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HIGHER SCHOOL OF ECONOMICS

Mariia I. Okuneva, Dmitriy B. Potapov

THE EFFECTIVENESS OF INDIVIDUAL TARGETING THROUGH SMARTPHONE APPLICATION IN RETAIL: EVIDENCE FROM FIELD EXPERIMENT

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Mariia I. Okuneva[1], *Dmitriy B. Potapov*[2]

THE EFFECTIVENESS OF INDIVIDUAL TARGETING THROUGH SMARTPHONE APPLICATION IN RETAIL: EVIDENCE FROM FIELD EXPERIMENT[3]

Smartphone applications are becoming an important marketing channel that allows to build long-term relationship with customers. The main advantage of advertising through this kind of media is an opportunity to individually target users with different offers, taking into consideration their characteristics and purchase history. However, little is known about the effectiveness of such practice. We use a purely randomized natural field experiment with 11338 customers of large Russian retail chain to understand factors that influence the effectiveness of advertising through smartphone application. We find that the impact of conducted advertising campaign either on number of purchases or purchase amount is slightly negative on average. While most previous studies report positive effect of advertising through mobile devices, we can explain the average negative effect by influence of small discount (less than 20%) offers on consumers' behavior. Holiday text of the message makes this effect even stronger. Consistent with the literature, the average effect of advertising depends on RFM characteristics of customers. However, the loyalty of consumers or different texts of an advertising message do not affect the effectiveness of advertising via mobile application. These results can help a retail chain to elaborate rules for individual targeting that assure more profits.

JEL Classification: M31, M37, C93, L86.

Keywords: mobile targeting, randomized field experiment, mobile application, advertising effectiveness.

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[1] National Research University Higher School of Economics - Perm. Group for Applied markets and Enterprises Studies. Research Assistant; E-mail: miokuneva2@gmail.com

[2] National Research University Higher School of Economics - Perm. Group for Applied markets and Enterprises Studies. Head of AMES group. HSE-Perm Deputy Director, Associate Professor. E-mail: dbpotapov@hse.ru

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Introduction

In the era of information technology many means of communication between a retailer and customers already exist: any store or the goods sold there can be advertised with the help of TV, newspapers, radio, SMS-messages, direct mail or the web site. At the same time, new marketing channels arise and open new opportunities for making customers aware of promotions, brands sold by a retailer and special offers. One of such channels is called ‘branded mobile apps’. The definition of these apps is given in the article (Bellman et al. 2011): “software downloadable to a mobile device which prominently displays a brand identity, often via the name of the app and the appearance of a brand logo or icon, throughout the user experience”. Branded applications developed by the retailer allow the user to have an access to their own purchase history, create ‘to buy’ list, seek the information about special offers, participate in events organized by the retailer, leave feedback or get extra relevant information (e.g. recipes, product place in the retail chain). In this research we explore the effectiveness of advertising provided through smartphone application developed by a retail chain involving stores of different size. The retailer we cooperate with is FMCG (fast-moving consumer goods) company that operates on offline market.

According to Portio Research (2013), mobile applications are becoming more popular: the number of people worldwide using mobile apps is forecast to rocket from 1.2 billion at the end of 2012 to 4.4 billion users by the end of 2017. This rapid growth of the market motivates retailers to create ‘branded applications’ aimed at building long-term relationship with loyal customers and attracting those consumers who enjoy using the most up-to-date media, such as mobile apps. Mobile advertising provided with these applications is ‘pull’ rather than ‘push’ (Valvi and West, 2015) because the decision to download the application is made by a user. This makes branded applications very specific media that needs further research. How do consumers perceive such applications? Is advertising through mobile apps effective? What types of advertising campaigns are more effective in apps (redemption of coupons, push-notifications informing about discounts, loyalty programs etc.)? An array of questions about consumer’s behavior in apps is important to answer because, in contrast to other media (SMS-messages, the Internet), a consumer dictates whether he or she wants to use the app and how much time a user is ready to spend on it.

This work contributes to the literature on advertising in two main ways. First, we investigate the effectiveness of advertising via relatively new promotional channel. We do not provide users of the application with electronic coupons but send them push-notification informing about the current discount for one of the products sold in the retail chain. This helps to make customers aware of relevant offers and does not imply additional costs for the company (such as cost of SMS-messages). In general, every user can find information about all the current discounts of the retail chain in mobile application. Nevertheless, customers are reluctant to read the information about all of them due to time costs. Sending push-notification about a particular offer can change purchasing behavior of customers. That is why it is necessary to realize which characteristics of consumers and promoted goods are important to improve the match between a user and the offer and consequently increase the effectiveness of advertising through mobile app.

Second, we find that the effect of advertising depends on the depth of discount mentioned in the message. While in the article by N. Fong, X. Luo (2015) it is assumed that 20% discount and no-discount effects of SMS-messages on purchase rates are equal, our results suggest that small discounts (less than 20%) can have a negative effect on number of purchases made by customers and purchase amount.

The main goals of this research are to understand how characteristics of offer correspond to consumers response rate and what metrics of past purchase behavior of customers improve the effectiveness of advertising campaign conducted via smartphone application. In order to understand who to target and with which offers, we would like

1. to estimate the effectiveness of advertising campaign through smartphone application (across discount depth, text of the message);
2. to concentrate on heterogeneous treatment effects, i.e. to investigate which characteristics of past purchase behavior of customers (RFM characteristics, brand loyalty) influence the effectiveness of advertising campaign;

To enable an accurate estimate of advertising effectiveness we conducted a randomized field experiment with the retail chain that developed branded application. Every user of the application was assigned to either treatment or control group. The user of application was considered as treated if he or she was sent push notification about one of the goods (SKU – stock keeping unit) sold in the chain. While various metrics can be used to measure the effectiveness of the advertising, purchase amount (the amount of money spent by the consumer) and the number of purchases in the period of advertising campaign are considered as dependent variables in this research. The results of this study should help to provide customers of the retail chain with more relevant advertising messages, that is to create rules for individualized targeting system.

The paper proceeds as follows. In section 2, we discuss prior work on the effectiveness of advertising and individual targeting. In section 3, we discuss the design of the field experiment and exploited model specifications in order to set up a framework for the analysis of advertising. Empirical results are presented in section 4. The section 5 concludes the paper.

Theoretical background

Our research is mainly related to three streams of the literature on advertising in Marketing and Economics that supplement each other: effectiveness of advertising, field experiments and personal marketing.

The effectiveness of advertising has become interesting for researchers and practitioners in marketing many years ago (Bagwell, 2008) and is covered in relation to TV (Lodish, 1995), store flyers (Gijsbrechts et al., 2003), coupon campaigns (Venkatesan et al., 2012), etc. The results reported in the literature are ambiguous. For example, Lodish in his work found out that only 49% of 360 advertising campaigns for different brands were statistically significant at the 20% level. The most relevant predecessors to our research are the papers exploring the effectiveness of the advertising provided via the Internet and mobile phones (SMS-messages, smartphone applications). The appearance of the Internet allowed to collect data about millions of users, target those who would respond more probably. It caused the development of recommendation systems, such as Amazon.com's personalized book and music recommendation (Arora, 2008). While the advertisements on the web sites have become better and more personal, the main question about the effectiveness of online advertising has remained undiscovered. Lewis and Reiley (2014b) have found that online advertisement leads to an increase of purchases by 5% (brick-and-mortar stores account for 93% of the growth). The authors underlined the complexity to find statistically significant effect of advertisement due to high variance of sales even with the use of large sample – 1,6 million of individuals.

Mobile marketing has its own advantages: SMS-messages can reach the person wherever he is that should make an ad more effective. Moreover, the customer can be targeted by time and even place (just near the store). In the article (Luo et al. 2013) the effectiveness of such practices is investigated using the sample of 12265 mobile phone users. The authors conducted large-scale randomized experiment and came to the conclusion that individually geographical and temporal targeting are effective, but simultaneous use of these two strategies can lead to different results. Merisavo (Merisavo et al., 2006) also identified the effectiveness of mobile advertising on the basis of field experiment and found that the effect of advertising varied across people with different content preferences and usage level of the mobile services. While X. Luo et al. (2013) consider only focal targeting, N. Fong, Z. Fang and X. Luo (2015) go one step further and explore the effectiveness of competitive targeting. Researchers vary three factors in the experiment (location of customers, discount size and time) and conclude that medium discount (40%) is optimal for focal targeting, whereas deep discount (60%) should be used for competitive targeting.

We observed many articles about the effectiveness of advertising campaigns in different media, but did not give clear explanation when the ad is considered effective. The problem is that different metrics can be used for this purpose: weekly sales (Lewis and Reiley, 2014a, 2014b), purchase intent (Goldfarb and Tucker, 2011; Bart et al., 2014), purchase probability (Luo et al., 2013), attitude toward advertised product (Bart et al., 2014), store traffic – weekly number of receipts per store outlet – (Gijsbrechts et al. 2003), trip revenue (Venkatesan et al., 2012), average daily expenditure (Merisavo et al., 2006) or purchase rate (Fong et al., 2015). The choice of the metric should be based on the purpose of the research and availability of data.

To our knowledge, no empirical research exists about the effect of advertising campaign run through mobile application on sales of the retailer. At the same time, Bellman (2011) investigated the effect of mobile apps on brand attitude and brand purchase intention. He has found that highly relevant to the person and informative apps are characterized by greater values of purchase intention. In terms of the current study, it means that personalization of the advertisement content should lead to an increase in the effectiveness of the branded app. Another research devoted to branded mobile apps (Eunice, 2013) examines engagement attributes and entertainment features common to such applications.

Because of the endogeneity problem that arises with regard to the relationship between advertising and sales (simultaneous causality), omitted variable bias or selection bias (Bagwell, 2008), randomized experiments are used more often to measure the effectiveness of advertising than observational data. For instance, one of the earliest experiments in this field (Ackoff, 1975) was devoted to the effect of advertising on Budweiser beer sales. According to Levitt (2009), experiments with private entities will be more popular in future and they will be aimed at testing and extending current economic theories. However, field experiments have specific limitations and drawbacks. One of the issues is associated with randomization bias that presents a serious problem in research devoted to medical trials or other laboratory experiments. At the same time, Harrison (Harrison et al., 2008) and Levitt (Levitt, 2009) assert that randomization bias is not an important limitation in other types of experiments (such as field experiments).

Other relevant to this research articles are concentrated on personalized targeting. One-to-one marketing, targeting and personalization are the important concepts of customer relationship management. Targeting, or one-to-one marketing, refers to “setting marketing policy differentially for different customers or segments” (Dong, 2009). Personalization is the form of one-to-one marketing that can be described as the process of identifying the best match between marketing mix and customer’s preferences by the company (Arora, 2008). The work written by P. Rossi (Rossi et al., 1996) was among the first that underlined and quantified the effectiveness of direct targeting. Authors found that revenue associated with target couponing can exceed mass market couponing by 2.5 times. Another article (Ansari and Mela, 2003) is concentrated on the effect of content targeting. According to Ansari and Mela, content personalization of e-mail letters can lead to an increase of click-throughs by 62%.

Targeted offers will be effective in terms of response rates, only if information provided to a customer is perceived as relevant. The trouble is to articulate what kind of variables (characteristics of past consumer behavior, demographic information, special features of offer) enable the researcher to determine whom to target and with what sort of advertising campaign. For instance, is it more effective to advertise the product to those who buy it frequently or to the customers that have never bought it? Zhang and Wedel (Zhang and Wedel, 2009) discussed this issue and concluded that loyalty promotions (aimed at customers who bought the target good on the prior occasion) are more effective in online stores than competitive promotions, offering products to those who didn't buy them, while the opposite is true for offline stores explored in this work .

According to Bose and Chen (2009) there are three main types of data used in direct marketing: external data (customers' geographic, demographic and lifestyle characteristics), customers' transaction records and feedback from consumers. Recency, Frequency and Monetary value (RFM) model, summarizing transaction data about buyers, is often used to select the customers that are worth targeting (Colombo, 1999). The most simple form of this framework assumes that response rate depends on following factors: how often the customer buys the product or visits the shop, how much the consumer spends on current and past transactions and how recently the last purchase has been made by a buyer.

The question about what products are more suitable for targeted promotions is rarely explored with the help of randomized experiments in the literature. We are familiar with two works in this field. Bart (Bart et al., 2014) proved that mobile display advertising of utilitarian products with higher level of involvement was more effective than advertising of hedonic goods with lower involvement in terms of consumers' favorable attitudes and purchase intentions. Blake et al. (2015) investigated product response heterogeneity but did not find significant difference in advertising effectiveness across various product attributes.

The main goal of our research is to understand the relationship between characteristics of customers, different content of the messages and the effectiveness of branded mobile advertising. This can help us to provide customers of the retail chain with more relevant advertising messages, that is to create some rules for targeting system. In order to understand *who* to target and with *which* offers, we would like to answer the following questions:

1) Is advertising effective?
2) Does the effect of advertising differ across characteristics of the message (text of the

message, discount depth)?

3) Is the effect of advertising heterogeneous across RFM characteristics of customers?
4) Does loyalty of customers influence the effectiveness of advertisement?

Methodology

Experimental Design

To enable unbiased estimate of ad effect, we use data from a field experiment performed in collaboration with the retail chain that includes the stores of different size, located in the city of Perm (one in top 15 largest cities in Russia with population more than 1 million people). The retailer developed branded smartphone application about a ½ year before the experiment. This application is beneficial for both customers who create purchase lists, use the app as a discount card, browse their purchase history and the retailer who can advertise through additional channel. The research is devoted to advertising via this up-to-date kind of media and individual targeting of push notifications (treatment).

The cornerstone of the study is the random assignment of application users to either one of the treatment groups or the control group. Control group members are not eligible to see any advertisement. The user of application is considered as treated if he or she is sent any push notification. The members of twelve treatment groups receive push notification about discount on one out of twelve products belonging to six product categories: coffee, tea, juice, dairy products, sweets and non-food. These products were chosen for the experiment from a wide range of commodities on which discount was offered during regular two weeks advertising campaign. Table I summarizes information about discounts on the advertised products and their prices before (P_0) and during (P_1) the campaign. Moreover, customers read one out of two text messages before reaching an application where they get an information about their individual offer (equal shares in each of 12 treatment groups see each of the texts):

Text 1: “Enjoy latest special offers in your favorite store”;

Text 2: “Be sure to make a purchase for a holiday”.

The users of the application did not know that they participated in an experiment and that the data could be used for the research. Therefore, our experiment can be classified as a “natural field experiment” according to Harrison and List (2004). To investigate the effectiveness of advertising across different product categories, the experiment exploits a control group and 12 treatment groups that vary the promotion. We have decided to exogenously change the advertised product category (not the products), because variation of particular products’ promotions is hardly useful in terms of additional information gain. For the purpose of the research we choose product categories that are sold in all the stores of the chain and advertise two products among each product category.

Table I. Characteristics of Advertised Products

	P_0	P_1	Discount
Coffee 1	1119	849	24
Coffee 2	124,9	94,9	24
Tea 1	499	349	30
Tea 2	79,90	59,90	25
Dairy product 1	78,5	64,9	17
Dairy product 2	59,4	45,9	23
Juice 1	86,9	58,9	32
Juice 2	61,5	42,9	30
Sweets 1	296,5	249,9	16
Sweets 2	66,9	59,9	10
Non-food 1	149	119	20
Non-food 2	139	100	28

Note. Table I summarizes information about discounts on advertised products and their prices before (P_0) and during (P_1) special offer period.

As mentioned, every customer was randomly assigned to one of the 13 groups. Two most common methods of randomization could be used – pure randomization and stratification in relation to different stores of the chain or past purchase characteristics of customers (frequency and recency of purchases, average basket amount). According to Miriam Bruhn and David McKenzie (2009), “in samples of 300 or more, the different methods perform similarly”. As the size of the sample in our research exceeds 300 customers, we used pure randomization method that balanced the characteristics of customers across treatment and control groups.

Our data describe individual customer purchases in the one year before the advertising campaign was run (the “pre-test” period) and one month after this date (the “post-test” period). We prove that customers were randomly assigned to groups by comparing differences in the most important historical variables – recency (days since last purchase), frequency (number of purchases during 14 months prior to the experiment) and monetary value (amount of money spent during a year; average basket amount). As none of the differences are statistically significant (Appendix I), we conclude that allocation of customers to either control or treatment groups was purely random.

Table II. The Number of Messages Containing Different Texts

	Text 1 (number of observations)	Text 2 (number of observations)	One message (number of observations)
Coffee 1	380	319	699
Coffee 2	408	326	734
Tea 1	387	342	729
Tea 2	401	313	714
Dairy product 1	414	283	697
Dairy product 2	427	300	727
Juice 1	402	299	701
Juice 2	413	282	695
Sweets 1	411	291	702
Sweets 2	421	301	722
Non-food 1	400	307	707
Non-food 2	414	297	711

Note. Table II summarizes information about the number of messages containing each of two texts.

The duration of the advertising campaign was 2 weeks: 2 March – 15 March 2015. Twelve treatment groups received one message on March 3rd. Information about how many people got the message with a certain text for every product can be found in Table II. After removing outliers (people who made more than 36 purchases in March), we considered 11338 consumers as the population under study. Descriptive statistics of dependent variables (number of purchases, purchase amount in two weeks of campaign) and historical RFM variables are presented in the Appendix II.

Empirical Strategy

In this part of the paper we will present all the models and their specifications used to answer the research questions mentioned above. First of all, three models will be used to estimate an average effect of advertising on number of purchases and purchase amount.

1. Average effect of advertising.

Here we pay attention only to average effect of advertising. To our best knowledge, there is no article about the effectiveness of advertising through branded mobile applications in retail. At the same time, the effectiveness of other digital media (SMS-messages, online advertising, mobile display advertising) has been explored in several papers. For instance, Blake et al. (2015) proved with the help of field experiments that eBay's advertising on Google had a small and statistically insignificant effect on sales. Lewis and Reiley (2014b) report a randomized field experiment that finds an increase in purchases of the retailer by 5% caused by advertising on Yahoo! This growing interest in ads effect is associated with new technological opportunities that allow researchers to carry out large-scale field experiments (1.6 million customers participate in the experiment conducted by Lewis and Reiley) and track important variables (customers' searching behavior, all online and offline purchases) that are required for measurement of causal effect. Still, some challenges persist to correctly estimate the causal effect of advertising. As Lewis and Reiley (2014b) mention, the effect of brand advertising is often diffuse and may be not as immediate as the effect of other types of advertising, such as direct mailing. One advertising campaign can be not enough to change purchase behavior of consumers. Our advertising is special: the retailer, informing customers about discounts, advertises not the products, but it's own brand increasing buyers' intention to choose its store for a shopping trip. That is why it is really difficult to predict whether our brand advertising will be effective on average in short and long term. Furthermore, the application is targeted at loyal customers who would like to know about all the discounts provided with the retailer. This can be the case that advertising can not change purchase habits of these people because they already value the retailer and are familiar with the take-off products offered in the chain.

In order to estimate the effect of conducted advertising campaign we use three models. The first dependent variable we investigate is the number of purchase occasions in the period of advertising campaign (two weeks) - *Q*. As this variable is discrete with an ordered metric (Q_i=0,1,2,…), classical linear regression is not appropriate (Blattberg, 2008). Classical linear regression assumes a normal error term and hence a continuous dependent variable, while in our sample 3548 customers (31%) did not complete any transaction (Q_i=0). This large number of zero values makes discrete characteristics of the date prominent and induces us to use Zero-inflated Poisson regression for the analysis. Estimates are obtained via maximum likelihood estimator. We believe that advertising, reminding a consumer about the retail chain or informing him or her about new discounts, will influence consumers' desire to make an additional purchase and prevent users of the application from switching to another store. The specification used to answer this research question is following:

$$\begin{cases} \Pr(Q_i = 0) = w_i + (1 - w_i) * \exp(-\lambda_i) \\ \Pr(Q_i = q) = (1 - w_i) * \dfrac{e^{-\lambda_i} * \lambda_i^q}{q!}; q = 1,2, \ \dots, \text{and} \ln(\lambda_i) = \beta X_i \end{cases} \tag{1}$$

$$\beta X_i = \beta_1 * \text{Exposed}_i + \varepsilon_i \tag{2}$$

where

$Exposed_i$ – a dummy variable that takes the value of 1 when the user is exposed to any single message.

The second dependent variable we are interested in is the amount of money spent by a consumer in the period of advertising campaign (two weeks) - *PA*. We will use two models to estimate treatment effect on purchase amount. First, we will use classical linear model as many researches use it to explore the effect of advertising.

$$PA_i = \beta X_i + \varepsilon_i \tag{3}$$

$$\beta X_i = \beta_1 * \text{Exposed}_i + \varepsilon_i \tag{4}$$

Second, we would like to take into account left-censored nature of our dependent variable. We assume that the customer has a latent demand for goods, denoted by $PA*$, that is not expressed as a purchase until some constant threshold, denoted by γ, is passed (Cameron and Triverdi, 2005). The basic idea is that we observe $PA*$ only when it exceeds a threshold. Furthermore, as expenditure data is better modeled as lognormal, we will deal with special case of Tobit model for lognormal data with a nonzero threshold. The threshold equals the minimum uncensored value of $\ln(PA_i^*)$. Maximum likelihood is used as an estimation method for this model.

$$PA_i = \begin{cases} PA_i^*, & if \ln(PA_i^*) > \gamma \\ 0 \ , & if \ \ln(PA_i^*) \leq \gamma \end{cases} \tag{5}$$

$$PA_i^* = \exp(\beta X_i + \varepsilon_i) \ , \qquad \varepsilon_i \sim N(0, \sigma^2) \tag{6}$$

$$\beta X_i = \beta_1 * \text{Exposed}_i + \varepsilon_i \tag{7}$$

In both specifications (2) of models (1), and (7) of model (5-6) β_1 is the coefficient of interest that is interpreted as the percentage difference in respective dependent variables between consumers who were exposed to the advertising and those who did not receive any message. Due to randomized nature of our experiment β_1 coefficient can be explained *only* as an effect of advertising campaign, while other factors (competitive or macroeconomic events) influence both treatment and control groups and cannot change the coefficient of interest. β_1-coefficient in the specifications (4) of model (3) is interpreted as an absolute difference in purchase amount between exposed to advertisement and control groups.

2. Heterogeneity of the effect of advertising across different characteristics of the message – discount depth and text of the message.

2.1. Discount depth.

We have divided all the advertised products into three groups based on the discount depth of the offers: discounts under 20%, discounts between 20% and 30% and discounts above 30%. The following discounts are typical for FMCG-companies operating in Russia. Discounts for the products from the first group are close to the minimum discount provided by the retailer. Discounts applied to the products from the third group are close to the maximum value .

In the article by N. Fong (2015) it is said that the medium discount (40%) is optimal for focal targeting and it leads to an increase in purchase rates. We consequently expect that making customers aware of higher discounts (30-32% in our experiment) will make customers to purchase more.

At the same time, as most of the application's users are loyal customers, they can be familiar with the average discount level in the retail chain. Sending such people the message containing information about small discounts may cause no extra intention to visit the chain.

We answer the question about influence of discount depth by jointly estimating the coefficients β_1, β_2 and β_3 in the following specification of models (1), (3) and (5-6):

$$\beta X_i = \beta_1 * Discount1_i + \beta_2 * Discount2_i + \beta_3 * Discount3_i + \varepsilon_i, \quad (8)$$

where

$Discount1_i$ – dummy variable that takes the value of 1 when the user is exposed to the advertisement of product discount for which is less than 20% and the value of 0 otherwise (control group serves as the baseline condition);

$Discount2_i$ – dummy variable that takes the value of 1 when the user is exposed to the advertisement of product discount for which is in the range 20-29% and the value of 0 otherwise.

$Discount3_i$ – dummy variable that takes the value of 1 when the user is exposed to the advertisement of product discount for which is greater than 29% and the value of 0 otherwise.

2.2. Text of the message.

Bertrand et al. (2010) explore the importance of advertising content and provide the evidence that messages that triggered intuitive (vs. deliberate) response were more effective. Researchers find that a 25% reduction in the interest rate had the same effect on loan demand as including a photo of an attractive woman or not providing the information about a particular use for the loan.

We also would like to test whether "creative" content of the message that we send to customers is important or not. We believe that the message "Be sure to make a purchase for a holiday" will be more effective because it reminds the consumer about a pleasant event and triggers "intuitive" response.

To measure the influence of the "creative" content (the second text associated with a national holiday) on number of purchase occasions and purchase amount we estimate the following specification of models (1), (3) and (5-6):

$$\beta X_i = \beta_1 * Text1_i + \beta_2 * Text2_i + \varepsilon_i, \tag{9}$$

where

$Text1_i$ – an indicator variable for assignment to the group that received the first (general) message;

$Text2_i$ – an indicator variable for assignment to the group that received the second message about a national holiday.

An estimated coefficients $\beta_1$and β_2 will show an average effect of advertising for groups that have received either the first or the second text relative to control group not being exposed to advertising.

3. Heterogeneity of the effect of advertising across RFM (Recency, Frequency, Monetary value) characteristics of customers.

3.1. Recency of the last purchase.

Experiments are rarely used in the literature to study heterogeneous effects of advertising. Two field experiments (Lewis and Reiley, 2014a; Johnson et al., 2014) explore heterogeneity of advertising effect in relation to demographic characteristics (age, gender) and location. At the same time, the only large scale field experiment that reports the dependence of advertising effect on recency of purchase was carried out by Blake et al. (2015). The authors find large and statistically significant effect of eBay advertising on consumers who have not purchased in over a year. The authors explain that this occurs due to informative function of advertising: the effect is significant for those who do not remember about offerings of eBay. Gonul and Shi (1998) get the same results for direct mailing: researchers apply estimable structural model to database of a national cataloger and find that it is not effective to mail to individuals at low recency levels.

To understand how the effect of advertising is influenced by the recency (how much time passed since last cutomer's purchase) interaction, the following specification of models (1), (3) and (5-6) is used:

$$\begin{gathered}\beta X_i = \beta_1 * \text{Exposed}_i + \beta_2 * \text{Exposed}_i * \text{Recency}_i + \beta_3 * \text{Exposed}_i * \text{Recency}_i^2 + \\ +\beta_4 * \text{Recency}_i + +\beta_5 * \text{Recency}_i^2 + \varepsilon_i \ ,\end{gathered} \tag{10}$$

where

Recency – log of the number of days since the last customer's purchase.

The following specification allows for quadratic form of relationship between these variables. The β_1 coefficient shows the effect of advertising for a customer who made a purchase in a store immediately before receiving an advertising message (when Recency equals zero).

We are interested in a relationship between treatment effect and RFM (recency, frequency, monetary value) variables because they take into account major characteristics of customers that can be extracted from transaction data.

3.2. Frequency of purchases.

The experiment conducted by Blake et al. (2015) provides empirical evidence for advertising effect heterogeneity in relation to both recency and the number of purchases by the user in the year prior to experiment. Researchers find the largest and significant effect of eBay advertising on sales of the company for consumers who have not completed eBay transactions in the year before the experiment. Authors explain that this finding supports informative view of advertising because the users characterized with small amount of purchases are less familiar with offerings of the company and its value. We suppose that in our experiment infrequent customers who downloaded the application will be highly affected by the presence of advertising because this will provide them with new and relevant information.

Gonul and Shi (1998) assert that it is not optimal to target those consumers who purchased many times from the catalog because such customers are likely to buy anyway. However, our case is a bit different because the branded mobile application is 'pull' kind of media. It means that the users download the application if they feel that they need it. The application is created for loyal customers in order to build long-term relationship. Consequently, we believe that frequent customers are loyal and will be influenced by the branded advertising aimed at loyal customers. Actually, this also can prove informative view of advertising because loyal customers download the application to know about all the discounts of the retailer, i.e. to get new information.

The analysis of heterogeneous effect of advertising through smartphone application in relation to frequency of purchases made by a consumer in 14 months prior to the experiment is performed by estimating the following specifications:

$$\begin{aligned}\beta X_i = \beta_1 * \mathrm{Exposed}_i + \beta_2 * \mathrm{Exposed}_i * Frequency_i + \beta_3 * \mathrm{Exposed}_i * Frequency_i^2 + \\ + \beta_4 * Frequency_i + \beta_5 * Frequency_i^2 + \varepsilon_i\end{aligned} \quad (11)$$

where

$Frequncy_i$ – the log of the expression: number of purchases for 14-months period before the campaign divided to *lifetime* of the consumer expressed in weeks. We define *lifetime* as the number of weeks between the first and the last transactions completed by the user.

3.3. Monetary value (average basket amount).

While we are not familiar with the articles where the relationship between effectiveness of advertising and monetary value of customers is discussed, we think that the effect of advertisement can vary across people with different average basket amount.

For the sake of completeness, we analyze the relationship between the effect of advertising campaign and monetary value of application users. We estimate the following specification:

$$\begin{aligned}\beta X_i = \beta_1 * \mathrm{Exposed}_i + \beta_2 * \mathrm{Exposed}_i * \mathit{Monetary\ value}_i + \\ +\beta_3 * \mathrm{Exposed}_i * \mathit{Monetary\ value}_i^2 + \beta_4 * \mathit{Monetary\ Value}_i + \\ +\beta_5 * \mathit{Monetary\ value}_i^2 + \varepsilon_i\end{aligned} \quad (12)$$

where

$\mathit{Monetary\ value}_i$ – total expenditure for 14 months prior to advertising campaign divided to the number of purchases made during the same period of time, thus it is average basket amount.

4. The effect of loyalty offer.

In order to give some practical recommendations to the retailer about *whom* to target and with *which* offer, we would like to understand how the effectiveness of advertising depends on previous *brand* purchase history of a customer. Zhang and Wedel (2009) define "loyalty promotions" as those delivered to customers who purchased the target brand on the prior purchase occasion. "Competitive promotions" are aimed at people who did not purchase the target brand on the prior purchase occasion. Researchers find that loyalty promotions are more profitable in online stores than competitive promotions. However, the expected profit in offline stores is higher if promotions are offered to customers who purchased competitor's brand previously.

In order to understand whether the effect of advertising is different for loyal and competitive offers, we estimate specification (12) of models (1), (3) and (5-6). The β_2 coefficient corresponds to the effect of loyalty offer:

$$\begin{aligned}\beta X_i = \beta_1 * \mathit{ExposureMP}_{1_i} + \beta_2 * \mathit{ExposureMP}_{1_i} * \mathit{MilkProd}1_i + \beta_3 * \mathit{MilkProd}1_i \\ + \varepsilon_i\end{aligned} \quad (13)$$

where

$\mathit{ExposureMP}_{1_i}$ – a dummy variable that takes the value of 1 when a user is exposed to the advertisement of the first dairy product and 0 when the user does not get any message (control group).

$MilkProd1_i$ – a dummy variable that takes the value of 1 for users who bought any good of the same brand as the first dairy product on the prior purchase occasion and the value of 0 otherwise.

In general, we are interested in the effect of loyal and competitive offers for each of the advertised brands, but the design of our experiment allows estimating the effect only for diary products frequently bought by customers. For other brands we do not have sufficient number of observation to identify the effect of advertisements on loyal customers.

Results

1. Average effect of advertising

In this section we present results about the effectiveness of conducted advertising campaign on average. Two main variables of interest are purchase amount of customers and the number of purchases in the period of advertising campaign.

We run a Zero-inflated Poisson regression to estimate the effect of advertising on number of purchases in two weeks (specification (2) of the model (1)). Tobit regression and linear regression are used for the analysis of the same treatment effect on post-test purchase amount (specification (4) of the model (3) and specification (7) of the model (5-6)). Control group consists of 1418 customers, whereas 8538 mobile application users received the message about one of the advertised products.

According to our results, the probability of the number of purchases being zero is higher for customers exposed to the advertisement (Table III). Moreover, advertising leads to a decrease in purchase amount ($\beta_1 = -0.137$).

Table III. Average Effect of Advertising

	Number of purchases		Purchase amount (OLS)	Purchase amount (Tobit model)
	$\Pr(Q_i = 0)$	$E(Q_i)$		
Exposed	0.041**	-0.024	-148.743	-0.137***
	(0.017)	(0.013)	(88.071)	(0.037)
Intercept	-0.844***	1.579***	2204.617***	5.241***
	(0.000)	(0.000)	(83.333)	(0.005)
Log likelihood	-25955			-21708
R^2_{adj}			0.0002	
Sample size	9956		9956	9956

Note. Table III reports the coefficients from estimating equations (2) , (4) and (6) on a sample of consumers who received only one advertising message or did not receive any message. Bootstrap clustered (across different groups) standard errors are in parentheses.

***Significantly different from zero, p<.01

**Significantly different from zero, p<.05

Results reported in the articles on the effectiveness of advertising are often ambiguous. For instance, Lodish et al. (1995) report the results of 360 advertising campaigns on TV and find that only 49% of such campaigns were statistically significant at the 20% level. Lewis and Reiley (2014b) discuss two reasons for small and insignificant effects that researchers get: high variance of a dependent variable and insufficient sample size. However, the only article to our knowledge where authors discuss the negative effect of advertising (Anderson et al., 2010) is devoted to the impact of deep discounts on long-run demand of customers who had recently paid a higher price for one of the advertised products. In our opinion, a negative average effect we get is associated with the influence of messages containing information about small discounts. We will further discuss this issue in the next section.

2. Heterogeneity of the effect of advertising across different characteristics of the message – discount depth and text of the message

2.1. Discount depth.

In the research by Fong et al. (2015) it is assumed that purchase rate in the case of 20%-discount should be the same as purchase rate in the no-discount case. Our experimental design enables us to investigate the impact of discount depth on number of purchases and purchase amount. We form three groups of discounts: under 20%, 20%-29% and discounts greater than 29%. Discount lower than 20% was assigned to three advertised products: Sweets1, Sweets2 and Dairy products1. The second group representing discounts from 20% to 29% consists of six advertised products: Non-food goods1, Dairy products2, Coffee1, Coffee2, Tea2 and Non-food goods2. The last group includes the following products: Juice2, Tea1, Juice1. The number of messages sent to customers with information about discounts under 20%, 20-29% and discounts greater than 29% is respectively 2121, 4292 and 2125.

We would like to note that the deepest discounts in this research (30%, 32%) are not considered as 'deep' in the literature. However, these were the deepest discounts in the retail chain during the advertising campaign.

In order answer the question about the effect of different discounts on number of purchases we run a Zero-inflated Poisson regression (specification (8) of model (1)). Specification (8) of the models (3) and (5-6) helps to estimate the treatment effect of three discount groups on purchase amount.

Table IV. The Effect of Discount Depth

	Number of purchases		Purchase amount (OLS)	Purchase amount (Tobit model)
	$\Pr(Q_i = 0)$	$E(Q_i)$		
Discount1	0.059**	-0.057***	-227.821**	-0.208***
	(0.027)	(0.016)	(110.311)	(0.080)

Discount2	0.041	-0.022	-180.670	-0.146***
	(0.024)	(0.021)	(96.112)	(0.039)
Discount3	0.022	0.004	-5.328	-0.050
	(0.048)	(0.019)	(105.165)	(0.108)
Intercept	-0.844***	1.579***	2204.617***	5.241***
	(0.000)	(0.000)	(84.328)	(0.005)
Log likelihood	-25948			-21707
R^2_{adj}			0.0006	
Sample size	9956		9956	9956

Note. Table IV reports the coefficients from estimating specification (7) of models (1), (3) and (5-6) on a sample of consumers who received only one advertising message or did not receive any message. Bootstrap clustered standard errors are in parentheses.

***Significantly different from zero, p<.01

**Significantly different from zero, p<.05

We find a very interesting result that messages containing information about small discounts (under 20%) have a negative impact on the number of purchases made by customers and their purchase amount (Table IV). We suppose that the negative average effect of advertising campaign we find is caused by the negative influence of small discounts. This can be the case that application users feel disappointed with promotions they are informed about because the offered discount is too small. Consequently, they make fewer purchases than those who did not receive any information.

2.2. Text of the message.

Here we investigate the relationship between the content of message and the effectiveness of advertising.

We test whether the message “Be sure to make a purchase for a holiday” (Text 2) will be more effective than Text 1 (“Enjoy latest special offers in your favorite store”). Text 1 is quite general, whereas the second text reminds the consumer about a pleasant event. Control group includes 1418 customers, 4878 people received one message containing the first text, 3660 consumers were sent one message with the second text.

Table V. Text of the Message

	Number of purchases		Purchase amount (OLS)	Purchase amount (Tobit model)
	$\Pr(Q_i = 0)$	$E(Q_i)$		
Text1	0.042	-0.010	-139.735	-0.130***
	(0.025)	(0.014)	(94.461)	(0.047)
Text2	0.039	-0.043**	-160.749	-0.147***
	(0.027)	(0.018)	(102.506)	(0.051)
Intercept	-0.844***	1.579***	2204.617***	5.241***
	(0.000)	(0.000)	(86.908)	(0.005)
Log likelihood	-25951			-21708
R^2_{adj}			0.0001	
Sample size	9956		9956	9956

Note. Table V reports the coefficients from estimating specification (13) of models (1), (3) and (5-6) on a sample of consumers who received only one advertising message or did not receive any message. Bootstrap clustered standard errors are in parentheses.

***Significantly different from zero, p<.01
**Significantly different from zero, p<.05

We estimate the specification (9) of models (1), (3) and (5-6) and find that, according to Zero-inflated Poisson model, only the second text has a negative effect on number of purchases made by customers (Table V). It can be the case the text about holiday and information about small discounts do not agree with each other. In general, we believe that the negative effect of texts we find (specification (9) of model (5-6)) is associated with the effect of small discounts.

3. Heterogeneity of the effect of advertising across RFM (Recency, Frequency, Monetary value) characteristics of customers.

3.1. Recency of the last purchase.

We expect that the effect of advertising can be dependent on recency of customer's last purchase. We test quadratic form of relationship between advertising effect and Recency variable (how much time has passed since a customer's last purchase) by estimating specification (10) of models (1), (3) and (5-6). Table VI reports the coefficients from estimating these models. We find quadratic form of relationship between the Exposed and Recency variables. This implies it is effective to target customers who did not visit a shop for a long time that is consistent with informative view of advertising. At the same time, customers who did not make any purchase for more than half a year are unlikely to respond to offers. Figure 1 describes the relationship between treatment effect on number of purchases (Model 1, second equation for E(Q)) and log of Recency variable. Blake et al. (2015) and Gonul and Shi (1998) get qualitatively the same results.

Table VI. Impact of Advertising By Recency of Prior Purchase

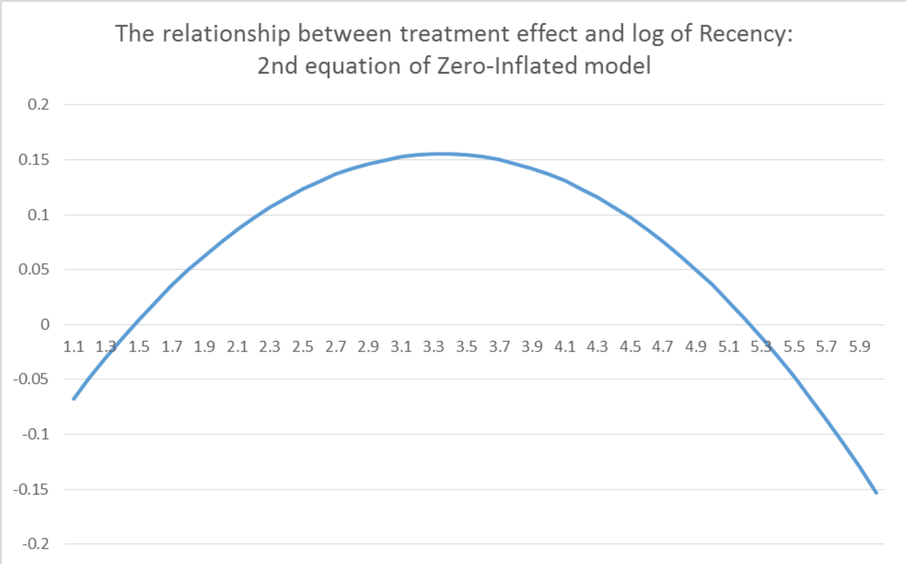
	Number of purchases		Purchase amount (OLS)	Purchase amount (Tobit model)
	$\Pr(Q_i = 0)$	$E(Q_i)$		
Exposed	0.331	-0.339***	-1082.01**	-0.369
	(0.210)	(0.091)	(449.848)	(0.445)
Exposed*Recency	-0.132	0.295***	735.272***	0.192
	(0.159)	(0.094)	(297.491)	(0.395)
Exposed*Recency^2	0.014	-0.044**	-108.453***	-0.019
	(0.029)	(0.020)	(44.091)	(0.075)
Recency	1.201***	-1.005***	-3906.675***	-1.092***
	(0.000)	(0.000)	(286.886)	(0.368)
Recency^2	0.015***	0.057***	466.046***	-0.230***
	(0.000)	(0.000)	(42.318)	(0.070)
Intercept	-4.386***	3.019***	8097.702***	9.273***
	(0.000)	(0.000)	(434.648)	(0.414)
Log likelihood	-21123			-18311
R^2_{adj}			0.233	
Sample size	9956		9956	9956

Note. Table VI reports the coefficients from estimating specification (9) of models (1), (3) and (5-6) on a sample of consumers who received only one advertising message or did not receive any message. Bootstrap clustered standard errors are in parentheses.

***Significantly different from zero, p<.01

**Significantly different from zero, p<.05

Figure 1. Heterogeneity of treatment effect across Recency variable.



Note. Horizontal axis: log of Recency variable. Vertical axis: treatment effect.

3.2.Frequency of purchases.

In this part of our work we explore interaction between *Frequency* and *Exposed* variables. We test quadratic form of relationship between frequency of purchases made by a customer within 14 months prior to the advertising campaign and treatment effect.

Table VII reports the coefficients from estimating specification (11) of models (1), (3) and (5-6). We find that the relationship between the variables of interest is quadratic.

To better understand the interaction between treatment effect and frequency of purchases we draw a graph (Figure 2) showing relationship between log of Frequency variable and the effect of advertising on number of purchases (Zero-inflated Poisson model, second equation).

The result that advertising is effective for infrequent customers is consistent with findings by Blake et al. (2015) and Gonul and Shi (1998). This can be explained by informative view of advertising because customers who rarely make purchases are often unfamiliar with offerings of the retail chain. However, Gonul and Shi (1998) highlight that it is not optimal to target those consumers who purchased many times. It is possible that we get an opposite result because of nature of the advertising campaign we run. Only those frequent customers who would like to get information about news and discounts of a retail chain download the application. So, they are sensitive to advertising messages sent through the application.

Table VII. Impact of Advertising by Frequency

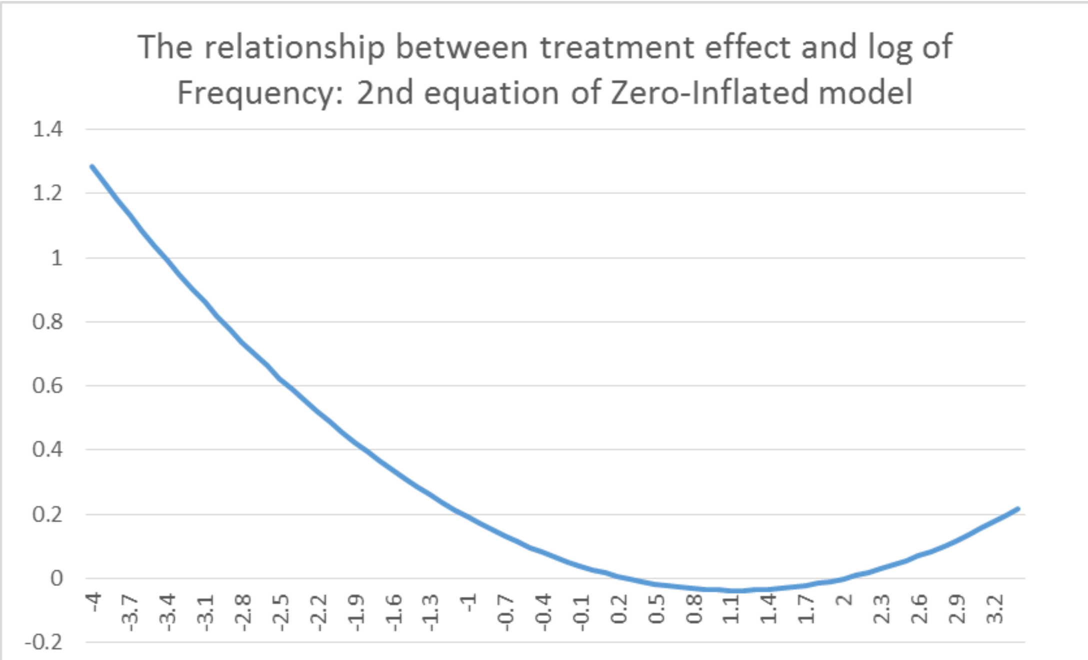
	Number of purchases $\Pr(Q_i = 0)$	Number of purchases $E(Q_i)$	Purchase amount (OLS)	Purchase amount (Tobit model)
Exposed	0.335***	0.027***	-188.736**	-0.333***
	(0.039)	(0.010)	(85.025)	(0.113)
Exposed*Frequency	-0.149***	-0.114***	2.898	-0.054
	(0.034)	(0.022)	(95.165)	(0.087)
Exposed*Frequency^2	-0.161***	0.050***	45.567	0.233***
	(0.038)	(0.014)	(51.374)	(0.072)
Frequency	-0.863***	0.838***	1546.943***	2.093***
	(0.000)	(0.000)	(85.743)	(0.081)
Frequency^2	0.147***	-0.033***	320.839***	-0.435***
	(0.000)	(0.000)	(46.779)	(0.067)
Intercept	-1.628***	1.001***	1744.077***	5.645***
	(0.000)	(0.000)	(78.071)	(0.105)
Log likelihood	-19722			-19160
R^2_{adj}			0.267	
Sample size	9956		9956	9956

Note. Table VII reports the coefficients from estimating specification (10) of models (1), (3) and (5-6) on a sample of consumers who received only one advertising message or did not receive any message. Bootstrap clustered standard errors are in parentheses.

***Significantly different from zero, p<.01

**Significantly different from zero, p<.05

Figure 2. Heterogeneity of treatment effect across Frequency variable.



Note. Horizontal axis: log of Frequency variable. Vertical axis: treatment effect.

3.4. Monetary value (average basket amount).

We suppose that the effect of advertising can also depend on the third important characteristic of customers – monetary value. We test quadratic form of relationship between log of average basket amount and the treatment effect.

Table VIII. Impact of Advertising by Monetary Value

	Number of purchases		Purchase amount (OLS)	Purchase amount (Tobit model)
	$\Pr(Q_i = 0)$	$E(Q_i)$		
Exposed	1.845	3.341***	-1767.948	-3.011
	(1.074)	(0.488)	(3529.878)	(5.264)
Exposed*Monetary value	-0.653	-1.088***	680.360	1.022
	(0.347)	(0.157)	(1263.218)	(1.728)
Exposed*Monetary value^2	0.057**	0.087***	-65.732	-0.088
	(0.028)	(0.013)	(111.286)	(0.141)
Monetary value	-3.787***	2.544***	-2630.840**	8.245***
	(0.000)	(0.000)	(1140.839)	(1.606)
Monetary value ^2	0.269***	-0.204***	366.270***	-0.555***
	(0.000)	0.000	(101.181)	(0.131)
Intercept	12.104***	-6.277***	4374.495	-24.188***
	(0.000)	(0.000)	(3165.504)	(4.891)
Log likelihood	-25640			-21234
R^2_{adj}			0.164	
Sample size	9956		9956	9956

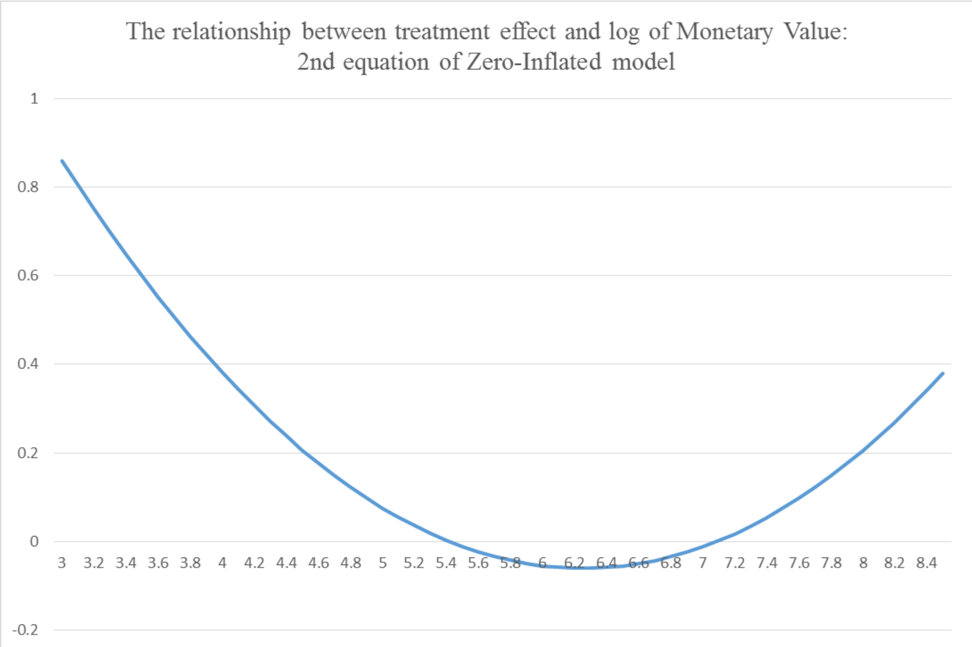
Note. Table VIII reports the coefficients from estimating specification (11) of models (1), (3) and (5-6) on a sample of consumers who received only one advertising message or did not receive any message. Bootstrap clustered standard errors are in parentheses.

***Significantly different from zero, p<.01

**Significantly different from zero, p<.05

Table VIII reports the coefficients from estimating specification (12) of models (1), (3) and (5-6). We find that the relationship between the monetary value of application users and the treatment effect is quadratic. Figure 3 represents this relationship. We can conclude that it is worth targeting customers with small monetary value and high monetary value.

Figure 3. Heterogeneity of treatment effect across Monetary value variable.



Note. Horizontal axis: log of Monetary value variable. Vertical axis: treatment effect.

4. The effect of loyalty offer.

Here we try to answer the main question of direct marketing – *who* to target *and* with *which* offer. We explore whether the effect of advertising is higher for loyal customers (those who have bought the product of the advertised brand at the last visit of the store).

Table IX. The Effect of Loyalty Offer

	Number of purchases		Purchase amount (OLS)	Purchase amount (Tobit model)
	$\Pr(Q_i = 0)$	$E(Q_i)$		
Exposure_MP1	0.067	-0.067	-195.595	-0.252
	(0.102)	(0.049)	(136.358)	(0.191)
Exposure_MP1*MilkProd1	-0.322	-0.129	16.362	0.266
	(0.541)	(0.152)	(741.256)	(0.645)
MilkProd1	-0.483	0.078	1865.33***	1.214***
	(0.314)	(0.086)	(444.922)	(0.370)
Intercept	-0.815***	1.573***	2078.332***	5.165***
	(0.062)	(0.027)	(79.519)	(0.124)
Log likelihood	-5593			-4614
R^2_{adj}			0.0213	
Sample size	2115		2115	2115

Note. Table IX reports the coefficients from estimating specification (12) of models (1), (3) and (5-6) on a sample of consumers who received only one advertising message or did not receive any message. Bootstrap clustered standard errors are in parentheses.

***Significantly different from zero, p<.01

**Significantly different from zero, p<.05

To answer this question we use only two groups of people: control group and group of customers who have received the advertisement of Dairy products 1 (as consumers frequently buy dairy products). We have 96 loyal customers (they have bought the product of the advertised brand on their last purchase occasion) in the control group, 43 loyal consumers – in the group of people who got the message about Dairy products 1. The number of other customers in the control group is equal to 1322, in the Dairy products 1 group – 654.

We find that there is no additional effect of advertising on loyal customers (Table IX). There is also no effect of competitive offers as β_2 coefficient is statistically insignificant. The reason for that might be the lack of data. Moreover, loyal customers can be defined on the basis of the whole historical purchases (not only the last purchase occasion). Such approach requires even more data though.

Conclusion & Discussion

This work contributes to the literature on advertising by presenting empirical findings about the effectiveness of advertising through a new and very special medium – branded mobile application. The main findings of our research are the following:

1. The impact of advertising campaign either on number of purchases or on purchase amount is slightly negative on average. This is due to small discount offers in conjuncture with holiday text.

2. No effect of different texts of the message is found.
3. The effect of advertising depends nonlinearly on RFM characteristics of consumers.
4. We find no additional effect on loyal customers (while the measure of loyalty we use is very simple and we have lack of data to answer this question).

To conclude, the effectiveness of advertising is dependent on recency of customer's last purchase, frequency of purchases, consumers' monetary value and the depth of discount provided to mobile application users. These results can help a retail chain to create some rules for individual targeting and understand who are more sensitive to advertising.

An average effect of advertising we get can be underestimated. Some customers turn "push" notifications off from their smartphones. Randomization procedure ensures that equal rates of consumers do not receive a message across all groups. Nevertheless, the users who did not get a message were not influenced by variation of offers. Therefore, aggregate difference between treatment and control groups is likely to be smaller than in the situation when all consumers are affected by advertisement. Thus, the effect we estimate is called "intention to treat effect". It means that we analyze all the customers that were treated. Dividing "intention to treat effect" by the share of users who actually have seen an advertisement leads to "treatment on treated" effect (Lewis and Reiley (2014b)) that can be greater and statistically significant. However, we do not have data about a share of such customers.

We believe that the main limitation of this study is associated with generalization problem that is common to field experiments. We carried out one experiment for a single retailer that makes it uncertain to what extent the results will generalize. Moreover, to make results more persuasive it is better to replicate an experiment. However, to the moment we had not an opportunity to do an experiment again and check whether we come out with the same results.

The last problem we would like to mention is that after entering the app via a push notification, the buyer could see three goods with the targeted product in the first place. The information about two other goods is unavailable to the date and we can not take this information into account when we analyze data. This can bias an estimate of advertising effect.

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Appendix

Appendix I. Check on Randomization Procedures

	Days since last purchase (recency)	Number of purchases/lifetime	Average basket amount (monetary value)	Number of observations
Control group	25.23	1.71	584.46	1418
	(1.14)	(0.04)	(11.52)	
Coffee1	29.24	1.69	598.91	699
	(1.85)	(0.06)	(39.22)	
Coffee2	27.26	1.63	585.21	734
	(1.75)	(0.06)	(22.40)	
Tea1	26.57	1.73	591.16	729
	(1.64)	(0.06)	(16.42)	
Tea2	26.22	1.60	577.24	714
	(1.69)	(0.05)	(15.85)	
Dairy product 1	28.10	1.65	569.01	697
	(1.83)	(0.06)	(18.60)	
Dairy product 2	25.88	1.69	579.13	727
	(1.64)	(0.06)	(15.96)	
Juice 1	24.94	1.76	581.97	701
	(1.65)	(0.06)	(18.96)	
Juice 2	27.11	1.61	564.17	695
	(1.79)	(0.06)	(16.81)	
Sweets 1	27.43	1.64	577.12	702
	(1.67)	(0.06)	(17.91)	
Sweets 2	25.78	1.71	588.60	722
	(1.77)	(0.06)	(17.40)	
Non-food goods 1	24.29	1.81	558.77	707
	(1.60)	(0.06)	(15.70)	

Non-food goods 2	25.74	1.63	570.72	711
	(1.57)	(0.05)	(17.62)	
Significance	F=0.94	F=1.04	F=0.40	
	p=0.51	p=0.41	p=0.98	

Note. Appendix I reports the mean values of each historical purchasing measure (calculated separately for each group). The statistics are calculated using purchases during the 14-month pre-test period, prior to the beginning of the advertising campaign (3rd March 2015). Standard errors are in parentheses. ANOVA was used to test the equality of averages between groups. Null hypothesis: the averages are identical.

Appendix II. Descriptive Statistics

a) Number of purchases (two weeks in the advertising campaign period)

	Mean	s.d.	Min	Max
Control group	3.39	3.90	0	25
Experimental groups – different goods				
Coffee 1	3.26	3.88	0	20
Coffee 2	3.19	3.64	0	19
Tea 1	3.47	3.98	0	22
Tea 2	3.06	3.58	0	21
Dairy product 1	3.09	3.75	0	24
Dairy product 2	3.28	3.70	0	21
Juice 1	3.52	3.91	0	20
Juice 2	3.16	3.80	0	20
Sweets 1	3.05	3.58	0	18
Sweets 2	3.30	3.70	0	20
Household chemical goods 1	3.67	4.12	0	18
Household chemical goods 2	3.21	3.67	0	19

b) Purchase amount (two weeks in the advertising campaign period, rub)

	Mean	s.d.	Min	Max
Control group	2 205	3 148	0	20 059
Experimental groups – different goods				
Coffee 1	1 973	3 014	0	22 585
Coffee 2	1 876	2 649	0	22 449
Tea 1	2 405	3 564	0	24 940
Tea 2	1 977	2 956	0	19 083
Dairy product 1	1 999	3 136	0	24 323
Dairy product 2	2 133	3 247	0	31 216
Juice 1	2 228	3 230	0	22 573
Juice 2	1 954	2 899	0	20 938
Sweets 1	1 851	2 877	0	29 756
Sweets 2	2 078	2 955	0	21 237
Household chemical goods 1	2 202	3 052	0	16 894
Household chemical goods 2	1 985	2 947	0	24 295

c) Recency of purchases (14 month prior to the advertising campaign, days)

	Mean	s.d.	Min	Max
Control group	25	43	3	353
Experimental groups – different goods				
Coffee 1	29	49	3	407
Coffee 2	27	48	3	394
Tea 1	27	44	3	396
Tea 2	26	45	3	361
Dairy product 1	28	48	3	406
Dairy product 2	26	44	3	357
Juice 1	25	44	3	317
Juice 2	27	47	3	408
Sweets 1	27	44	3	394
Sweets 2	26	48	3	383
Household chemical goods 1	24	42	3	406
Household chemical goods 2	26	42	3	359

d) Frequency of purchases (14 month prior to the advertising campaign, times per week)

	Mean	s.d.	Min	Max
Control group	1.71	1.67	0.03	25.25
Experimental groups – different goods				
Coffee 1	1.69	1.67	0.02	17.33
Coffee 2	1.63	1.51	0.02	8.75
Tea 1	1.73	1.60	0.03	8.46
Tea 2	1.60	1.46	0.02	9.31
Dairy product 1	1.65	1.57	0.02	10.05
Dairy product 2	1.69	1.51	0.03	8.81
Juice 1	1.76	1.54	0.02	8.36
Juice 2	1.61	1.48	0.03	12.30
Sweets 1	1.64	1.67	0.04	20.47
Sweets 2	1.71	1.60	0.02	10.74
Household chemical goods 1	1.81	1.58	0.02	8.06
Household chemical goods 2	1.63	1.46	0.03	8.41

e) Monetary value (14 month prior to the advertising campaign, rub)

	Mean	s.d.	Min	Max
Control group	584	434	20	4 378
Experimental groups – different goods				
Coffee 1	599	1 037	36	25 116
Coffee 2	585	607	20	11 308
Tea 1	591	443	25	3 455
Tea 2	577	423	20	2 549
Dairy product 1	569	491	19	4 596
Dairy product 2	579	430	33	3 780
Juice 1	582	502	13	5 322
Juice 2	564	443	19	4 452

Sweets 1	577	475	50	5 569
Sweets 2	589	468	47	3 979
Household chemical goods 1	559	417	22	3 969
Household chemical goods 2	571	470	18	5 689

Authors:

1. Mariia Okuneva, National Research University Higher School of Economics - Perm. Group for Applied markets and Enterprises Studies. Research Assistant; E-mail: miokuneva2@gmail.com

2. Dmitriy Potapov, National Research University Higher School of Economics - Perm. Group for Applied markets and Enterprises Studies. Head of AMES group. HSE-Perm Deputy Director, Associate Professor. E-mail: dbpotapov@hse.ru