action: The Impact of Incentive and Customer Characteristics on Direct Mailing Effectiveness

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Abstract

This study investigates the effect of call-to-action (CTA) direct mailings (DMs) on customers' purchase behavior and how this effect is moderated by incentive type as well as customer characteristics. The authors analyze individual purchase behavior of a panel of 179,525 customers across 40 Dutch optical retailers over 9 years. The empirical results show that CTA DMs that include an incentive have a higher positive impact on customer's purchase probability compared with those without an incentive. Furthermore, non-monetary incentives, especially utilitarian ones, have a higher positive impact than monetary incentives. Our results also show that customer heterogeneity plays an important role in the influence of CTA DMs on purchase incidence. More specifically, CTA DMs have a higher impact on purchase incidence for customers with higher past purchase frequency, lower purchase recency, longer relationship duration and for customers who received DM more recently and frequently. The results of the study provide valuable insights for managers allocating their direct marketing budget: it is better to use non-monetary (preferably utilitarian) incentives and to target customers based on relationship history as well as DM history.

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Keywords: Call-to-action direct mailings; Monetary incentives; Non-monetary incentives; Customer heterogeneity; Retailing; Purchase incidence

Introduction

For decades, direct mailing has been the workhorse of direct marketing. Direct mailing is one of the most popular marketing communication channels, accounting for 19% of all direct marketing expenditures in the US, standing higher than any other direct marketing channel (Direct Marketing Association 2015). A large portion of these mailings are call-to-action direct mailings (hereafter abbreviated as CTA DMs), that aim to directly influence customer buying behavior, e.g., visit a store or make a purchase, oftentimes by providing some kind of incentive (Prins and Verhoef 2007; Rust and Verhoef 2005; Verhoef 2003). In today's marketplace, retailers frequently communicate via such CTA DMs, while customer's response rate is quite low, approximately 5% on average for such DMs (Direct Marketing Association 2017). Hence, it is crucial for the

retailers to understand how to effectively influence a customer's purchasing decision via DM communications.

CTA DMs can be divided based on the type of incentive. DMs can use either monetary or non-monetary incentives. While monetary incentives are typically price discounts, the most frequently used type of non-monetary incentives are premiums; a product or service for free or at a relatively low price (D'Astous and Jacob 2002; Palazon and Delgado-Ballester 2013). Among the non-monetary incentives, a distinction can be made between DMs including a hedonic versus a utilitarian premium. According to Palazon and Delgado-Ballester (Palazon and Delgado-Ballester 2013), hedonic incentives may provide more experiential consumption, fun, enjoyment, pleasure and excitement, whereas utilitarian premiums are primarily instrumental and functional. Sometimes retailers invite customers via CTA DMs to visit the store and trigger them to make a purchase, without explicitly rewarding customers for taking this action. The sales promotion literature has shown that different promotional incentives have

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different mechanisms to influence customers' buying behavior (Foubert et al. 2017; Palazon and Delgado-Ballester 2009). While there is some research done in a sales promotion context, at this moment it is largely unknown whether and how these DM incentives have a differential effect on the probability of customers responding to the CTA DM.

Previous studies have demonstrated that customer's response to direct marketing is highly heterogenous and have called for further research on the moderating effects of customer and relationship characteristics (Gázquez-Abad et al. 2011; Rust and Verhoef 2005). More specifically, retailers can differentiate their DM communications based on customer differences in relationship history (such as recency, frequency and monetary value (RFM) measures), communication history (how recently and frequently customers have received DMs) and socio-demographics (age and gender) (Neslin et al. 2013; Rust and Verhoef 2005). While past research has investigated some of these customer characteristics (e.g., Gázquez-Abad et al. 2011; Rust and Verhoef 2005), we are the first to investigate an extensive set of customer characteristics on the impact of CTA DMs on customer purchase behavior and thereby provide additional insights on the moderating role of these characteristics.

In summary, we investigate (1) the differential impact of various CTA DM incentives on purchase incidence; and (2) whether and how the influence of a CTA DM on purchase incidence is moderated by a customer's relationship history, DM history and socio-demographic characteristics. Table 1 shows most relevant previous studies and highlights the contribution of this paper relative to the existing literature. Our findings shed more light on the conditions under which CTA DM's effectiveness can be enhanced and, hence, will be

useful for managers in shaping their direct marketing strategy. As the Table 1 illustrates, we have a unique stance in the literature, as we are the first to investigate the impact of the incentive type as well as a large set of consumer characteristics, in the context of CTA DMs.

In pursuit of our research objectives, we shaped a conceptual framework (Fig. 1) that includes: (i) CTA DM as the main antecedent, (ii) type of incentive (no incentive, monetary, non-monetary hedonic, non-monetary utilitarian), and (iii) relationship history, DM history and socio-demographic characteristics as potential moderating variables. We use a probit model in which we control for the endogeneity of DMs, following (Van Diepen, Donkers, and Frances 2009). We use a purchase and DM database of a panel of 179,525 customers across 40 optical retailers in the Netherlands from 2008 to 2016 in order to answer the research questions.

We organize the remainder of this article as follows. We begin with a discussion of our conceptual framework and hypotheses. Subsequently, we discuss our data and model. Then, we present the empirical results pertaining to the impact of CTA DM on purchase incidence and several moderators. We conclude with a discussion of the findings, implications, and limitations.

Conceptual Framework and Hypotheses

Main Effect of CTA DMs

CTA DMs focus mainly on directly influencing customer's buying behavior, for instance by providing an incentive (*call*) that triggers customer responses (*action*) (Prins and Verhoef

Table 1
Literature overview.

Paper	Context	Focal construct/objective	Outcome measure	Endogeneity correction	Moderators			
					Incentive type	Relationship history	DM history	Socio-demos
Thomas, Feng, and Krishnan (2015)	Non-profit	Impact of CTA DM	Donation incidence	Y	N	N	N	N
Feld et al. (2013)	Financial service and non-profit	Impact of CTA DM design characteristics	Opening and keeping rate	N	N	N	N	N
Gázquez-Abad et al. (2011)	Retailing	Impact of CTA vs. relational DM	Purchase incidence, amount, number of visits and products purchased	N	N	[Y] ^a	[Y]	N
Van Diepen, Donkers, and Frances (2009)	Non-profit	Impact of own and competitive CTA DM	Donation incidence	Y	N	[Y]	N	N
Donkers et al. (2006)	Non-profit	Optimization of CTA DMs	Donation incidence and amount	Y	N	N	N	N
Gönül and Ter Hofstede Hofstede (2006)	DM service company	Impact of frequency and timing of CTA DM	Donation incidence and amount	N	N	N	N	N
Rust and Verhoef (2005)	Financial service	Optimization of marketing interventions including DMs	Profit	N	N	Y	N	Y
Verhoef (2003)	Financial service	Impact of CTA DM vs. mass communication	Change in customer share	N	N	N	N	N
Bawa and Shoemaker (1987)	Retailing	Impact of CTA DM	Brand choice probability	N	N	N	N	N
Our study	Retailing	Impact of CTA DM	Purchase incidence	Y	Y	Y	Y	Y

^a We indicate in brackets when a characteristic was included as a main effect in the paper, yet was not investigated as a moderator of DM effectiveness.

2007; Rust and Verhoef 2005) or, in cases where such incentives are not included, by providing customers a (textual) trigger (*call*) to respond (*act*) now. The focal aim of such DMs is to encourage customers to react within a short period of time, by including a specific ‘call to action’ that stimulates them, for instance, to visit the store and make a purchase.

According to reciprocal action theory, direct marketing communications positively influence repurchase, because firm investments in customer relationships result in psychological bonding, as customers perceive a greater resource investment by the firm. Consequently, customers feel obliged to return “good for good” by making a purchase (Bagozzi 1995; De Wulf and Odekerken-Schröder 2003; Godfrey, Seiders, and Voss (2011)). Moreover, information directed toward customers to reduce the effort required as well as the uncertainty surrounding a decision increases the confidence associated with the decision and is viewed positively by customers (Fitzsimons and Lehmann 2004). Previous studies have confirmed this positive CTA DM effect on a variety of behavioral measures (e.g., purchase incidence, frequency and amount, (Gázquez-Abad et al. 2011); customer retention, (Rust and Verhoef 2005); customer retention and lifetime value, Risselada, Verhoef, and Bijmolt (2014).

On the other hand, CTA DM may also work negatively, following reactance theory (Brehm 1966) that posits that customers may resist marketing efforts perceived as an effort to manipulate them, exercise control over their purchasing, or limit their freedom of choice (Godfrey, Seiders, and Voss (2011)). A CTA DM may be seen in such a way and may therefore diminish or, at extremes, backlash on customer purchase behavior (Fitzsimons and Lehmann 2004; Godfrey, Seiders, and Voss (2011)). Several studies have reported a negative effect of unsolicited marketing communications (Fitzsimons and Lehmann 2004; Gázquez-Abad et al. 2011; Simonson, Carmon, and Curry (1994)). Given the prevalence of arguments in both directions, the following hypothesis is proposed:

H₁ : A CTA DM has a (a) positive, or (b) negative effect on purchase incidence.

Moderators

In the first subsection below, we focus on the difference in effectiveness between a DM with vs. without an incentive. Next, we differentiate between monetary and non-monetary incentives, then split the latter in hedonic vs. utilitarian. In the second subsection, we discuss the moderating impact of customer characteristics (relationship history, DM history and socio-demographics).

The Moderating Role of CTA DM Incentive

CTA DM with vs. without an incentive. Building on reactance theory, unsolicited CTA DMs with incentive may be perceived by customers as an attempt to manipulate their choices and therefore, may lead to reactance, where customers try to “punish” the offending marketers Simonson, Carmon, and Curry (1994). Conversely and relying on reciprocal action theory, CTA DMs that use an incentive can also be conceived by customers as an extra effort and resource investment. As a result, customers may have a higher likelihood to reciprocate the retailer’s action by making a purchase. Empirical research has found some support for the latter: (Bawa and Shoemaker 1987) found that marketing communications that provide customer with an incentive lead to higher customer shares and additional sales (Bawa and Shoemaker 1987). In a similar vein, (Arora and Stoner 1992) also found that response rates are higher for DMs with an incentive compared to those without. Finally, the customer may value the incentive itself, which also suggests a larger effect of the CTA DM with an incentive. Still, as we cannot rule out the reactance effect a priori, we formulate opposing hypotheses:

Fig. 1. Conceptual Framework.

H₂. : A CTA DM with an incentive has a (a) lower, or (b) higher impact on purchase incidence compared to ones without an incentive.

CTA DM with monetary vs. non-monetary incentive. The incentives of CTA DMs can be framed as monetary, where customers receive a price reduction or percentage off, or non-monetary, where customers receive a gift when making a purchase of a specific product in the store. This difference between incentive types has been shown to require different levels of information processing (Nunes and Park 2003). According to (Sinha and Smith 2000), customers perceive monetary incentives as a reduced loss because they are in the same metric as the product prices. Non-monetary incentives are perceived as separate gains due to their incommensurate nature (Nunes and Park 2003). According to Diamond and Sanyal (Diamond and Sanyal 1990), a loss reduction tends to have a relatively small impact, which causes customers to prefer promotions that are framed as gains, leading to non-monetary incentives outperforming monetary ones. On the contrary, many studies stated that a non-monetary incentive might not be as effective as a monetary incentive (Foubert et al. 2017). First, a non-monetary incentive is more likely to be perceived as a marketing gimmick to boost sales (Simonson, Carmon, and Curry (1994). Customers may attribute this to the brand's low quality and the fear of disappointing sales (Blattberg and Neslin 1990). As a result, customers may feel manipulated and may therefore refuse to act in accordance with the suggested behavior (Brehm 1966). Second, Thaler (Thaler 1985) argues that monetary incentives enable customers to hedge against uncertainty about future needs and product performance. Money saved from a discount is completely fungible and can be allocated flexibly, while the benefits of non-monetary rewards are fixed (Heilman, Nakamoto, and Rao (2002); Leclerc 1997). Finally, non-monetary rewards can be seen as a form of indulgence and the purchase may therefore be hard to justify. When taking advantage of monetary rewards, customers are perceived as smart shoppers (Gedenk, Neslin, and Ailawadi (2010); Simonson, Carmon, and Curry (1994). As we have arguments for both sides, we pose the following hypotheses:

H₃. : A CTA DM with a non-monetary incentive has a (a) higher, or (b) lower impact on purchase incidence compared to a monetary CTA DM.

CTA DM with a hedonic vs. utilitarian non-monetary incentive. Research has shown there is a fundamental difference between goals that hedonic and utilitarian non-monetary incentives pursue (e.g., (Chitturi, Raghunathan, and Mahajan (2007); Palazon and Delgado-Ballester 2013)). While hedonic incentives tend to provide more experiential consumption, fun, enjoyment, pleasure and excitement, they are also more difficult to be justified because hedonic consumption can arouse guilty feelings (Palazon and Delgado-Ballester 2013). On the other hand, building on justification-based theory developed by (Okada 2005), customers may prefer hedonic

premiums when they would see the CTA DM as a promotional offer, because the justification of choice is easier in a promotional context. In such a context, the sense of guilt is mitigated as the benefit is offered for free (Palazon and Delgado-Ballester 2013). Hence, we propose that:

H₄. : A CTA DM with a hedonic non-monetary incentive has a (a) lower, or (b) higher impact on purchase incidence compared to a CTA DM with a utilitarian non-monetary incentive.

The Moderating Role of Relationship History, DM History and Socio-Demographics

Following the direct marketing and CRM literature (e.g., (Reinartz and Kumar 2003; Rust and Verhoef 2005; Verhoef 2003)), we focus on three types of customer characteristics that may moderate the impact of CTA DMs on purchase behavior: (i) characteristics that relate to the relationship and prior behavior of customers exposed in the company (relationship duration, purchase frequency, and recency of purchase); (ii) characteristics that relate to the retailer's prior DM communication with customers (DM recency and frequency) and (iii) socio-demographics (age and gender). We will discuss each of these variables below.

Impact of purchase frequency. Customer behavior models rooted in learning theories suggest that customers, in general, like to simplify their decisions by reducing the complexity of the decision-making situation (Jayachandran et al. 2005; Sheth and Parvatiyar 1995). Customers who purchase more frequently, or so-called heavy users, have gained more experiences that they can store, process, and retrieve to use in subsequent purchase decision situations. They also tend to have developed an ability to more easily distinguish among stimuli they may receive (Sheth and Parvatiyar 1995). Thus, heavy users have higher capabilities in terms of understanding and engaging with firm contacts compared to less experienced users. Relationship marketing literature has also demonstrated that customers with higher purchase frequency are more likely to respond in a positive way to a DM (Fader and Hardie 2007; Liu 2007). Therefore, we propose:

H₅. : The impact of a CTA DM on purchase incidence is higher for customers with higher purchase frequency.

Impact of purchase recency. If a customer has not purchased for a long time, then it is likely that s/he has stopped being a customer. For these customers, a CTA DM may be perceived as a persuasion attempt by the retailer to influence their purchasing decisions and the reactance response for this group of customers may grow stronger (Fitzsimons and Lehmann 2004). There is some empirical evidence that indicates that customers with higher recency (longer time since last purchase) are indeed less likely to respond to marketing efforts (e.g., Bult et al. 1997; Neslin et al. 2013; Van Diepen, Donkers, and Franses (2009)). Thus, we propose the following:

H₆. : The impact of a CTA DM on purchase incidence is lower for customers with a longer time since last purchase.

Impact of relationship duration. Customers in the early phases of a relationship do not yet have much experience with the company. As the duration of the relationship increases, the level of intimacy also increases, leading to an increased richness of the customer's impressions about the firm (Swann and Gill 1997; Verhoef, Franses, and Hoekstra (2002)). Therefore, a customer with higher relationship duration has a better evaluation of a new received DM and might engage more with it. Empirical findings in the relationship marketing literature support this reasoning Verhoef, Franses, and Hoekstra (2002). Hence, we hypothesize that:

H₇. : The impact of a CTA DM on purchase incidence is higher for customers with a longer relationship duration with the retailer.

Impact of DM frequency. Communication frequency has an important impact on a customer's reaction to future contacts (Drèze and Bonfrer 2008; Neslin et al. 2013). Receiving many DM communications may trigger reactance against the repeated message (Campbell and Keller 2003). In extremes cases, customers with high levels of DM frequency in the past may develop negative attitudes and defensive strategies with regard to yet another DM from that company as a result of irritation (Ansari, Mela, and Neslin 2008). Conversely, information in memory decays and fades away more slowly, when customers are confronted with a message again and again (Sheth and Parvatlyar 1995). Consequently, for the customers who frequently receive communications, information processing is simplified through repetition of a (similar) message. Given the prevalence of arguments in favor of both sides, we hypothesize:

H₈. : The impact of a CTA DM on purchase incidence is (a) lower, or (b) higher for customers with a higher DM frequency.

Impact of DM recency. Not only does prior communication frequency impacts customers' reactions to a new DM, also the recency of the previous communication has been shown to play an important moderating role (Drèze and Bonfrer 2008; Neslin et al. 2013). The moderating impact of DM recency on the effect of CTA DMs on purchase incidence can also be predicted by saturation and information overload mechanisms on the one hand, and the role of memory and repetition of the message on the other hand. According to Van Diepen, Donkers, and Franses (2009), after receiving CTA DMs in short time intervals, additional DMs send to customers will be ignored because of DM clutter (Van Diepen, Donkers, and Franses 2009). However, relying on the advertising literature, receiving messages with shorter intervals may enhance the impact of the message on the memory (Sheth and Parvatlyar 1995), resulting, in our case, in increased effects of a CTA DM for customers who have received other DMs more recently. Hence we have a two-sided hypothesis:

H₉. : The impact of a CTA DM on purchase incidence is (a) higher, or (b) lower for customers with a longer time since they received the last CTA DM.

Impact of socio-demographics. Research comparing young and older customers has concentrated on differences in the information-processing abilities needed to evaluate a product (Smith and Baltes 1990). Most previous studies conclude that information processing declines with age (Gilly and Zeithaml 1985). Older people have lower information-processing capabilities; and therefore, their reactions to marketing communications might also decline. Yet, reactance theory indicates that young people possess higher reactance than older people, mainly because older people are more prepared to manage several dimensions of reactance (Brehm 1966). Hence, younger customers may exhibit a negative attitude toward a received CTA DM because they perceive it as an attempt of retailers to limit their freedom of choice. The research by (Simpson and Mortimore 2015) shows that as age increases, favorable perceptions for DM increase and (Barnes and Peters 1982) revealed that the elderly tend to have more positive attitudes toward DMs. Hence:

H₁₀. : The impact of a CTA DM on purchase incidence is (a) higher, or (b) lower for younger customers.

Similar to age, gender often appears as a moderator variable in marketing studies (Saad and Gill 2000). Drèze and Bonfrer (Drèze and Bonfrer 2008) argue that a more positive attitude for females may be due to higher female involvement in the purchase process. Therefore, we predict:

H₁₁. : The impact of a CTA DM on purchase incidence is lower for males than for females.

Methodology

Empirical Setting and Data

To test our hypotheses, we examine customer purchase behavior of a large group of 40 optical retailers in the Netherlands. These optical retailers are independent and do not belong to large chains. There is also no overlap in their trading area, so customers in our dataset are uniquely linked to one retailer. A marketing consultancy firm coordinates the customer databases for these retailers and provided us the data for this project. Given the high involvement and low purchase frequency of consumer durable products such as optical product categories (Mittal 1989), the main objective of the DMs is to help retailers to attract the attention of existing customers with their offers and trigger them to make a purchase. The usage of CTA DMs to influence purchase behavior of existing customers is wide-spread, and extends well beyond the setting of optical retailing (see Table 1 for an overview of other retail sectors where CTA DMs are widely used). We obtained a unique dataset with information on purchase as well as DM history (for instance, timing and details of the CTA DMs sent by the retailers) of all customers for these 40 optical retailers across nine years (2008–2016).

For our analyses, we use all customers who (1) made at least two purchases within the observation period (to rule out "trial" customers that make just one single purchase in nine years), (2) received at least one CTA DM (to make sure we focus on customers that pass the selection criteria of receiving such a CTA

DM), and (3) are 18+ (to exclude children) and have valid information on age, gender and registration date (to make sure we can operationalize the independent variables). We believe that our sample selection criteria are very lenient and reasonable, because we use an observation window of 9 years, and the focus of this paper is on the impact of CTA DMs and the moderation effect of incentive types and customer characteristics. These constraints leave us with 179,525 customers across the 40 retailers. The smallest retailer has 906 customers, while the largest one has 12,915 customers. CTA DMs have been sent to customers on a quarterly basis and each retailer sends CTA DMs to the customers registered in their database (the marketing consultancy firm helps them with doing this, so that we can be confident that CTA DMs are designed and sent in an identical way). On average, customers receive 3.6 CTA DMs across these nine years, while they make 4.08 purchases during this period.

Measures

Dependent Variable

The outcome variable in our research is customer purchase incidence in each quarter during the estimation period (2009–2016), equal to one if the customer i makes a purchase in quarter t . The reason for choosing quarter as our time unit is that customers at optical retailers do not purchase glasses or lenses every day or even every month; unlike other industries such as fast-moving consumer goods, where customers make purchases on a daily or weekly basis. Our data support this claim since the median inter-purchase time is 192 days. Furthermore, retailers in our dataset send DMs on a quarterly basis as a common practice.

The estimation window for a customer starts the first quarter of 2009 if a customer was client before 2008 or one year after the customer registers (typically purchases) for the first time if the customer was a new customer/registered during the observation period. The first year (Q1–Q4 2008 for those that registered before; and the first year for new customers) is used as initialization period for the independent variables. The reason that we start modeling a customer's behavior after his/her first purchase is that retailers start sending DMs after a customer enters their database. The estimation window for each customer ends at the last quarter of our observation period (Q4 2016).

Independent Variables

The variable operationalization is described in detail in Table 2. We use dummy variables to indicate whether a customer has received a CTA DM in a quarter. We removed 109 (0.0005%) customers who received more than one CTA DM in a quarter, because this pattern is not in line with the company's policy of not sending customers multiple DMs per quarter. If there was a CTA DM, we categorized which type of incentive was included. These incentives were split into non-monetary incentives, monetary incentives, and CTA DMs without incentive based on their content. DMs that are inviting customers to visit the store and/or make a purchase, without indicating any reward after taking this (visit/purchase) action are labeled as CTA DMs without incentive. A CTA DM that provides a customer with a monetary reward, like a price

discount or a buy one get a second for free offer, was identified as a monetary incentive. A CTA DM that rewards a customer's purchase with a gift was classified as a non-monetary incentive. A further distinction was made between a hedonic and utilitarian non-monetary incentive, building on (Palazon and Delgado-Ballester 2013). For instance, a gift such as a piece of artwork was labeled as hedonic, while a sun tan crème that offers a very functional benefit was classified as utilitarian.

The incentive characteristics for each of the CTA DMs were coded independently by two coders based on the original visual provided by the data provider. Cross-checks between the two coders showed high inter-rater reliability for all of the data accumulated (see for a similar approach, (Feld et al. 2013)). Intensity of CTA DMs varies across the quarters in a sense that retailers send more DMs in quarter 2 (April–June) and 4 (October–December) than in quarter 1 and 3. CTA DMs mainly stimulate existing customers to purchase, for instance, new glasses and therefore are focused on cross-selling; an objective that does not vary across incentive types. Monetary incentives appear either as a percentage discount on the purchase of a new pair of glasses or as the offer to receive a second pair of glasses for free. Non-monetary incentives, on the other hand, include a reward such as a free collection item, an artwork or a free sun cream. Across all CTA DMs sent to customers, the average value of monetary incentives is 15 euro and of non-monetary incentives is 34.6 euro. We control for these value differences in the analysis (see Section **Control variables**). Of the total CTA DM campaigns between 2008 to 2016 in our study, 60% included an incentive, and about one-third of these ones are with a monetary incentive and two-thirds are with a non-monetary incentive. The latter is further divided in 33.4% of CTA DMs with an utilitarian incentive and 66.6% with a hedonic incentive. Taking into account the number of DMs sent to customers between 2008 and 2016 per incentive type, customers received in 31.52% of the cases a CTA DM with no incentive, in 30.46% of the cases a CTA DM with a monetary incentive and in 38.48% of the cases a CTA DM with a non-monetary incentives, split between 46.2% and 53.8% for, respectively, utilitarian and hedonic incentives.

Next, we operationalize relationship history measures. For purchase frequency, we use the customer's last year (past four quarters) to calculate this variable (similar in spirit to (Van Diepen et al. 2009)). We discount the purchase incidence in each quarter by weighting with a decay parameter (0.75) for each quarter and then summing them up to capture fading. Purchase recency is defined as the number of quarters without a purchase immediately preceding the current period. Therefore, a higher recency means longer duration since the previous purchase. Customer relationship duration is measured as the number of quarters since a customer has been registered in the retailer's database. We use a similar operationalization to calculate past DM communications: DM frequency is calculated by summing the occurrence of CTA DMs in each of the past four quarters, and discounting them with a decay parameter (0.75) for each quarter. DM recency is the number of quarters with no DM received (similar to (Van Diepen, Donkers, and Franses 2009)).

Table 2
Variable Operationalization.

Variables	Operationalization	Equation
CTA_DM	Dummy variable that indicates whether a customer i has received a CTA DM in quarter t .	
Relational_DM	Dummy variable that indicates whether a customer i has received a relational DM in quarter t .	
Store_DM	Dummy variable that indicates whether a customer i has received a store-specific DM in quarter t .	
Relationship history		
Purchase_frequency	Sum of purchase incidence of customer i in each quarter weighted with a decay parameter (0.75) for each quarter going back up to four quarters in the past ($t-4$, $t-3$, $t-2$, $t-1$).	$\sum_{t=t_q-4}^{t=t_q-1} \delta^{t_q-t} * Incidence_{it}$, where t_q is the calendar time of the current quarter and $\delta = .75$
Purchase_recency	Number of quarters with no purchase of customer i going back up to the start of that customer's observation window (Q1 of 2008 for those customers that were already in the dataset before the observation window, or the first quarter that a new customer registers (typically purchases) for the first time).	$t_q - t_{ip}$, where t_{ip} is the last calendar time where customer i made a purchase (or in the case of no purchase, the start of the observation window) and t_q is the calendar time of the current quarter
Relationship_duration	Number of quarters since the first purchase/registration of customer i in the retailer's database.	$t_q - t_{ir}$, where t_{ir} is the calendar time where customer i registered for the first time and t_q is the calendar time of the current quarter
DM history		
DM_frequency	Sum of the CTA DM dummies of customer i in the past four quarters ($t-4$, $t-3$, $t-2$, $t-1$), discounted with a decay parameter (0.75).	$\sum_{t=t_q-4}^{t=t_q-1} \delta^{t_q-t} * CTADM_{it}$ where t_q is the calendar time of the current quarter and $\delta = .75$
DM_recency	Number of quarters with no CTA DM for customer i going back up to the start of that customer's observation window.	$t_q - t_{i,cta_dm}$, where t_{i,cta_dm} is the last calendar time where customer i received a CTA DM (or in the case no CTA DM was received, the start of the observation window) and t_q is the calendar time of the current quarter
Socio-demographics		
Age	Age of customer i measured in years.	
Gender	Indicator variable for customer i 's gender (male = 1).	
Control variables		
Value_Incentive	Market value of the incentive (in €) at the time that the incentive was send to customers.	
Relational_DM_frequency	Sum of relational DM dummies of customer i in the past four quarters ($t-4$, $t-3$, $t-2$, $t-1$), discounted with a decay parameter (0.75).	$\sum_{t=t_q-4}^{t=t_q-1} \delta^{t_q-t} * RelationalDM_{it}$ where t_q is the calendar time of the current quarter and $\delta = .75$
Store_DM_frequency	Sum of store-specific DM dummies of customer i in the past four quarters ($t-4$, $t-3$, $t-2$, $t-1$), discounted with a decay parameter (0.75).	$\sum_{t=t_q-4}^{t=t_q-1} \delta^{t_q-t} * StoreDM_{it}$ where t_q is the calendar time current quarter and $\delta = .75$
Relational_DM_recency	Number of quarters with no relational DM for customer i going back up to the start of that customer's observation window.	$t_q - t_{i,rel_dm}$, where t_{i,rel_dm} is the last calendar time where customer i received a relational DM (or in the case no relational DM was received, the start of the observation window) and t_q is the calendar time of the current quarter
Store_DM_recency	Number of quarters with no store-specific DM for customer i going back up to the start of that customer's observation window.	$t_q - t_{i,store_dm}$, where $t_{i,store_dm}$ is the last calendar time where customer i received a store-specific DM (or in the case no store-specific DM was received, the start of the observation window) and t_q is the calendar time of the current quarter
Lag_CTA_DM	The lagged value of the CTA_DM of the previous quarter (t-1).	
Lag_Relational_DM	The lagged value of the Relational_DM of the previous quarter (t-1).	
Lag_Store_DM	The lagged value of the Store_DM of the previous quarter (t-1).	
AVG CTA_DM	Average number of CTA DMs that customer i has received up until quarter t , going back up to the start of that customer's observation window.	$\frac{\sum_{t=t_i}^{t=t_q} CTADM_{it}}{(t_q - t_i + 1)}$, where t_q is the calendar time of the current quarter, t_i is the start of customer i 's observation window
GDP_GrowthRate	Percentage of GDP increase at quarterly level, compared to the same quarter in the previous year.	
Instrumental variables		
Attractiveness of DM across all customers	Number of customers who received a CTA DM in quarter t across all 39 competitive retailers, divided by the total number of customers in that quarter across these 39 competitive retailers. (idem for relational DM)	$\frac{\sum_{j=1}^{j=39} \sum_{i=1}^{i=nj t_q} CTADM_{ijt_q}}{\sum_{j=1}^{j=39} nj t_q}$, where i goes from 1 to $nj t_q$ (the number of active customers at retailer j in quarter q), and j captures the 39 competitive retailers
Attractiveness of DM across the customers of a retailer	Number of customers other than customer i that are receiving a CTA DM at retailer j in quarter t , divided by the total number of customers of retailer j in quarter t minus one. (idem for relational DM)	$\frac{\sum_{i=1}^{i=nj t_q-1} CTADM_{ijt_q}}{nj t_q - 1}$, where i goes from 1 to $nj t_q$ (the number of active customers at retailer j in quarter q)

Table 3
Descriptive statistics of variables^a.

	Variable	Mean	SD	Min.	Max.
DM	CTA DM	0.12	0.32	0	1
	Relational DM	0.20	0.40	0	1
	Store DM	0.07	0.26	0	1
Relationship history	Purchase frequency	0.18	0.35	0	2.05
	Purchase recency	8.60	7.35	1	36
	Relationship duration	14.51	8.78	1	32
DM history	DM frequency	0.23	0.331	0	1.73
	DM recency	8.31	7.7	1	36
Socio-demographics	Age	58	16	18	90
	Gender (male = 1)	0.44	0.5	0	1
Control variables	Value of incentive (in €)	2.22	12.22	0.057	100
	Relational DM frequency	0.43	0.49	0	2.05
	Store DM frequency	0.14	0.28	0	2.05
	Relational DM recency	7.54	8.02	1	36
	Store DM recency	11.37	8.04	1	36
	Average CTA DM per customer	0.12	0.081	0	0.66
	GDP growth rate per quarter (percentage)	0.23	0.67	−3.5	1.14

^a Note that these descriptives are for the variables as they are operationalized in Table 2. That is, we use carryover measures (with decay parameters) for the purchase frequency and the DM frequency measures, and include the zero observations when calculating the market value of the incentive. Recency and relationship duration are expressed in quarters.

Control Variables

We control for the effects of several other variables in our study. First, we add the market value (monetary value, expressed in €) of the incentives that were offered in the CTA DMs at the time they were offered to a customer. We do this to make sure that our results are not affected by differences in monetary value of the incentives included in CTA DM. Second, we control for other DMs sent to customers as well as their recency and carryover effects. Retailers may send some other DM to customers with a very different objective from CTA DMs that are the focus of this study. One type is store-level DMs, informing customers about shop-specific news (for instance, construction works, remodeling at the store, etc.). Another type includes DMs that are sent to customers after making a purchase. These DMs are not CTA mailings and their explicit purpose is to reinforce the relationship with the customers (Verhoef 2003). Since the objective of these two types of DMs is merely fostering the relationship with the customer or inform them about store-specific news, without inviting any specific action such as making a purchase, they are not the focus of this research. Third, we include the lagged effect of all three DM types (CTA DM, relational DM, and store-level DM), to capture the delay in response of customers to a DM received in the last quarter. Fourth, we include the average number of CTA DMs that each customer has received in order to control for cross-sectional correlation of the DMs with the random intercept, following Datta, Foubert, and van Heerde (2015). Fifth, we include the GDP growth rate as a proxy for the state of the economy in our model, to control for any effect it might have on purchase incidence. Finally, we control for (unobserved) differences between quarters, years and retailers by including quarter, year and store dummies.

Table 3 presents descriptive statistics for the variables. The DM history measures for CTA DMs point to a low level of carryover (average DM frequency of 0.23) and a long time of not

receiving CTA DMs (about 8.31 quarters). The average purchase frequency (as operationalized in Table 2, that is, with the summed and decay-weighted logarithm) equals 0.18, with a substantial variation (SD = 0.35). Furthermore, customers do not buy during 8.6 quarters (about 2 years), again with quite some variation (SD = 7.05), and the average relationship length is 14.51 quarters (about 3.5 years). 44% of our sample are males and the average age of customers is 58 years. Average GDP growth rate is 0.23%, with variations between −3.5% and 1.14% and the monetary value of incentives as observed in the dataset (including the zero observations) is 2.2€. If we calculate the average value of the incentive across the CTA DM campaigns with an incentive only, it amounts to 27.6€ on average.

Model

We model individual i 's purchase decision at quarter t , $t = 1, \dots, T$ using a probit regression. The corresponding equation can be written as:

$$\begin{aligned}
 \Pr(PI_{it} = 1) = & \beta_0 + \beta_1 CTA_{DMit} \\
 & + \left(\sum_{type=1}^{type=3} \beta_{2,type} CTA_{DMit} * Incentive_{type} \right) \\
 & + \left(\sum_{char=1}^{char=7} \beta_{3,char} CTA_{DMit} * Consumer_{char} \right) \\
 & + \left(\sum_{char=1}^{char=7} \beta_{4,char} Consumer_{char} \right) \\
 & + \left(\sum_{control=1}^{control=12} \beta_{5,control} Variable_{control} \right) \\
 & + \left(\sum_{dummy=1}^{dummy=50} \beta_{6,dummy} Shop/Year/Season_{dummy} \right) + \delta_i + \epsilon_{it}
 \end{aligned} \quad (1)$$

In line with the measures described above, we include the incentive types (first brackets: monetary, non-monetary hedonic, non-monetary utilitarian) and the interactions of the consumer characteristics (second brackets: purchase frequency,

purchase recency, relationship duration, DM frequency, DM recency, age and gender). Next to the main effects of these consumer characteristics (third brackets), we include the control variables (market value of the incentives, other DM measures, average CTA DM, GDP growth rate; fourth brackets) and the shop, year and season dummies (fifth brackets). We use random effects in the probit model to capture unobserved heterogeneity across customers (Van Diepen, Donkers, and Franses 2009). All independent variables, with the exception of the dummy variables, are mean-centered for ease of interpretation.

With several independent variables, multi-collinearity might be a concern. Table 4 provides the correlations between variables. Checking the variation inflation factors (VIFs), there are some variables with VIF values above the recommended value of 10 ((Hair et al. 2010), p. 204), namely the two most recent year dummies (2015 and 2016) and the main effect of customer relationship duration. This is not unsurprising, given the operationalization of relationship duration where relationship duration increases as the year increases (see also robustness checks section below).

A crucial issue that needs to be addressed in our modeling approach is that retailers may use target selection techniques to decide which customers receive a CTA DM. That is, retailers do not send CTA DMs randomly to every customer and rather take into consideration the likelihood of making a new purchase and select customers with high purchase probabilities. Building on Germann, Ebbes, and Grewal (2015), we introduce an equation that explains the decision to send DMs by retailers in order to control for this endogeneity (control function approach). We add instrumental variables (IVs) that explain the retailer's DM decisions, at the same time making sure they are not correlated with the error term of the purchase incidence equation. As instruments, we use two measures that capture the (unobserved) attractiveness of CTA DMs among retailers. We conjecture that CTA DMs are likely to be more attractive, when more consumers (at other retailers) and more consumers (at the focal retailer) receive the CTA DM in that quarter. Hence, we use (i) the prevalence of a CTA DM across the other retailers in the same quarter t (the % of customers at other retailers receiving the CTA DM) and (ii) the prevalence of a CTA DM across all customers of the same retailer in the same quarter t (the % of customer of the retailer, except the focal customer, receiving the CTA DM). See for more details on the operationalization of these instruments in Table 2. We also control for the endogeneity of relational DMs with the same logic for selecting instruments.

Instruments are conceptually good, when they are relevant and do not correlate with the error term of the purchase incidence equation. The prevalence of the DM across all customers reflects the decisions of a large number of retailers at different locations. It therefore is indicative of the attractiveness of a certain DM. It is unlikely that these retailers collectively make decisions to send one particular DM to their customers, given that they are located in different areas, and do not belong to the same chain. In addition, the prevalence of DMs within customers of a retailer can capture the idea that some DMs are

inherently more interesting for customers which can influence the decision of a particular retailer to distribute these DMs among its customers. Our instruments are uncorrelated with the omitted variables that affect the customer's purchase incidence decision, mainly because the purchase decision of an individual customer cannot be influenced by the prevalence of a DM across all customers as well as all customers within a specific retailer, simply because that customer is not aware of the purchase decisions of other customers.

We also tested for the strength and validity of our IVs, in line with Germann, Ebbes, and Grewal (2015)'s recommendations. Using the Wald test of the exogeneity ((Wooldridge 2010), pp. 472–477) to test the endogeneity issue with multiple potential endogenous regressors, we reject the null hypothesis of no endogeneity ($p < .01$), which confirms that endogeneity indeed exists. First, to check for the strength of the IVs to explain each endogenous variable in the first stage, we follow the approach suggested by (Stock and Yogo 2005). We reject that our instruments are weak because all first stage F-statistics for IVs are higher than Stock-Yogo weak ID F-test critical values (at 5%). Hence, the IVs are sufficiently strong. Second, testing for the validity of our instruments, the Hansen J test is not significant for the model (p. 15), which suggests that the null hypothesis (the IVs are uncorrelated with the error term) cannot be rejected. Thus, the IVs are valid.

Estimation Results

We estimate four versions of the probit model predicting customer purchase decisions, with different levels of aggregation for incentive types. This approach allows us to compare the coefficients of different types of incentive, depending on what is hypothesized in H1 to H4. In model 1, all CTA DMs, no matter what incentive they include, are represented by a single dummy variable to see the overall effect of CTA DMs on purchase incidence, which allows us to test H1. In model 2, we combine all CTA DMs with an incentive, either monetary or non-monetary, into one variable, to test H2 on how a CTA DM with an incentive performs compared to a CTA DM without incentive. In a similar vein, in model 3, we separate monetary and non-monetary (not distinguishing between hedonic and utilitarian) incentives using a dummy variable, to check the relative performance of monetary and non-monetary incentives as stipulated in H3. Finally, in model 4 (presented in Eq. 1), we have separate dummy variables for monetary, non-monetary utilitarian and non-monetary hedonic incentives, to test H4 by comparing the coefficients of the latter two and to test H5–H10. Table 5 gives an overview of our estimation results. Because of space constraints, we do not provide the results of the first stage (endogeneity-correction) models, nor for the retailer dummies, but they can be provided upon request. We compared the results of the purchase incidence model corrected for endogeneity (see Table 5) with the model that is not corrected for endogeneity (see Appendix A). This comparison indicates that correcting for endogeneity makes the effect of CTA DM as well as the interaction with incentive types smaller in size, and

Table 4
Correlations between variables.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
CTA_DM	1														
Hedonic	0.529	1													
Utilitarian	0.399	−0.031	1												
Monetary incentive	0.427	−0.033	−0.025	1											
*Purchase_frequency	−0.426	−0.243	−0.211	−0.197	1										
*Purchase_recency	0.293	0.411	0.005	0.048	−0.486	1									
*Relationship_duration	0.235	0.600	−0.242	−0.134	−0.035	0.530	1								
*DM_frequency	0.202	0.355	0.019	−0.065	−0.172	0.347	0.244	1							
*DM_recency	−0.113	−0.125	−0.089	0.006	0.202	−0.170	0.099	−0.648	1						
*Age	0.101	0.041	0.197	0.188	−0.200	0.104	−0.103	0.036	−0.178	1					
*Gender (male = 1)	0.638	0.333	0.258	0.272	−0.293	0.196	0.141	0.129	−0.075	0.048	1				
Purchase_frequency	−0.126	−0.071	−0.061	−0.058	0.268	−0.131	−0.012	−0.048	0.055	−0.054	−0.086	1			
Purchase_recency	0.091	0.130	0.000	0.014	−0.154	0.319	0.169	0.110	−0.054	0.033	0.061	−0.524	1		
Relationship_duration	0.071	0.205	−0.090	−0.052	−0.007	0.183	0.349	0.083	0.036	−0.037	0.042	−0.070	0.514	1	
DM_frequency	0.075	0.126	0.009	−0.021	−0.062	0.122	0.086	0.348	−0.225	0.013	0.048	−0.136	0.200	0.158	1
DM_recency	−0.056	−0.054	−0.038	−0.004	0.080	−0.066	0.033	−0.240	0.367	−0.067	−0.037	0.152	−0.096	0.120	−0.644
Age	0.035	0.015	0.062	0.060	−0.064	0.033	−0.031	0.012	−0.056	0.310	0.017	−0.174	0.108	< 0.001	0.088
Gender (Male = 1)	< 0.001	−0.002	0.002	−0.001	−0.009	0.004	−0.004	0.000	−0.002	−0.008	0.275	−0.038	0.020	< 0.001	0.001
Value_incentive	0.482	0.207	−0.025	0.827	−0.222	0.271	0.241	0.037	0.022	0.147	0.308	−0.065	0.085	0.079	0.015
Relational_DM	0.059	−0.015	0.052	0.041	−0.036	−0.054	−0.049	0.002	−0.022	0.025	0.040	−0.005	−0.145	−0.088	0.058
Relational_DM_frequency	0.102	0.005	0.072	0.046	−0.069	−0.041	−0.041	0.034	−0.055	0.039	0.067	−0.075	−0.155	−0.094	0.159
Relational_DM_recency	−0.091	−0.011	−0.061	−0.050	0.076	0.017	0.053	−0.046	0.100	−0.047	−0.061	0.074	0.206	0.272	−0.153
Store_DM	0.149	0.121	0.063	0.094	−0.087	0.077	0.089	0.059	−0.033	0.028	0.094	−0.056	0.039	0.072	0.085
Store_DM_frequency	0.091	0.113	0.012	−0.018	−0.043	0.084	0.108	0.111	−0.071	−0.019	0.055	−0.068	0.124	0.194	0.230
Store_DM_recency	−0.063	−0.030	−0.030	−0.027	0.040	< 0.001	0.039	−0.053	0.103	−0.003	−0.040	0.039	0.098	0.244	−0.146
lag_CTA_DM	−0.103	−0.017	−0.056	−0.057	0.036	−0.014	−0.002	0.053	−0.019	−0.007	−0.067	−0.088	0.086	0.068	0.692
lag_Relational_DM	0.050	−0.008	0.043	0.017	−0.033	−0.038	−0.029	0.007	−0.022	0.022	0.032	−0.035	−0.113	−0.066	0.081
lag_Store_DM	−0.001	0.034	−0.032	−0.043	−0.001	0.014	0.046	0.051	−0.022	−0.020	−0.002	−0.046	0.051	0.082	0.137
AVG_CTA_DM	0.252	0.171	0.087	0.096	−0.174	0.088	0.022	0.223	−0.225	0.048	0.161	−0.208	0.093	0.000	0.443
GDP_growth	0.016	0.062	−0.308	0.218	−0.017	0.053	0.098	0.022	−0.006	0.007	0.009	−0.031	0.159	0.330	0.054

	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
CTA_DM															
Hedonic															
Utilitarian															
Monetary incentive															
*Purchase_frequency															
*Purchase_recency															
*Relationship_duration															
*DM_frequency															
*DM_recency															
*Age															
*Gender (male = 1)															
Purchase_frequency															
Purchase_recency															
Relationship_duration															
DM_frequency															
DM_recency	1														
Age	−0.177	1													
Gender (Male = 1)	−0.006	−0.011	1												
Value_incentive	0.001	0.047	< 0.001	1											
Relational_DM	−0.081	0.044	0.004	0.018	1										
Relational_DM_frequency	−0.184	0.078	0.007	0.032	0.220	1									
Relational_DM_recency	0.330	−0.091	−0.011	−0.032	−0.272	−0.668	1								
Store_DM	−0.053	−0.015	−0.001	0.138	0.036	0.101	−0.080	1							
Store_DM_frequency	−0.153	−0.027	−0.002	0.027	0.057	0.127	−0.121	0.116	1						
Store_DM_recency	0.334	0.038	−0.003	−0.016	−0.098	−0.180	0.346	−0.096	−0.573	1					
lag_CTA_DM	−0.382	0.033	. < 0.001	−0.054	0.040	0.102	−0.088	0.022	0.138	−0.082	1				
lag_Relational_DM	−0.096	0.045	0.004	0.006	−0.041	0.742	−0.425	0.061	0.060	−0.098	0.065	1			
lag_Store_DM	−0.088	−0.015	−0.002	−0.029	0.034	0.084	−0.075	0.009	0.714	−0.352	0.142	0.037	1		
AVG_CTA_DM	−0.473	0.144	−0.001	0.134	0.137	0.250	−0.313	0.107	0.185	−0.268	0.235	0.141	0.102	1	
GDP_growth	−0.021	−0.018	< 0.001	0.190	−0.038	−0.048	0.072	0.068	0.019	0.031	0.048	−0.031	−0.003	0.035	1

Table 5
Model estimation results^a.

Variables	Model 1		Model 2		Model 3		Model 4	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Intercept	−1.010**	0.019	−1.011**	0.019	−1.020**	0.019	−1.057**	0.022
CTA_DM	0.151**	0.005	0.125**	0.007	0.112**	0.007	0.105**	0.008
Incentive			0.044**	0.008				
Monetary incentive					0.001	0.009	0.001	0.009
Non-monetary incentive					0.108**	0.010		
Hedonic							0.072**	0.016
Utilitarian							0.114**	0.010
CTA_DM * Relationship history								
*Purchase_frequency	0.060**	0.011	0.060**	0.011	0.052**	0.011	0.051**	0.011
*Purchase_recency	−0.011**	0.001	−0.011**	0.001	−0.011**	0.001	−0.012**	0.001
*Relationship_duration	0.003**	0.001	0.003**	< 0.001	0.007**	0.001	0.007**	0.001
CTA_DM * DM History								
*DM_frequency	0.063**	0.013	0.057**	0.013	0.064**	0.013	0.065**	0.013
*DM_recency	−0.005**	0.001	−0.005**	0.001	−0.005**	0.001	−0.005**	0.001
CTA_DM * socio-demographics								
Age	0.004	< 0.001	0.004*	0.000	0.004*	< 0.001	0.004**	< 0.001
*Gender(male = 1)	0.014**	0.006	0.014**	0.006	0.015**	0.006	0.015**	0.006
Relationship history								
Purchase_frequency	0.584**	0.004	0.584**	0.004	0.584**	0.004	0.584**	0.004
Purchase_recency	−0.015**	< 0.001	−0.015**	< 0.001	−0.015**	0.000	−0.015**	< 0.001
Relationship_duration	0.011**	0.001	0.011**	0.001	0.011**	0.001	0.011**	0.001
DM history								
CTA_DM_frequency	0.165**	0.004	0.165**	0.004	0.164**	0.006	0.165**	0.004
CTA_DM_recency	0.003**	< 0.001	0.003**	< 0.001	0.003**	< 0.001	0.003**	< 0.001
Socio-demographics								
Age	−0.006**	< 0.001	−0.006**	< 0.001	−0.006**	< 0.001	−0.006**	< 0.001
Gender (male = 1)	−0.048**	0.003	−0.048**	0.003	−0.048**	0.003	−0.048**	0.002
Control variables								
Value_incentive	0.001**	< 0.001	0.001**	< 0.001	0.0001	< 0.001	0.0001*	< 0.001
Relational_DM	−0.209**	0.004	−0.208**	0.004	−0.207**	0.005	−0.207**	0.004
Relational_DM_frequency	0.064*	0.003	0.064*	0.003	0.064**	0.004	0.064**	0.003
Relational_DM_recency	0.002**	< 0.001	0.002**	< 0.001	0.002**	< 0.001	0.002**	< 0.001
Store_DM	−0.035**	0.004	−0.036**	0.004	−0.036**	0.004	−0.037**	0.004
Store_DM_frequency	0.010	0.004	0.010	0.004	0.009	0.004	0.009	0.004
Store_DM_recency	−0.0003	< 0.001	−0.0003**	< 0.001	−0.0001	< 0.001	−0.0001	< 0.001
AVG CTA_DM	−2.726**	0.019	−2.727**	0.019	−2.700**	0.019	−2.700**	0.019
Lag_CTA_DM	−0.095**	0.004	−0.094**	0.004	−0.094**	0.004	−0.094**	0.004
Lag_Relational_DM	0.039**	0.005	0.039**	0.005	0.040**	0.005	0.039**	0.005
Lag_Store_DM	0.039**	0.005	0.040**	0.005	0.040**	0.005	0.041**	0.005
GDP_growth	0.005	0.041	0.003	0.003	0.001	0.003	0.003	0.003
Quarter								
Q2	0.046**	0.003	0.048**	0.003	0.050**	0.003	0.050**	0.003
Q3	0.055**	0.003	0.056**	0.003	0.056**	0.003	0.056**	0.003
Q4	0.027**	0.004	0.026**	0.004	0.025**	0.004	0.025**	0.004
Year								
2010	−0.034**	0.005	−0.033**	0.005	−0.033**	0.005	−0.032**	0.005
2011	−0.075**	0.008	−0.074**	0.008	−0.072**	0.005	−0.073**	0.005
2012	−0.174**	0.011	−0.172**	0.011	−0.168**	0.007	−0.170**	0.007
2013	−0.248**	0.013	−0.245**	0.013	−0.238**	0.009	−0.240**	0.009
2014	−0.320**	0.014	−0.318**	0.014	−0.311**	0.010	−0.314**	0.010
2015	−0.396**	0.015	−0.396**	0.015	−0.382**	0.012	−0.384**	0.012
2016	−0.502**	0.016	−0.502**	0.016	−0.492**	0.014	−0.494**	0.014

* $p < .05$ (two-sided) ** $p < .01$ (two-sided).^a Because of space constraints, we do not provide the results of the first stage (endogeneity-correction) models, nor for the retailer dummies, but they can be provided upon request.

is therefore important to apply (Ebbes, Papies, and Van Heerde 2011).

Hypotheses Tests

Main Effect of DMs

To test H1, we look at model 1, where we have one dummy variable that captures all forms of CTA DM. The significant positive coefficient of the CTA DM ($\beta = 0.151$, $p < .01$) indicates that such DMs have a positive impact on the customer's purchase probability and therefore, H1(a) is confirmed. Note that this coefficient should be interpreted as the effect of the CTA DM for females at the mean value for all continuous moderators (because they were mean-centered), due to the interaction terms in the model.

The Moderating Role of DM Incentive

To test H2, we focus on model 2, where we can interpret the coefficient of the dummy variable that captures whether a CTA DM had an incentive. This coefficient indicates the additional effect of an incentive beyond the main effect of sending a CTA DM (which is captured by the baseline coefficient). Given the positive significant coefficient of the incentive variable ($\beta = 0.044$, $p < .01$), we can conclude that a CTA DM with an incentive has a higher impact on purchase incidence than a CTA DM without an incentive. Thus we find support for H2(a).

In model 3, we estimate the coefficients of monetary and non-monetary incentives and compare these to test H3. To assess whether the coefficients of monetary versus non-monetary incentives are significantly different from each other, we calculate the difference between these coefficients and divide it by the standard error derived via the Delta method (Greene 2003). This comparison is significant ($p < .01$). The coefficient of the non-monetary incentive ($\beta = 0.108$, $p < .01$) is significantly higher than that of the monetary incentive ($\beta = 0.001$, $p = .13$), with the latter not being significantly different from the no incentive CTA DM. Thus, we conclude that non-monetary incentives have a higher (more positive) impact on purchase incidence compared with monetary incentives, supporting H3(a).

We further test whether the coefficients of non-monetary hedonic and utilitarian incentives in model 4 are significantly different from each other. Parameter tests of the difference between these coefficients show that the difference is significant ($p < .01$). Hence, H4a is supported. Although both a CTA DM with a non-monetary hedonic ($\beta = 0.072$, $p < .01$) as well as one with a utilitarian incentive ($\beta = 0.114$, $p < .01$) positively influence a customer's purchase incidence compared to a CTA DM without an incentive, our results also indicate that a utilitarian incentive has a higher impact on customer purchase incidence than a hedonic one.

The Moderating Role of Customer Characteristics

For the hypotheses tests of the moderating role of customer characteristics, we focus on model 1, but the results are robust across the four versions of the model (see Table 5). To enhance

the interpretation of the interaction effects, we estimate and test the simple effect of the CTA DM at different levels of the moderators, which is called a spotlight test (Spiller et al. 2013). In particular, we calculate the simple effect of a CTA DM (and its significance level) for low (one standard deviation below the mean value) and high (one standard deviation above the mean value) levels of the moderators. We also calculate threshold values (see (Melis et al. 2015) for a similar approach) to identify the range of the moderator values where the simple effect of the CTA DM is significant. The results are presented in Table 6.

Relationship history. The positive significant coefficient of the interaction between a CTA DM and purchase frequency ($\beta = 0.060$, $p < .01$) shows that the impact of a CTA DM on purchase incidence is more pronounced for customers with higher purchase frequency (support for H5). The impact of CTA DMs on purchase incidence is positive and significant for all values of purchase frequency as observed in our data and increases as purchase frequency increases.

The coefficient of the interaction term between the CTA DM and purchase recency is negative and significant ($\beta = -0.011$, $p < .01$) (support for H6). The spotlight analyses show that the effect of CTA DM on purchase incidence is highly positive at the low purchase recency value (mean value minus 1 SD), and lower but still positive at the high level (mean value plus 1 SD). The effect of CTA DM is positive and significant at a wide range of recency levels, namely for 1 to 21.6 quarters. However, it is decreasing and becomes negative and significant at the very high levels of time since purchase (25.7 quarters and higher).

The significant and positive coefficient of the interaction between relationship duration and the CTA DM ($\beta = 0.003$, $p < .01$) indicates that effect of the CTA DM on purchase incidence increases as the duration of the relationship between the customer and retailer increases (support for H7). The effect is positive and significant across all values of relationship duration as observed in our data and increases as the relationship duration goes up.

Table 6
Overall effect of CTA DM at different levels of continuous moderators.

Total effect CTA_DM	Low level of moderator	High level of moderator	Range of values where the effect is significant and negative	Range of values where the effect is significant and positive
Purchase_frequency	0.128**	0.149**	–	[0, 1.86]
Purchase_recency	0.226**	0.074**	[25.7, 32]	[1, 21.6]
Relationship_duration	0.104**	0.195**	–	[1, 32]
DM_frequency	0.139**	0.261**	–	[0, 2.05]
DM_recency	0.186**	0.025**	–	[1, 32]
Age	0.002**	0.278**	–	[18, 70]

We use non-mean-centered values and define low = mean – 1 SD (or 0, if mean – 1 SD < 0), high = mean + 1 SD. The hypotheses are two-sided with p -values: * $p < .05$, ** $p < .01$. The minimum and maximum values in the reported ranges are the ones observed in the dataset.

DM history. The interaction between the CTA DM and DM frequency is positive and significant ($\beta = 0.063$, $p < .01$), suggesting that message repetition works (support of H8(b)). The impact of CTA DM frequency on purchase incidence increases as the value of CTA DM frequency increases and is significant at the whole range of values of CTA DM frequency. The coefficient of the interaction between CTA DM and DM recency is negative and significant ($\beta = -0.005$, $p < .01$), which indicates that the impact of CTA DM on purchase incidence decreases if the time since the last CTA DM mailed to this customer increases (support of H9(b)). The impact of the CTA DM on purchase incidence is positive and significant in the whole range of recency values as observed in our data.

Socio-demographics. The results show that a CTA DM has a higher influence on stimulating older customers to make a purchase ($\beta = 0.004$, $p < .01$), supporting H10(b). The simple effect of a CTA DM on purchase incidence is small but significant at low age values and increases at higher age levels. Lastly, the interaction term between CTA DM and gender is positive and significant ($\beta = 0.014$, $p < .01$). The effect of CTA DMs on purchase likelihood is higher for males than females. This is in contrast to our expectations where males were expected to be less likely to react to a CTA DM than females (no support for H11).

The Impact of Control Variables

Table 5 shows that quarter and year dummies are all significant, indicating that not controlling for these variables would potentially cause an omitted variable bias. Also, the retailer dummies (omitted because of space constraints) are all significant. The impact of the market value of the incentive used in the CTA DM on purchase incidence is positive and significant in all models (except model 3), in line with the expectation that the higher the market value of the incentive involved, the more likely consumers are to make a purchase. Next, controlling for the effect of other DMs that a customer receives is important, given the significant effects of current (captured by the dummy variables) as well as past DMs (captured by recency and frequency measures of these DMs). Negative effects of both ‘current’ relational DMs and store-specific DMs on purchase incidence may seem unexpected, but store-specific DM communication is typically send when there is a disruption at the store or its environment; and relational DM is often send to build a relationship instead of generating purchases in the same period. The lagged effects of all three DMs are significant. It is negative for the CTA DM which suggests that consumers that received a CTA DM in the previous quarter are less likely to make a purchase in the following quarter, while the opposite holds for relational and store DMs where consumers are more likely to make a purchase in the quarter following the one where they received such a DM. The average number of CTA DMs that customers have received is significant and negative, which may capture the effect that customers who receive more direct marketing are less likely to purchase in the first place. The coefficient of GDP growth rate is not significant. Finally, the main effects of the

moderator variables on purchase incidence are in line with the expectations, corroborating the validity of our model: customers are more likely to make a purchase at the retailer when they have made more purchases in the past, have bought more recently, are with the retailer during a longer time, received CTA DM more frequently and more recently, are younger and are female.

Simulation

To assess the effect size of changes in customer characteristics as well as incentive types on purchase probability, we simulate a meaningful change in values of each explanatory variable (± 1 SD from the mean for continuous variables and from 0 to 1 for binary variables), while fixing other continuous variables at their mean and dummy variables at a certain value, then compute the predicted change in purchase probability. By doing this, we gain insights in the effect size for a change in the value of a variable of interest on purchase probability. We use model 1 to calculate the predicted purchase probabilities for changes in the customer characteristics, and model 4 for changes in the incentive types. Result of these simulations are provided in Table 7.

The results show that targeting a customer with a CTA DM (irrespective of the incentive) increases a customer’s purchase probability from 15.6% to 19.5% in comparison with not sending a CTA DM. A CTA DM with an utilitarian incentive increases a customer’s purchase probability the most (21.7%),

Table 7
Simulation results^a.

Variable	Value range	Purchase probability	
		Model 1	Model 4
No CTA DM		15.6%	15.6%
Overall effect of CTA DM (irrespective of incentive)		19.5%	–
Effect of CTA DM without incentive		–	18.4%
Effect of CTA DM with monetary incentive		–	18.5%
Effect of CTA DM with non-monetary hedonic incentive		–	20.5%
Effect of CTA DM with non-monetary utilitarian incentive		–	21.7%
Effect of CTA DM for changes in:			
Relationship history	Purchase frequency	Low (0)	16.5%
		High (0.5)	26.3%
	Purchase recency	Low (1)	24.8%
		High (16)	15.7%
	Relationship duration	Low (6)	16.3%
		High (22)	23.0%
DM history	DM frequency	Low (0)	18.1%
		High (0.5)	21.6%
	DM recency	Low (1)	19.8%
		High (16)	19.2%
Socio-demographics	Age	Low (42)	20.2%
		High (73)	18.8%
	Gender	Female	19.5%
		Male	18.6%

When doing the simulations, we fixed the non-focal continuous variables at their mean and the non-focal dummy variables at a fixed given number (quarter = 4, year = 2013, male = 0 and shopdummy25 = 1).

^a Low = mean of continuous variables - 1 SD; High = mean of continuous variables + 1 SD.

closely followed by a hedonic incentive (20.5%), while the monetary incentive only slightly increases the purchase probability (18.5%) compared with a CTA DM without an incentive (18.4%). Table 7 further shows that the CTA DM effect on customer's purchase probability is affected more by changes in values of relationship history variables compared to changes in values of DM history and socio-demographics. For instance, the predicted purchase probability varies between 16.5% and 26.3% when a CTA DM is mailed to a customer with low versus high value of purchase frequency. DM frequency also plays a role because the predicted purchase probability increases from 18.1% to 21.6% if the value of DM frequency changes from low to high. The moderating roles of DM recency, age and gender are relatively small in terms of effect size, indicated by the low differences in predicted purchase probabilities.

To illustrate implications for retailer targeting decisions based on customer characteristics, we computed how much customer's purchase probability changes if a retailer would target two very different customers (while the customer profiles are hypothetical, they are viable in the dataset). Customer A is a 42 year old male who does not purchase very frequently (purchase frequency in last four quarters = 0, time since last purchase = 5 quarters), has a low relationship duration (6 quarters) and receives CTA DMs not very frequently (low CTA DM frequency = 0, long time since last time received a CTA DM = 5 quarters). Customer B is a 73-year-old female who purchases frequently (high purchase frequency = 0.5, short time since last purchase = 1 quarter), has a high relationship duration (22 quarters) and receives CTA DMs from retailers often (high CTA DM frequency = 0.5, short time since last time received a CTA DM = 1 quarter). The purchase probability of customer A changes from 10.9% to 13.2% by receiving a CTA DM, while purchase probability of customer B changes from 24.8% to 37.1%. This indicates that the predicted purchase probability increases much more if the retailer targets Customer B instead of Customer A.

As managers need to decide on the monetary value of the incentive as well as on the incentive type, it is interesting to assess the relative importance of these CTA DM decisions. To do so, and following the procedure described above, we calculate the effect size of the monetary value of incentives on purchase probability. More specifically, we show that the purchase probability increases only by 0.3% (from 19.5% to 19.8%, respectively) if the monetary value of the CTA DM incentive increases by one standard deviation from its mean. This change is very small compared to when the CTA DM type changes: 3.2% (if a non-monetary utilitarian CTA DM is sent instead of a monetary one) or 2.0% (if a non-monetary hedonic CTA DM is sent instead of a monetary one). We therefore conclude that the value of the incentive matters much less than the type of incentive (monetary vs. non-monetary).

Robustness Checks

To check whether the model results are robust, several alternative models have been tested. First, we changed the level

of aggregation of our analysis from quarter to year. This change did not result in substantively different findings. Hence we decided to stick to quarterly level data analysis. Second, we tested the sensitivity of our result to the selection of IVs. Instead of using the two IVs that we discussed above, we used another IV, namely the prevalence of a DM across other retailers in quarter t , to replace one of these IVs (we did this robustness check twice). The parameters and corresponding significance levels of other variables were hardly affected. Third, given the high VIF value for the main effect of the relationship duration variable, we excluded that variable and its interaction with the CTA DM. The findings for the rest of variables stayed the same, mitigating the concerns regarding multi-collinearity. Fourth, there is some evidence in the literature Van Diepen, Donkers, and Franses (2009) that suggests that the interaction of a CTA DM with purchase recency might have an inverted U-shaped form, that is, an intermediate level of purchase recency resulting in a more significant impact than a very high or a very low level of purchase recency. We added the quadratic term of the interaction to our model, however, it was not significant. Fifth, we did sensitivity analyses on the decay parameters used in the operationalization of DM frequency and purchase frequency. Results for parameters between 0.7 and 0.9 suggest that our results are not sensitive to the decay parameter value. Therefore, we use 0.75, because this number is most commonly used in the direct marketing literature (Gázquez-Abad et al. 2011). Sixth, we split the DM frequency and recency variables per incentive level, leading to different DM frequency and recency variables for CTA DMs with a monetary and non-monetary incentive. The operationalization of these recency/frequency variables at the incentive level was similar in spirit to the one we used at the aggregate level. By including these variables in interaction with the CTA DM dummy, we test whether there exist a wear-out effect (Ansari et al. 2008), that predicts that the frequent and/or recent use of monetary (non-monetary) incentives decreases the impact of the CTA DM on purchase incidence. This split between monetary and non-monetary frequency plus recency did not result in a model fit improvement, nor did it change the substantive findings.

Discussion

Given the very large expenditures retailers dedicate to direct marketing communications in consumer durables (Gázquez-Abad et al. 2011), such as optical products in our study, understanding under which conditions a DM is effective in triggering a purchase is a relevant issue for both academics and retailers. In a context like ours that is characterized by low purchase frequencies and high involvement (Grewal, Mehta, and Kardes 2004), it becomes critical for retailers to target customers with the right offers in order to keep close contact with existing customers. Our primary goal in this research was to develop insights on the impact of CTA DMs with different incentive types. In addition, we were also interested in the moderation effects of customer characteristics. This study adds to the existing knowledge on the impact of CTA DMs on

customer's purchase incidence in the retail context, by investigating the impact of a variety of incentives types, a large set of consumer characteristics and this in a setting of consumer durables (notably optical retailing).

The Moderating Role of CTA DM Incentive

The unique dataset analyzed in this study reveals that a CTA DM with an incentive has a higher impact on customer's purchase behavior, compared with a CTA DM without an incentive. Customers perceive a CTA DM with an incentive, as an extra effort and resource investment from retailer to foster the relationship. Consequently, customers reciprocate a retailer's action by making a new purchase, in line with what (Arora and Stoner 1992) found. Next, we found that the impact of a CTA DM on purchase incidence depends on the type of incentive. Our results show that non-monetary incentives are more influential compared to monetary incentives in stimulating customers to make a purchase. As demonstrated by (Nunes and Park 2003), non-monetary incentives are perceived as separate gains due to their incommensurate nature, which makes it difficult to convert them into a common unit of measurement. Hence, we find that in our research, customers attach a higher perceived value to these non-monetary incentives than to monetary ones. Another interesting finding is that among the two possible non-monetary incentive, a CTA DM with a utilitarian incentive has a slightly higher impact on customer's purchase probability, compared to a CTA DM with a hedonic incentive. This is in line with the stream of research that argues that justification for the incentive is easier for utilitarian rewards that are primarily instrumental and functional, leading to less guilty feelings for such incentives than for hedonic incentives (Palazon and Delgado-Ballester 2013).

The Moderating Role of Customer Characteristics

Our findings substantiate the idea that customer heterogeneity in response to CTA DMs exists. More specifically, our results show that customers who purchase more frequently have an even higher purchase incidence when receiving a CTA DM. Customers with higher purchase frequency are heavy users and according to the relationship marketing literature, heavy users engage more with a firm because they developed higher capabilities in terms of understanding and engaging with firm contacts compared to less experienced users. Our results support the idea that this makes them more likely to react positively to firm offers (Fader and Hardie 2007; Neslin et al. 2013).

Next, a CTA DM has a lower effect on purchase incidence for customers with high purchase recency values (and thus, longer time since past purchase), compared to customers who have purchased more recently. According to reactance theory, when (almost) defected customers receive DMs, they find these DMs more manipulative and irritating than other (more 'active') customers (Fitzsimons and Lehmann 2004). Moreover, the longer the time since the last purchase, the more likely a lapsed customer is to have shifted to a new retailer or simply

to have developed new behaviors (Thomas, Blattberg, and Fox 2004). Our results thus support the idea that customers with higher elapsed purchase time may ignore the newly received CTA DM.

The CTA DM effect increases also as the duration of customer relationship increases. This suggests that as the duration of the relationship increases, the level of intimacy also increases, leading to an increased richness of the customer's impressions about the firm (Swann and Gill 1997). The relationship marketing literature has shown that 'strong' customer relationships are those in which customers have maintained a longer relationship, as the parties acquire experience and get to know what they can expect from one another (Bolton 1998). Our results support this idea, by showing that customers with a longer relationship are more likely to react to a CTA DM. Taken together, our results are in line with well-established findings in customer relationship management literature that suggests to target customers based on RFM variables as well as relationship age with the firm (Rust and Verhoef 2005).

Not only does the customer relationship history play a critical role, the impact of a CTA DM on purchase incidence also depends on DM history. Our results reveal that how recent and frequent a customer received DM in the past plays a significant role: customers who received DM with higher frequency and lower recency have a higher probability to make a purchase when targeted with a new CTA DM. This corroborates with the idea suggested in advertising literature that repeated exposure to advertising can lead to familiarity, a positive attitude toward the company, and less likelihood of the customer 'forgetting' the company over time (Naik and Piersma 2002).

Finally, we found that socio-demographics like age and gender play significant albeit small roles: older customers and males are more likely to make a purchase when targeted with a CTA DM. Contrary to our prediction, CTA DMs have more impact on the purchase decision of males. One potential explanation can be found in the product category under study, which seems to make especially male consumers likely to respond to a call-to-action for an extra pair of glasses, while female consumers are more likely to make a purchase (without a CTA DM) as is evidenced by the significant negative main effect of gender.

Managerial Implications

The findings from our study provide valuable insights for retailers. First, our results suggests that it pays off to provide customers with a non-monetary incentive. Our results challenge the practice of some retailers who spend substantial amounts of their budget on sending DMs with monetary incentives (e.g., price discounts) in pursuit of stimulating customers to buy. We demonstrate that retailers can enhance customer's purchase probability by more than 14.6% if they switch from sending a CTA DM with a monetary incentive to a non-monetary incentive, especially with an utilitarian one.

Second, our findings show that targeting customers based on their relationship history and DM history significantly affects the customer's purchase probability. For instance, targeting customer with a high rather than low purchase frequency with a CTA DM can increase a customer's purchase probability by 59%. For the relationship duration, the purchase probability increases by 41% if retailers target a customer with relatively high relationship duration (22 quarters) instead of a customer with low relationship duration (6 quarters). Targeting customers with a low (1 quarter) vs. a high purchase recency (16 quarters) increases purchase probability by 57%. Targeting customers based on RFM measures thus pays off, in line with customer relationship management practices.

Third, we encourage retailers to get to know their customers better, by keeping track of some essential information like purchases made, timing of DMs sent and to a lesser extent socio-demographics, because this enables retailers to manage DM strategies more effectively. Our research substantiates that a retailer can leverage customer and transaction data to increase purchases via a more refined direct marketing strategy. After acquiring such information, it also makes sense for retailers to invest in internal data analysis skills necessary to take advantages of such data.

Limitations and Suggestions for Future Research

In this study, we examined a large group of optical retailers across the Netherlands. Comparable to other empirical studies, the first question is whether our findings are generalizable to other contexts as well. In this research we focused on optical retailers that belong to consumer durables and that are characterized by low purchase frequency and high involvement level. There is a need to extend this study to other consumer durable categories, but certainly also to high purchase frequency and low involvement categories. A second limitation of this study is that we could not observe the full behavioral response of a customer to a DM and focused on purchase incidence only. Next to investigating other aspects of consumer purchase behavior, future research could also refine this measure by, for instance, investigating the intermediate stages of the direct mail response, such as the opening and keeping rates of DMs (Feld et al. 2013). Third, our data captures the actual behavior of customers (purchase incidence) and retailers (timing and frequency of sending DM). It was not collected with the purpose of theory testing. Our results are indicative of the relevance of the various drivers, but field experiments should be carried out to disentangle the causal influences and corroborate the validity of our findings. However, such field experiments would be quite costly and hard to implement, given the number of moderators and control variables in our model. A next limitation is that our data do not cover the competition. This concern is, however, alleviated because the retailers that we study are spread over the Netherlands and they do not compete for the same customers. Finally, we focus on CTA DMs targeted to existing customers (i.e., customers that already made a purchase at the company in the past). Studies

that focus on how CTA DMs may help with acquiring new customers would complement our study.

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Appendix A

Result of model without controlling for endogeneity.

Variables	Coef.	SE
Intercept	−1.117**	0.024
CTA_DM	0.065**	0.006
<i>Non-monetary incentive</i>		
Hedonic	0.183**	0.016
Utilitarian	0.195**	0.012
Monetary incentive	0.018	0.009
CTA_DM * relationship history		
*Purchase_frequency	0.092**	0.020
*Purchase_recency	−0.035**	0.001
*Relationship_duration	0.013**	0.001
CTA_DM * DM history		
*DM_frequency	0.103**	0.027
*DM_recency	−0.009**	0.001
CTA_DM * Socio-demographics		
*Age	0.004**	<0.001
*Gender (male = 1)	0.011	0.006
Relationship history		
Purchase_frequency	1.009**	0.008
Purchase_recency	−0.023**	0.001
Relationship_duration	0.006**	0.001
DM history		
DM_frequency	0.256**	0.008
DM_recency	0.006**	< 0.001
Socio-demographics		
Age	−0.072**	0.007
Gender (male = 1)	−0.100**	0.005
Control variables		
Value_incentive	0.0003*	0.000
Relational_DM	−0.143**	0.005
Relational_DM_frequency	−0.009*	0.005
Relational_DM_recency	0.009**	< 0.001
Store_DM	−0.084**	0.007
Store_DM_frequency	0.073**	0.008
Store_DM_recency	< 0.001	< 0.001
AVG_CTA_DM	−3.421	0.027
Lag_CTA_DM	−0.054**	0.004
Lag_Relational_DM	0.022**	0.005
Lag_Store_DM	0.023**	0.006
GDP_growth	0.002	0.003
Quarter		

(continued)

Variables	Coef.	SE
2	0.052**	0.003
3	0.051**	0.003
4	0.033**	0.004
Year		
2010	−0.045**	0.005
2011	−0.080**	0.007
2012	−0.177**	0.009
2013	−0.255**	0.010
2014	−0.323**	0.013
2015	−0.392**	0.015
2016	−0.507**	0.017

* $p < .05$ (two-sided) ** $p < .01$ (two-sided).

Because of space constraints, the results of the coefficients of the retailer dummies are omitted.

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