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Барсукова Виктория Алексеевна

ИССЛЕДОВАНИЕ ПОВЕДЕНИЯ ОТТОКОВЫХ КЛИЕНТОВ РЕСТОРАННОЙ СЕТИ

RESEARCH ON BEHAVIOR OF CHURN CUSTOMERS IN THE RESTAURANT CHAIN

Выпускная квалификационная работа - БАКАЛАВРСКАЯ РАБОТА

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Рецензент	Руководитель
Куга Я.Т.	к.э.н.,
	А.М. Лозинская

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Content

Abstract

The current paper is devoted to the research of the behavior of the churn customers in a restaurant chain through the data from its loyalty program. It is important for companies to pay more attention to the segment of churn customers as when customers churn they take away profitability that could potentially bring to the firm. We use linear regression, probit model and Heckman model in order to estimate churn customers' behavior. Analysis performed on the customer data after conducting experiment within which customer were offered extra points. It was found that churn customers are tend to response on presenting them extra points, but the average sum of bills of those customer who were not given points is higher.

Аннотация

Данное исследование посвящено изучению поведения оттоковых клиентов в ресторанной сети посредством использования данных имеющейся у ресторанной сети программы лояльности. Компаниям важно изучать поведение оттоковых клиентов, так как когда клиенты перестают пользовать услугами компании, они уносят с собой прибыль, которую потенциально могли принести компании. Для того чтобы проанализировать поведение оттоковых клиентов были использованы линейная регрессия, probit-модель и модель Хэкмана. Анализ проводился на клиентских данных после проведенного эксперимента, в рамках которого клиентам предлагались дополнительные бонусы. Было установлено, что оттоковые клиенты склонны реагировать на подаренные им бонусы, однако средний чек клиентов, получивших бонусы и пришедших во время акции ниже, чем средний чек клиентов, которые не получили бонусы, но тоже пришли.

Introduction

It is commonly believed, that nowadays building customer relationships is a quite challenging task for business due to the rapid growth of unit-economy, which have led to changes in customers' behavior. They pretend to personalized experience and custom solutions in everything: the ability to use the product, communications, and services. These changes have been driven primarily by advances in information technology and the ubiquity of brands (Reinold and Tropp, 2012) that lead to customers` easy switching between brands.

The main objective for firms that are pretended to remain competitive is to be able to retain customers, as when customers churn they take away profit that could potentially bring to firm (Kumar and Reinartz, 2012). That is why firms should catch and take into consideration all changes in churn customer[1] behavior to build the process of acquisition and retention more meticulous and attractive to customers.

Previous literature is devoted to research on the process of acquisition and retention (Kumar and Reinartz, 2012 Gustafsson et al., 2005). All scholars agree that acquisition costs are much higher than the cost of retention. This encourages firms to pay more careful attention to the segment of churn customers, while scholars are interested in building prediction models of churn with methods of machine learning that reflects in a massive bulk of recent papers (Qaisi, 2018, Mozer, et al., 2000).

The challenge of churn customers is typical for most service industries. The current paper is focused on the discovering restaurant industry as previously it is considered that people are not prone to change their usual places for dinner and lunch (Keaveney, 1995). Today customer behavior in this industry is constantly changing (McKenzie, 2016) and it is important for restaurants to research and understand their customers.

[1] Churn customers – customers who no longer use service of the firm

The objective of the current paper is to research churn customers` behavior in the restaurant chain. To achieve this goal we have to solve the following problems (tasks):

1. to analyze theoretical and empirical studies on churn customer behavior;
2. to determine the proxy for customer behavior;
3. to determine the methodology of the research;
4. to conduct an analytical analysis of the available data;
5. to conduct an econometric analysis of the data;
6. to interpret results obtained from econometric models;
7. to draw the main conclusions about churn customer behavior in the restaurant chain and propose limitation.

We use linear regression, probit model and Heckman model in order to estimate churn customers behavior with respect to their probability to visit at least one restaurant from restaurant chain again and their sum of bills. Models are built on three subsamples as data from conducted experiment is used for researching. Experiment was carried out within marketing campaign that was launched in the Rosinter Restaurants Holding last winter. Churn customers were presented 250, 350 and 450 extra points within the promotion.

It was found that presenting extra points contributes to customer’s probability to come back for any case of 250, 350 or 450 points. However, the average sum of bill before points’ usage during the promotion campaign of returned customers who were given extra points is less than the average sum of bills of churn customers who visited restaurant but were not presented extra bonuses. It is due to problem of sample selection bias that was confirmed.

According to the tasks presented above, we can divide the paper into several parts. The first is the overview of previous literature about churn customer behavior. The next part is devoted to the explanation of the research question and the design of the research. Further, there is a description of methodology where it is explained the relevance of using linear regression, probit-model and Heckman-model, it is explained the necessity of using several subsamples and it is given the description of all dependent variables. The next part is included data description. Further empirical results are presented and their interpretation is given. The final part is devoted to making a conclusion and discussing a few limitations.

Literature Review

Trends in customer behavior

Today there is strong competition between firms (Gordini and Veglio, 2017) because of almost all markets are saturated by goods and services. Due to this fact firms have to compete for every customer constantly. In this context building, long-term customer relationship is a relevant way to increase profitability for firms (Coussement et al., 2010). That is why it is crucial for them to research and comprehend deeply their customers` behavior.

There are two major trends in customers' behavior that are highlighted by Kumar and Reinartz (2012) – *demographic change*s and *behavioral changes*. These trends should be taken into account by firms that are going to be successful in the market. Table 1 shows the subgroups of changes included in each trend.

Table 1

Trends in customer behavior

Demographic changes	**Behavioral changes.**
Aging population	Time scarcity
Increasing diversity of customers	Intolerance for low service levels
Increasing individualization	Decreased loyalty

Source: (Kumar, Reinartz, 2012)

According to these authors, demographic changes illustrate the growth of customer diversity, while behavioral changes reflect customers` response to market offers. Let us consider these changes in more details:

Demographic changes

Speaking about the *aging population*, it is important to take into consideration that the birth rate falls, the population in some countries decreases. All of these lead to fundamental changes in the composition of customers. Further, *customers* are becoming *more multinational* due to the trend and the possibility of migration to developed countries that make markets more culturally diverse. A new segment of customers with different preferences are appearing and as a result, vendors should meet *customers` ethnically diverse* needs in goods and services. Moreover, firms should understand the customer behavior of different ethnical groups in order to develop a more customer-oriented marketing campaign. And the last but not least trend – *increasing individualization* is associated with changing in behavior and composition of the family. For example, there is a tendency of appearing single-parent families or families where both partners are passionate about the career. Firms should take into account personal interest of each family member rather than assume family`s homogeneity.

Behavioral changes

Kumar and Reinartz (2012) point out that shifts in the use of media, availability of information and attitude toward convenience causes a change in customer behavior.

To begin with, nowadays various kinds of activities compete for people`s time. *Time scarcity* makes customers reorganize their daily routine and make it more time-consuming. Due to this trend customers tend to react negatively when firms set time constraints. This new behavioral trait should encourage firms to be more time-conscious and be able to provide products and when the consumer needs it

Moreover, customers have become more demanding and *intolerance for low service levels*. Their expectations are becoming higher every day and they react negatively to failures. This may lead to *decreasing loyalty* and as a result switching (Tamaddoni et al. 2014). That is why realizing this behavioral characteristic of customers firms should constantly work to retain them in order to stay competitive.

Triggers of customer behavior

Besides Gustafsson et al. (2005) referring to earlier studies note that there are two categories of triggers that could influence customer behavior and they should be taken into account.

Situational triggers reflect something that makes customers to stop using of some services or vice versa begin to use. The examples of such triggers are demographic or economic changes or just lack of need.

Reactional triggers reflect something that just dissatisfies customers, for instance, poor performance of services that leads to switching and churning.

To sum up, developing and understanding customer behavior and its changes are the core of success for firms in the consumer-centric market condition

Churn customers

There are three main processes in firms regarding customers – acquisition, retention and return that are the central components of Customer Relationship Management (Min et al, 2015). The last two mentioned (retention and returning) are should be introduced because (as was discussed above) customers are prone to switch quickly from good to good and from services to services due to a huge amount of choice on market. Besides, a lot of scholars point out that the cost of retaining and returning are less than acquisition costs (Coussement, 2010; Renjith, 2017; Qaisi et al., 2018, Ahn et al., 2006, Athanassopoulos, 2000)That is why companies pay more attention to customers who are going to stop using their product (Gordini and Veglio, 2017) in order to prevent this. Leaving customers are called *«churn»* (Kumar and Reinartz, 2012). Renjith (2017) gives a more comprehensive definition:

Churn customers are defined as active customers who are leaving the company and discarding the services due to the dissatisfaction of the services and/or due to better offering from other companies.

Churn customers is a big challenge for companies, as when they leave, they take away profitability that could potentially bring to the company. Moreover, Athanassopoulos (2000) proposes three main reasons why customer retention is crucially important for firms:

- Costs on acquisition are five time more than cost on retention;
- Customers with whom long-term relationship is build are not tend to response to competitors. Moreover, their opinions and comments may contribute to the acquisition of new customers. However, their negative response may be expensive for firm.
- Insignificant improvements in customers` retention leads to significant increase in profitability.

That is why it is crucially important to research the behavior of churn customers and their characteristics in order to understand how to communicate and build long-term relationships with them.

In previous literature, there are two main directions in researching churn customers (Zhang et al., 2012): some scholars devote their papers to determinants of churn customers to reveal their behavior; others build prediction models using methods of machine learning. It worth noting that a massive bulk of literature revolves around telecommunication and Internet industry due to the availability of information about customers an opportunity to collect data.

Determinants of customer churn

To begin with the pool of studies are focused on exploring only few factors of customer churn, for example dissatisfaction or loyalty, rather than estimation of models which are included all relationships among various factors, such as customer dissatisfaction, switching costs, service usage and other customer-related variables (Ahn et al., 2006). For instance, Keaveney (1995) just only finds out reasons for customers` switching and churning and classifies them into 8 categories:

- «Pricing» Category is included reasons for switching due to high prices, price increases, unfair pricing practices, and deceptive pricing practices;
- «Inconvenience» Category is included all critical incidents in which the customer felt inconvenienced by the service provider's location, hours of operation, waiting time for service, or waiting time to get an appointment;
- «Core Service Failures» Category is included all critical incidents that were due to mistakes or other technical problems with the service itself;
- «Service Encounter Failures» Category is included reasons for switching due to employees' behaviors or attitudes: if employees were uncaring, impolite, unresponsive, or unknowledgeable;
- «Employee Responses to Service Failures» Category included critical switching incidents in which customers switched, not because of a service failure, but because service providers failed to handle the situation appropriately;
- «Attraction by Competitors» Category when customers switch to service which is more personable;
- «Ethical Problems» Category is included reasons for switching due to dishonest behavior, intimidating behavior, unsafe or unhealthy practices, and conflicts of interest;

- «Involuntary Switching» Category included involuntary switching because the service provider had moved, the customer had moved, or the insurance company or other third-party payer had changed alliances

Keaveney (1995) highlights that it is important for managers to realize that six from eight aforementioned reasons are under the firm's control: «Pricing», «Inconvenience», «Core Service Failures», «Service Encounter Failures», «Employee Responses to Service Failures», «Ethical Problems». And managers may take attempts to prevent churning. Keaveney’s (1995) study even offers particular actions for managers.

Ahn et al. (2006) discovering mobile telecommunications service industry in South Korea explore four determinants of churn customer: customer dissatisfaction, switching cost, service usage, and customer status. He comes to the conclusion that customer's *dissatisfaction* and therefore intention to churn are dependent on the reliability of services (speed of connection, call drop). This confirms previous results obtained by Madden et al. (1999) on the market of Internet providers in Australia. Referring to Bendapudi and Berry (1997) Ahn et al. (2006) point out that customers tend to maintain the relationship with firms for one of two reasons: they have to do it (there are some constraints) or they want to do it (in case of loyalty). *Switching cost* is a barrier for customers to churn as in the services industry customers used to accumulate bonuses through the loyalty program. And in the case of churning, they will lose all preferences of membership in the loyalty program, all bonuses, and discounts. Moreover, results obtained by Ahn et al. (2006) affirm that those customers who are more sensitive to action less brand-loyal. *Service usage* is measured individually for each industry, on the whole, it is determined as an average monthly fee and used as one of the most defining behavioral predictors of customer churn, that was also found out by Buckinx and Poel (2005).Some customers do not suddenly churn from a service provider. In fact, they either decide not to use it on a temporary basis or are suspended by the service provider due to payment problems. Examples of these statuses are active, non-active and suspended.

To sum up, previous papers argue that there are a lot of reasons and factors for customers' churn. Satisfactions, switching cost, demographic characteristics and propensity to change service usage are the general determinants of churn.

Prediction of customer churn

Prediction of churn may be supposed as the solution of classification problem when the customer is classified as churn or not churn. Machine learning methods are the most used approaches in these types of problems. Researches offer different models of customer churn prediction: decision trees (Hung et al., 2006; Qaisi, 2018) support vector machines (Coussement and Poel, 2008), neural networks (Song et al., 2006), evolutionary algorithms (Au et al., 2003), knn, logistic regression (Mozer, et al., 2000), Naive Bayes (Qaisi, 2018), rule induction (Qaisi, 2018).

In an era of big data development, it is extremely important for companies to be able to understand their customers and predict their potential outflow. That is why today both scientists and practitioners are striving to develop a qualitative model that could most accurately predict the churn This may allow firms to more carefully develop their marketing campaigns, taking into account the peculiarities of the churn of customers, as well as taking into account what actions may provoke churn . Understanding which customer is likely to become churned and for what reason, firms will be able to develop personalized offers for customers to encourage them to stay.

Recent studies are paid more attention to the methodology and comparison of the quality of model predictions (Qaisi et al, 2018, Coussement and Poel, 2008). The results indicate that the quality of the methods used to predict depends on the purpose of the study. If the goal is to find out whether the client is chun, then SVM and decision trees will do. And if the task is to predict the probability that the customer will stop using the services of the company, then in this case it is better to use logistic regression. Linear classifier requires the least computational power while neural networks are the most.

Research Question

It seems to be important for companies to pay more attention to the segment of churn customers, as when customers churn and end the relationship, it impacts the firm in several ways. First, the firm incurs a loss of revenue from the customers who have defected. Second, the firm loses the opportunity to recover the acquisition cost incurred on the defected customers, thereby increasing the pressure to break even. Third, the firm loses the opportunity to up-sell/cross-sell to customers who have defected, and this loss can be treated as a loss of potential revenue. Fourth, there are some "lost" social effects such as influencing other customers on product/service adoption and potential negative word-of-mouth. Finally, firms must also invest additional resources to replace those lost customers with new customers, thereby draining the firm's resources already impacted by the loss of customers. Moreover, the cost associated with customer acquisition is much greater than the cost of customer retention (Siber, 1997).

The current paper is devoted to the research of the behavior of the churn customers in a restaurant chain through the data from its loyalty program[2] as it is one of the most accessible ways for the company to collect information about customer behavior. When a customer signs up in a loyalty program, he/she shares its contacts, demographic information, and then after taking part in the loyalty program, the customer’s purchasing preferences are also available for analyzing. Due to the information gathered companies are able to make suggestions about customer behavior and promptly detect customers who stop using the services actively. This information allows building more personalized communications with customers, which make them feel valued and understood. More than that, both companies and consumers benefit from such communications adjusted to preferences of individuals: companies can increase the probability of purchase by raising the response of people to their messages while consumers win from

[2] A loyalty program is a set of marketing tools aimed at retaining and returning customers.

receiving only those messages, which are relevant to them and make them return over and over.

The restaurant industry is the one where loyalty programs are actively developed. Restaurant chains use the variety of ways to retain and return customers such as presenting points, discounts, cashback, gamification[3] and so on. However, a deep examination of the customer behavior is necessary to make more informed decisions about the segments: to whom to send a gift, to whom a discount, and who would respond to a double cashback in the form of points.

This paper aims to investigate the behavior of churn customers in the restaurant chain when customers receive extra points. Due to the reasons discussed above it is crucially important for a company to reveal, *whether there is a difference in the churn customers' behavior when they are given different numbers of points.*

As it was discussed in the previous section one of the methods to explore people's behavior is an experiment. Our study is focused on the research of churn customers' behavior by analyzing the results of an earlier conducted experiment.

As we research customer behavior in the restaurant chain, it is important to clarify which customers can be considered the churn customers in this industry and what is meant by customer behavior.

There is the need to pay attention to the necessity of proper separation churn customers from visitors with rare consumption that is normal for them. In order to do this in a proper way the criterion by which customers may be separated should be chosen as accurately as possible. In the restaurant industry, this criterion is the recency of the last visit.

Further, it should be pointed out that we investigate the behavior of the churn customers through two variables – the probability of a customer's return and the sum of his bills. The probability of coming back illustrates customer's propensity, intentions to continue using the services of the restaurant. The current

[3] Gamification - a process of enhancing a service with affordances for gameful experiences in order to support users (Huotari and Hamari, 2017)

paper is focused on the research of the probability of customers' return after getting them extra points in the loyalty program. The sum of bills gives the opportunity to discover a customer's willingness to pay. This allows us to analyze which customers from «the churn» are returned – those who tend to pay more or less.

Moreover, customers received a different amount of points in order to reveal the most attractive number of remuneration for them, which would contribute to increasing the business profits. This gives us a chance to analyze the behavior of the customers more thoroughly and compare customers' responses to the treatment with a different depth.

Methodology

Linear regression models

In the restaurant industry, a customer is classified as «churn» if he does not make any transaction within 155 days.[4]

As we discussed above, we are interested in researching the behavior of the churns after presenting them with extra points in the loyalty program. This means that we observe two types of bills – the bill before using points and the bill after using them.

The sum of bills before using points is supposed to be a more representative character of customer behavior. Through this sum, we may reveal customers' willingness to spend more or less after receiving extra points. Speaking about the sum of bills after using points, this sum is more relevant for the restaurant chain in terms of the profitability, because it clearly shows the real amount of money spent by the customers.

So, we compare the results of the linear regression models – when *the sum of bills before points' usage* is dependent variable (1) and when the *sum of bills after points' usage* is dependent variable (2). Models are estimated with ordinary least squares (OLS). We are interested in the estimated coefficient for *Treatment* as it shows a change in customer's behavior after presenting points. The econometric model is as follows:

$$Sum\ of\ bills\ before\ points'\ usage\ = \beta_0 + \beta_1 Treatment + \sum_{i=2}^{n} \beta_i Covariates_i + \epsilon \quad (1)$$

[4] Natalia Pinevich - senior CRM-marketer of the studio of integrated CRM-marketing Out of Cloud,

$$Sum\ of\ bills\ after\ points'\ usage\ = \beta_0 + \beta_1 Treatment + \sum_{i=2}^{n} \beta_i Covariates_i + \epsilon \tag{2}$$

where: *Sum of bills* – the sum of customer's bills before/after points' usage;

Treatment – dummy variables, reflecting whether customer receive points or not;

Covariates – fixed characteristics of each customer, control variables;

ϵ – Error term;

β_0 – Intercept;

β_1 – Estimated coefficient for *Treatment* that shows, how to change customers' *Sum of bills* before/after points' usage compared to customers who do not receive any points;

$\beta_{i \dots n}$ – Estimated coefficient for *Covariates*;

n – Number of *Covariates*.

The regression model is estimated with a full set of control variables by which we consider customer characteristics:

- Type of restaurant that is preferred more by customer
- Category of food that is preferred more by customer
- Type of consumption: in the restaurant or through delivery
- The place of consumption: the city or transport hubs
- Customer behavior: his average bill.
- Recency

It worth noting, that in this case customer characteristics are called *covariates*. It should be noted that an important property of the covariates is that the *Treatment* (making some impact on customers, for example, presenting extra points) should not make an effect on them. An example of the covariates is the set of characteristics that an object possessed before it was treated (Ениколопов, 2009).

Probit model

We also analyze customer behavior with respect to the probability of coming back to the restaurant due to the points received. For this purpose we estimate a probit model with the maximum likelihood (ML) (3) where the dependent variable is binary: 1 – if the customer has visited the restaurant, 0 – otherwise. The model is estimated with the same control variables as estimated in regression models. We are interested in the estimated coefficient for *Treatment* again as it shows the customer's intention to come back. In order to interpret the results, the average marginal effects are calculated.

$$Visit = \begin{cases} 1, & customer\ visited\ restaurant\ during\ the\ action \\ 0, & customer\ did\ not\ visit\ restaurant\ during\ the\ action \end{cases}$$

$$Visit = \beta_0 + \beta_1 Treatment + \sum_{i=2}^{n} \beta_i Covariates_i + \epsilon \quad , \qquad (3)$$

where: *Visit* – dummy variable, which characterizes the customer's return;

Treatment – dummy variables, reflecting whether customer receive points or not;

Covariates – fixed characteristics of each customer, control variables;

ϵ – Error term;

β_0 – Intercept;

β_1 – Estimated coefficient for *Treatment* that shows what effect *Treatment* has on customers' desire to come back;

$\beta_{i \dots n}$ – Estimated coefficient for *Covariates*;

n – Number of *Covariate.*

Heckman Model

There is a reason to believe that the returned churn customers self-select themselves on the basis of some unobservable factors (maybe they are discount lovers) that can lead to the problem of sample selection bias. This problem causes biased estimates in linear regression. Moreover, people' s decision to come back may be correlated with their decision to spend money. When certain assumptions hold, the Heckman Model (Heckman, 1979) is a statistical approach that can be used in such a scenario to estimate an asymptotically unbiased effect of *Treatment.*

The Heckman Model makes assumptions about the relationship between two equations in an underlying behavioral model: a response schedule (5), (6) and a selection function (4).

To find the estimates of the parameters, the two-step Heckman procedure was used. Control variables for the first step are the same as the significant controls from the probit-model estimation listed above; control variables for the second step are the same as the significant controls from the linear regression estimation also listed above. It worth noting, that control variables for these two steps should be different at least by one variable to be able to identify the Heckman model.

$$Visit = \beta_0 + \beta_1 Treatment + \sum_{i=2}^{n} \beta_i Covariates_{i}^{visit} + \delta_i \qquad (4)$$

where: *Visit* – dummy variable, which characterizes the customer's return;

Treatment – dummy variables, reflecting whether customer receive points or not;

$Covariates_{i}^{visit}$ – fixed characteristics of each customer

δ_i – Error term;

β_0 – Intercept;

β_1 – Estimated coefficient for *Treatment* that shows what effect *Treatment* has on customers' desire to come back;

$\beta_{i \ldots n}$ – Estimated coefficient for *Covariates*;

n – Number of *Covariate*

$$Sum\ of\ bills\ before\ points'\ usage = \alpha_0 + \alpha_1 Treatment + \alpha_2 \lambda + \sum_{i=3}^{n} \alpha_i Covariates_{i}^{bill} + \epsilon_i \qquad (5)$$

$$Sum\ of\ bills\ after\ points'\ usage = \alpha_0 + \alpha_1 Treatment + \alpha_2 \lambda + \sum_{i=3}^{n} \alpha_i Covariates_{i}^{bill} + \epsilon_i \qquad (6)$$

where: *Sum of bills* – sum of customer's bills before/after points' usage;

Treatment – dummy variables, reflecting whether customer receive points or not;

$Covariates_{i}^{bill}$ – fixed characteristics of each customer;

$\lambda(Visit) - \frac{\varphi(visit)}{\Phi(visit)}$, will almost control for bias in the estimate α_1

ϵ_i – Error term;

α_0 – Intercept;

α_1 – Estimated coefficient for *Treatment* that shows, how customers' *Sum of bills* change before/after points' usage in comparison with the customers who do not receive any points;

α_2 – Defined as the product of ρ and σ. Because σ is always positive, if ρ is positive, this suggests that the *Treatment* effect estimated without the Heckman Model correction would be biased upward. If ρ is negative, it suggests that the *Treatment* effect estimate without the Heckman Model correction would be biased downward.

$\beta_{i...n}$ – Estimated coefficient for *Covariates*;

n – Number of *Covariates*

The models listed above (linear regression, probit model, Heckman model) are estimated on three subsamples – for customers who received 250 points, for customers who received 350 points and for customers who received 450 points. A different number of points were given in order to conduct the experiment that will be discussed in the next section. This allows us to compare customers' response to the different treatment depth and make a suggestion about churn customers' behavior.

Moreover, before interpreting the results we should make sure that the aforementioned experiment is randomized. This means that customers were treated randomly and their characteristics did not determine customers' membership in the treatment or control .The treatment group consists of the churn customers who were given points, while the control group consists of the churns who were not given points. So, we need to estimate a linear regression and probit-model with *Covariates* and without them (with only *Treatment* as an independent variable). To check the randomization we compare estimated coefficients for *Treatment* with Covariates and without them in both models: if the estimates have close meanings, the same significance, and sign, we can argue that the experiment is randomized.

Data

This study is devoted to the research of the customer behavior through analyzing the experiment which was carried out in Rosinter Restaurants Holding (Rosinter) in spring 2018.

We have data on 283521 churn customers of the Rosinter Restaurants Holding (Rosinter) (http://www.rosinter.ru/). Rosinter is the leading casual dining chain operator in Russia and the Commonwealth of Independent States (CIS). It operates its key proprietary brands IL Patio (Italian cuisine), Shikari (Pan Asian cuisine), Planet Sushi (Japanese cuisine), American Bar & Grill (American cuisine), Mama Russia (Russian cuisine). Besides, it develops the international brands TGI Fridays (American cuisine) and Costa Coffee (coffee shops) under a franchise agreement.

The Company's key markets are located in Russia, the CIS and Central Europe including Baltic countries. Rosinter is listed on the Moscow Exchanges MICEX and RTS (moex.com) under the stock ticker ROST. The Company opened its first restaurant in 1990 in Russia and is widely regarded as one of the successful pioneers and founders of the modern industry of hospitality in Russia.

The aforementioned restaurant chain has a loyalty program since 2014, which is called «Honored Guest». This loyalty-program allows Rosinter to build customer relationships and communication. Participation in this program gives customers an opportunity to receive points when they make a purchase at any restaurant of the Rosinter chain. Further, customers may pay up to 50% of the bill with accumulated points.

In 2017, Rosinter decided to develop a multi-channel platform[5] in order to diversify communication, investigate customers' reactions and make the

[5] Multichannel marketing is the implementation of a single strategy across multiple channels or platforms, thus maximizing opportunities to interact with prospective customers. A channel might be email, a print ad, a retail location, a website, a promotional event, a mobile app, SMS messaging, a product's package, or word-of-mouth. The goal of multichannel is to give consumers a choice and allow them to buy when and where they want to.

communication more personalized. For these reasons customers have been segmented with respect to the value they bring to the business. This was done using previously identified 40 behavioral characteristics, which were supplemented by RFM-metrics (Recency-Frequency-Monetary).

It should be pointed out, that previously, Rosinter used to make this kind of decisions based on the past customer behavior and expert opinion of the marketer. But taking into account the trend of personalization marketing department clearly states it is necessary to conduct experiments and deeper explore customer behavior.

The idea of the marketing campaign that was launched to conduct the experiment is to attract customers by presenting them extra points within the promo «Points as a gift» and give them the opportunity to pay up to 50% of the bill during the promo campaign (from April 20 to May 3). It was decided that such mechanics would be interesting for customers and more profitable to business than, for example, direct discounts or other mechanics.[6]

The minimum number of points was 250, since points can pay up to 50% of the bill, and the average cost of 1 dish is ~ 400 rub. The reward threshold was raised to 350 and 450 points in order to compare the effect and people' reaction.

As a result, the churn customers were allocated into four groups:

- Customers, who were presented 250 points
- Customers, who were presented 350 points
- Customers, who were presented 450 points
- Control Group (customers, who were not presented any points)

Customers who were not treated form 46% of 283521churn customers (130633), while the treatment group is 54% (152888). The number of customers in each group and the treatment depth they had to go can be clearly seen in the Table 2

[6] Наталья Пиневич – старший CRM-маркетолог студии комплексного CRM-маркетинга Out of Cloud, (27)

Table 2

Treatment Depth

Treatment Depth	Number of Customers
250 points	47883
350 points	56740
450 points	48265
Control Group (0 points)	130633
Total number	283521

The Table 3 shows how many customers with the different treatment depth had responded. This information makes it possible to suggest that 350 points are more attractive for customers and are more likely to facilitate customer returns, as a larger proportion of those who received 350 points (compared to those who received a different number of points) visited the restaurant.

Table 3

Proportion of customers visited the restaurant during the action

	Treatment group	Control group
250 points	1.34 %	1.16%
350 points	2.21 %	1.16%
450 points	1.68 %	1.16%

The table 4 shows that only for those churn customers who were given 250 points the average sum of bills before points' usage is higher compared to the control group. This suggests that 250 points stimulate customers to increase the sum of bills.

Table 4

Descriptive Statistics of the sum of bills during the marketing campaign

	250 points		350 points		450 points		Control Group	
	Before usage	After usage	Before usage	After usage	Before usage	After usage	Before usage	After usage
mean	227su2	1962.8	2058	1622.1	1828	1366.5	2158	2028.6
st.dev	345	329	326	299	298	276	1774	1774
min	140	74	45	45	139	69	140	117
max	48312	48312	11518	11518	15512	15062	29867	29867
obs.	643	643	1254	1254	815	815	1524	1524

We have data on 31 controls variables which descriptive statistics are presented in Appendix 1. They are distributed in groups:

Brand Name – in this group all restaurants of Rosinter are represented and we can see what share of expenses from total expenses in the restaurant chain customer leaves in the particular restaurant;

Category of food – in this group all category of food in Rosinter Restaurants are represented and we can see what share of expenses from total expenses in the restaurant chain customer leaves on each food category;

Type of consumption – this group is represented what share of expenses from total expenses in the restaurant chain customer leaves on delivery or taking away;

Place of consumption – this covariate shows the average bill of customer for his transactions in restaurants in Transport hubs.

Previous behavior – this covariate is presented by the previous average customer's bill.

So, the average customer in our dataset is characterized by previous average bill of 1772 rubs and his recency is 584 days. His average bill in transport hubs is 184 rubs that allows us to suggest that he is not often traveler. He prefers to spend more money on alchol and not-alchol dtings and hot meal. Besides the average customer is tend to visit IlPatio and PlanetaSushi as his share of expenses from total expenses prevails over the rest brands.

Empirical results

First of all, we estimate 3 linear regressions for dependent variables *sum of bills before points' usage* (Table 5), 3 linear regressions for dependent variables *sum of bills after points' usage* (Table 5), 3 probit-models for binary dependent variable (1 – if customer has visited restaurant, 0 – otherwise) (Table 6) and 6 Heckman-models with the same dependent variables (Table 7). All the models are estimated for churn customers when they are given the different number of points to compare results.

Linear regression

Estimation of the linear regressions allows us to conclude that sum of bills before and after points' usage for customers who were presented 350 and 450 points are less than the one for the churn customers who were not given extra points but made transactions during the marketing campaign. This conclusion is made due to the negative estimated coefficients for *Treatment* (Table 5, (4), (5), (6)) which reflects that customers were presented points.

Let us consider each case of the treatment depth in a more detailed way. Unfortunately, we cannot make any conclusion about the churn customers' behavior who were given 250 points, because *Treatment* is not significant in (1) and (2) (Table 5). As it was discussed above there are two types of bills in our dataset – before points' usage and after that. For 350 points in (3) (Table 5) *Treatment* is not significant that is why we are not able to make any suggestion about customers' response on *Treatment* with respect to their intention to spend money. However, we can clearly see that *Treatment* has a negative statistically significant effect on the customer's bill after points' usage (4). This means that the average sum of the bill of the customers who received 350 points and made a transaction during the marketing campaign is 387 rubs less than the average sum of the bill of the customers who did not receive 350 points and made transactions during the marketing campaign.

Table 5

Estimation of linear regressions for all Treatment depth

	250 points		350 points		450 points	
Variables	Before usage (1)	After usage (2)	Before usage (3)	After usage (4)	Before usage (5)	After usage (6)
Treatment	**147.05 (98.23)**	**-40.05 (98.02)**	**-83.37 (60.70)**	**-387.33*** (60.07)**	**-257.05*** (68.28)**	**-622.08*** (68.44)**
Recency	0.69*** (0.21)	0.97*** (0.21)		0.48*** (0.14)		0.48*** (0.15)
Avg_Basesum	0.48*** (0.02)	0.45*** (0.0281)	0.29*** (0.02)	0.25** (0.02)	0.24*** (0.02)	0.20*** (0.02)
TransportHabs			-0.11*** (0.04)	-0.11*** (0.04)	-0.08 (0.05)	-0.06 (0.05)
Meal_Soupbread	6002.13* (3220.20)	6105.89* (3213.36)	5769.94** (2551.63)	5941.38** (2524.41)	6618.05** (2592.81)	6737.27*** (2588.75)
Extra_Hooka	27231.62*** (4090.18)	24500.11*** (4081.50)	21280.75*** (2865.50)	18891.73*** (2835.08)	23542.90*** (2890.36)	
Meal_Burger			-856.64 *** (294.31)			
PlanCoffee	5176.43** (2191.05)	5608.07** (2186.40)				
Shikari						113.36 (202.66)
TGIFridays			449.78* (110.72)	238.32*** (82.56)	293.24*** (88.78)	271.50*** (89.15)
Intercept	948.55*** (107.96)	776.31*** (107.73)	1544.38 *** (59.37)	1316.28*** (78.99)	612.10*** (60.47)	1397.93*** (82.05)
N	2167	2167	2778	2778	2336	2336
$R^2_{adj.}$	0.136	0.129	0.090	0.0843	0.089	0.0371
F-statistic	69.44	54.5	40.42	37.54	39.18	90.96
Prob (F-statistic)	0	0	0	0	0	0

Notes: Standard errors in parentheses, * p<0.05, ** p<0.01, *** p<0.001

In contrast to the previous treatment depth, we are able to analyze the customer behavior of those who received 450 points before points' usage. Model (5) clearly shows that *Treatment* has a negative statistically significant effect on the customer's bill before points' usage. This means that the churn customers (from the Treatment group) are not motivated to raise the sum of the bill by getting an extra 450 points.

Vice versa, the average sum of bills before points' usage for the churn customers from the Control group is even higher than the average sum of bills before points' usage for the churn customers from the Treatment group. Speaking about customer behavior after points' usage it is evident from Model (6) that as well as for the previous model *Treatment* has a negative statistically significant effect on customer's bills. Moreover, after points' usage, the average sum of bills for the churn customers from the Treatment group is even lower regarding the average sum of bills before. Of course, it is due to the fact that these customers spent their points.

To sum up, when a churned customer receives extra points he tends to spend less than a churned customer who did not receive any points.

Probit model

Nevertheless, we confidently argue that churn customers are prone to respond to presenting extra points regardless of their number. In any case of 250,350 or 450 treatment depth churn customers are tend to come back and make transactions. Presenting 350 extra points has a little more effect on people's probability to visit restaurant chain again. As we can see from Table 6 *Treatment* has a positive statistically significant effect on customer's probability to come back (7), (8), (9).

Table 6

Average Marginal Effects of Probit-model and 1st step in Heckman-model for different treatment depth

	250 points (7)	350 points (8)	450 points (9)
Treatment	0.002*** (0.000)	0.007 *** (0.001)	0.005 *** (0.001)
Recency	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Avg_Basesum	0.000** (0.000)	0.000*** (0.000)	
TransportHabs	0.000*** (0.000)	0.000*** (0.000)	0.000** (0.000)
Other_Other		0.000 (0.003)	
Meal_Extraingr	-0.015* (0.009)	-0.021 (0.013)	
Drink_Noalco		-0.003 (0.002)	
Meal_Burger		-0.003 (0.002)	
ILPatio	-0.006*** (0.002)	-0.014*** (0.003	-0.018*** (0.004)
PlanSushi	-0.007 *** (0.002)	-0.015*** (0.004)	-0.018*** (0.004)
Shikari	-0.008*** (0.002)	-0.018 *** (0.004)	-0.020*** (0.004)
TGIFridays	-0.003 (0.00)	-0.011*** (0.004)	-0.016*** (0.004)
AmBar	-0.009*** (0.003)	-0.020*** (0.005)	-0.023*** 0.005
PlanCoffee	-0.012 (0.008)	-0.015** (0.008)	-0.029*** (0.010)
Costa		-0.010* (0.004)	-0.015*** (0.004)
Delivery	0.008*** (0.00)	0.008*** (0.002)	0.007*** (0.002)
TakeAway			0.004 (0.002)
Intercept	-0.03*** (0.005)	-0.044*** (0.004)	-0.037*** (0.004

Notes: Standard errors in parentheses, * p<0.05, ** p<0.01, *** p<0.001

Randomization check

It is necessary to check the conducted experiments on randomization and for that reason we built linear regressions and probit-models with all covariates[7] and with the only *Treatment* as independent variables and compared them. The results are presented in Appendix 2 in Table 1and Table 2, where it is clearly seen that estimated coefficients for *Treatment* are similar in the models without covariates and the models including them for all of the estimated models. This makes us convinced that all the experiments are randomized. That is why further estimations are carried out without verification in randomization.

Heckman-model

Besides, there is a problem of a sample selection bias, which is confirmed only for customers who have presented 450 points as λ of Heckman is statistically significant (Table 7, (14)). This means that OLS-estimates are biased and we cannot trust them. Moreover, *Treatment* is positive statistically significant that shows us that churn customer are motivated by 450 extra points to visit restaurants and spend even more than estimated by OLS (Table 5, (5))(estimate of *Treatment* is biased downward in the liners regression). It should be pointed out that due to the significance of λ there is an assumption that churn customers' decision to come back is positively interconnected with customers' willingness to pay.

[7] The list and significance of all included covariates in Appendix номер.

Table 7

Estimation of 2nd step in Heckman-model for all Treatment depth

	250 points		350 points		450 points	
Variables	Before usage (10)	After usage (11)	Before usage (12)	After usage (13)	Before usage (14)	After usage (15)
Treatment	**92.14 (108.06)**	**-100.18 (107.83)**	**-52.18 (66.48)**	**- 351.18** (144.47)**	**-230.10*** (69.80)**	**-508.01*** (112.99)**
Recency	1.66* (0.82)	2.03** (0.21)		0.27*** (0.75)		-0.32 (0.65)
Avg_Basesum	0.47*** (0.02)	0.44*** (0.02)	0.29*** (0.02)	0.25** (0.02)	0.24*** (0.02)	0.20*** (0.02)
TransportHabs			-0.12** (0.04)	0.12** (0.04)	-0.08 (0.05)	-0.09 (0.05)
Meal_Soupbread	5722.41* (3228.01)	5799.66* (3220.93)	5819.65** (2551.84)	6006.07* (2535.75)	6646.96** (2591.53)	6919.51*** (2588.75)
Extra_Hooka	27267.96*** (4090.18)	24539.89*** (4080.86)	21301.06*** (2865.39)	18889.04*** (2835.57)	23605.74 *** (2889.08)	
Meal_Burger			-861.13 *** (294.32)			
PlanCoffee	5379.39** (2197.13)	5830.27** (2192.31)				
Shikari						70.16 (205.48)
TGIFridays			458.13* (110.96)	249.83*** (92.57)	299.22*** (88.79)	316.63*** (95.97)
λ	**-841.29 (690.38)**	**-921.03 (688.87)**	**136.87 (119.00)**	**168.59 (612.59)**	**244.56* (132.95)**	**735.34 (579.57)**
Intercept	2706.01* (1446.24)	2700.34* (1443.07)	1200.28*** (305.00)	966.85 (1272.15)	1004.75*** (335.66)	-133.32 (1209.67)
ρ	-0.4	-0.4	-0.1	-0.1	0.15	0.08
N	2167	2167	2778	2778	2336	2336
$R^2_{adj.}$	0.1404	0.1291	0.0905	0.08404	0.09026	0.08046
F-statistic	51.56	54.5	35.54	32.85	34.1	26.54
Prob (F-statistic)	0	0	0	0	0	0

Notes: Standard errors in parentheses, * p<0.05, ** p<0.01, *** p<0.001

Summary of empirical results

- Churn customers who were presented 250 points tend to visit restaurants again.
- Churn customers who were presented 350 points tend to visit restaurants again. At the same time, their spending is less than the spending of the churn customers who were not given any extra points but nevertheless visited the restaurants. This follows from the fact that people from Treatment group used their points – as we can see the difference in bills between Treatment and Control groups 387 is close to the number of points 350.
- Churn customers tend to respond to presenting 450 extra points, and this treatment may encourage them to make transactions in restaurants again. We can also see that in any case (before and after points' usage) churn customers who were treated spend less than customers who were not treated.

This allows us to make the assumption that points attract such customers who love gifts and react to them. This assumption is confirmed when churn customers are offered 450 points. According to the (14) (Table, 7) sample selection, this problem is confirmed. That allows us to conclude that the decision of people to come to the restaurant during the marketing campaign is due to their intention to spend less.

Conclusion

The current paper is discussed the problem of churned customers that firms face due to a huge amount of goods and services offered on the market. This variety leads to customers' easy and inexpensive switching between services. That is why firms should eager to build long-term relationship with customers and constantly enhance their loyalty to brand in order to prevent their churn.

In the current paper behavior of churn customers of Rossinter is analyzed. Customer behavior is considered as the probability of a customer's return and the sum of his bills. Research is carried out on the data from marketing campaign that was launched through the experiment. During the 2 weeks (from April 20 to May 3) one part of churn customers (treatment groups) were targeted by the promotion «Points as a gift» and another (control group) remained not treated. Moreover, the analyzed experiment is randomized. This means that customers were treated randomly and their characteristics did not determine customers' membership in the treatment or control groups.

Churn customer behavior is researched by estimation linear regression, probit model and Heckman model with the *sum of bills before points' usage*, the *sum of bills after points' usage* and probability to come back as dependent variables on three subsamples – customers who were presented 250, 350 and 450 bonuses, respectively. We are focused on two types of customer bill as we observe the sum of bill before points' usage and after that. From our opinion, the sum of bill before points' usage explains churn customers' behavior better as it reflects the initial customer's intention to spend money. *The sum of bills after points' usage* is more relevant for researching firm's profitability after marketing campaign as this variable reflects the real amount of money that customer has brought. First of all, we were interested in the estimated coefficient for variable *Treatment* that shows whether a customer received points or not.

Results obtained from probit model estimation makes us confident that presenting points is positive influence customer behavior. However, average marginal effect of this treatment is quite small, that may mean that extra points only slightly prompted customers to return. Besides, the most effect on probability to come back has 350 points rather than 450 points. This result makes us suppose that there are customers are more prone to the action in the subsample of 350 points.

Quite ambiguous results are obtained from estimation of liner regressions. We cannot make any suggestion about bills of customer who were given 250 points as *Treatment* is not significant, whereas the average bill before points' usage of these customers during marketing campaign is higher than the average bill of customers from control group. This result confirms the necessity of using econometric methods for researching customer behavior. Without regression we could consider that due to giving 250 points customer's bill increases, but insignificance of *Treatment* gives an opportunity to suppose that there are other reasons of bill's increase.

Speaking about two another subsamples, we can make conclusion that customers, who received 350 and 450 points have bills that are lower than bills of customers from control group. For customers from 450 points subsample we can analyze sum of bills before points' usage that characterizes customer intention to pay, and we can conclude that these customers had come back and spent less.

Sample Selection bias is confirmed only for customers from 450 points subsample. This means that decision of these churn customers to visit restaurants is correlated with intention to pay less. We may suggest that 450 points attract points-lovers – people, who are sensitive to action, but not brand-loyal (Ahn et al., 2006). These churn customers returned only due to the intention to spend less.

Besides, some limits of the research should be taken into consideration. First of all, we research behavior of churn customers in one restaurant chain only, that means that there could be different results in other restaurant chain due to customer heterogeneity and uniqueness of the restaurants. Moreover we are limited by the data that restaurant chain gives access to. This may lead to existing of some significant factors that influence customer's behavior and his/her decision to come back and his willingness to pay. It worth noting that this limit exists always as it is almost impossible to take into account customers' thoughts.

To sum up, presenting extra points to churn customer differently affect their behavior – customers are coming back but are not prone to pay more. These results could be useful for marketers in firms to design marketing campaign more carefully and thoughtfully. As we can see, mechanic of presenting points is suitable only for returning churn customers. Perhaps, discount or presenting gift may demonstrate other results.

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Appendix

Appendix1

Descriptive Statistics of Covariates

	Covariate	mean	sd	min	max	obsv.
	Recency (days)	584.8	ggggg	167.0	1256.0	283521
Previous behavior	*Avg_Basesum (rubs)*	1772		9	44150	283521
Place of consumption (rubs)	*TransportHabs*	183.2		0	33189	283521
Category of food (share of expenses from total expenses in the restaurant chain)	*Other*	0.02787		0	1	283521
	Meal_Extraingr	0.0071		0	1	283521
	Meal_Dessert	0.04042		0	1	283521
	Meal_Hot	0.28524		0	1	283521
	Meal_Karri	0.0003		0	0.864	283521
	Meal_Soupbread	0.0003		0	1	283521
	Meal_Fish	0.0012		0	1	283521
	Drink_Noalco	0.1797		0	1	283521
	Drink_Alco	0.1166		0	1	283521
	Meal_Sushi	0.0764		0	1	283521
	Meal_Salad	0.0653		0	1	283521
	Meal_Extra	0.0101		0	1	283521
	Extra_Hooka	0.0003		0	1	283521
	Meal_Snack	0.0486		0	1	283521

	Meal_Burger	0.05456		0	1	283521
	Meal_Soup	0.0494		0	1	283521
	Meal_Other	0.0040		0	1	283521
	Meal_Lean	0.0013		0	1	283521
Restaurant Brand (share of expenses from total expenses in the restaurant chain)	*Ilpatio*	0.562		0	1	283521
	Plansushi	0.1646		0	1	283521
	Shikari	0.0264		0	1	283521
	Tgifridays	0.2007		0	1	283521
	Ambar	0.015		0	1	283521
	Mamarus	0.0016		0	1	283521
	Plancoffee	0.0041		0	1	283521
	Costa	0.0168		0	1	283521
Type of consumption (share of expenses from total expenses in the restaurant cha in)	*Delivery*	0.02986		0	1	283521
	Takeaway	0.01322		0	1	283521

Appendix 2

Randomization check

Table 1

Average marginal effects

	250 points		350 points		450 points	
Treatment	0.002 (0.000)	0.002 (0.000)	0.007 (0.001)	0.007 (0.001)	0.005 (0.001)	0.005 (0.001)
Recency		0.000 (0.000)		0.000 (0.000)		0.000 (0.000)
Avg_Basesum		0.000 (0.000)		0.000 (0.000)		0.000 (0.000)
TransportHabs		0.000 (0.000)		0.000 (0.000)		0.000 (0.000)
Other		0.000 (0.004)		-0.004 (0.004)		0.003 (0.004)
Meal_Extraingr		-0.013 (0.012)		0.025 (0.013)		-0.016 (0.012)
Meal_Dessert		0.000 (0.004)		0.000 (0.004)		0.002 (0.004)
Meal_Hot		0.001 (0.003)		-0.004 (0.003)		0.002 (0.003)
Meal_Karri		-0.015 (0.029)		0.022 (0.023)		0.010 (0.024)
Meal_Soupbread		0.036 (0.023)		0.030 (0.028)		0.018 (0.025)
Meal_Fish		-0.016 (0.016)		-0.010 (0.017)		-0.010 (0.017)
Drink_Noalco		-0.004 (0.003)		0.006 (0.004)		-0.002 (0.003)
Drink_Alco		-0.003 (0.003)		-0.005 (0.003)		-0.001 (0.003)
Meal_Sushi		0.000 (0.003)		-0.003 (0.003)		0.000 (0.003)
Meal_Salad		-0.002 (0.004)		-0.004 (0.004)		0.001 (0.004)
Meal_Extra		-0.018 (0.009)		-0.004 (0.009)		-0.012 (0.009)
Extra_Hooka		-0.013 (0.028)		-0.004 (0.027)		-0.006 (0.026)
Meal_Snack		0.000 (0.004)		-0.003 (0.004)		0.001 (0.004)
Meal_Burger		-0.005 (0.003)		-0.007 (0.004)		0.000 (0.004)
Meal_Soup		0.004 (0.004)		-0.001 (0.004)		0.004 (0.004)
Meal_Other		0.019 (0.013)		-0.002 (0.016)		0.018 (0.013)
Meal_Lean		-0.001		-0.006		-0.015

		(0.013)		(0.015)		(-0.017)
Ilpatio		-0.013 (0.004)		-0.017 (0.004)		-0.019 (0.004)
Plansushi		-0.015 (0.004)		-0.019 (0.004)		-0.019 (0.004)
Shikari		-0.016 (0.004)		-0.021 0.004		-0.020 (0.004)
Tgifridays		-0.009 (0.004)		-0.013 (0.004)		-0.015 (0.004)
AmBar		-0.015 (0.005)		-0.023 (0.005)		-0.022 (0.004)
MamaRus		-0.016 (0.010)		-0.011 (0.009)		-0.029 (0.012)
PlanCoffee		-0.019 (0.009)		-0.017 (0.008)		-0.029 (0.010)
Costa		-0.006 (0.005)		-0.013 0.005		-0.013 (0.005)
Delivery		0.007 (0.002)		0.007 (0.002)		0.007 (0.002)
TakeAway		0.001 (0.003)		0.003 (0.003)		(0.004) 0.003
Intercept	0.002** (0.001)	-0.037 (0.005)	0.010*** (0.001)	-0.038 (0.005)	-0.07*** (0.001)	-0.037 (0.001)
N	2167	2167	2778	2778	2336	2336
LL	-11775.25	-11702.2	-14318.95	-0.00001	-12476.54	-12339.43
AIC	23554	23468	28642	70	24957	24743

Table2

Estimation of linear regressions for randomization check

	250 points				350 points				450 points			
	Before usage		After usage		Before usage		After usage		Before usage		After usage	
Treatment	113.40 (105.84)	147.05 (98.23)	-68.59 (104.44)	−45.62 (98.61)	-100.54 (63.59)	-84.52 (60.97)	-406.49*** (62.25)	-387.33*** (60.07)	-330.17*** (70.91)	-263.73*** (68.81)	-662.12*** (69.43)	-613.92*** 67.96
Recency				0.99 *** (0.21)		0.15 (0.14)		0.47** (0.14)		0.24 (0.15)		0.50*** (0.15)
Avg_Basesum		0.47*** (0.03)		0.44 *** (0.03)		0.27*** (0.02)		0.22*** (0.02)		0.21*** (0.02)		0.17*** (0.02)
TransportHabs		-0.05 (0.07)		-0.04 (0.07)		-0.11** (0.04)		-0.12** (0.04)		-0.09 (0.05)		-0.08 (0,05)
Other		342.90 (723.33)		321.95 (720.44)		324.55 (519.51)		239.68 (513.29)		516.07 (537.21)		518.66 (530.54)
Meal_Extraingr		788.46 (2270.07)		1086.83 (2261.79)		-1103.75 (1711.39)		-929.96 (1690.92)		-162.94 (1652.38)		225.52 (1631.86)
Meal_Dessert		106.46 (788.57)		140.07 (785.36)		-449.92 (547.25)		-441.25 (540.70)		-120.36 (572.04)		-94.84 (564.94)
Meal_Hot		316.65 (554.56)		302.03 (552.26)		-78.57 (384.03)		-169.91 (379.43)		45.01 (412.07)		11.23 (406.95)
Meal_Karri		1845.05 (7699.20)		1927.32 (7667.87)		-269.18 (2201.58)		-419.27 (2175.24)		-3868.77 (3579.64)		-2972.61 (3535.19)
Meal_Soupbread		5559.10 (3315.74)		5758.96 (3302.07)		5434.48* (2604.74)		5626.24* (2573.59)		6754.69* (2637.70)		6867.32** (2604.95)
Meal_Fish		-1846.35 (2979.30)		-1744.99 (2966.91)		-2112.11 (2060.09)		-2121.60 (2035.45)		-2261.53 (2253.71)		-1957.38 (2225.72)
Drink_Noalco		341.32 (682.88)		368.13 (680.07)		525.57 (467.72)		475.96 (462.12)		419.78 (496.52)		436.37 (490.35)
Drink_Alco		496.75 (614.58)		367.18 (612.03)		325.47 (421.37)		185.03 (416.33)		608.42 (450.45)		526.76 (444.85)
Meal_Sushi		138.72 (568.63)		119.80 (566.29)		356.62 (386.71)		351.28 (382.08)		495.33 (419.55)		504.62 (414.34)

Meal_Salad		503.83 (706.62)		546.26 (703.89)		11.81 (489.05)		-45.41 (483.20)		224.77 (499.40)		230.91 (493.20)
Meal_Extra		-746.30 (2053.41)		-799.10 (2044.88)		1219.08 (1274.32)		1070.47 (1259.083)		1143.35 (1445.16)		974.20 (1427.22)
Extra_Hook a		27184.67* ** (4156.12)		24601.98** * (4139.05)		21032.52*** (2895.01)		18572.80* ** (2860.39)		23346.52*** (2917.49)		20846.53 *** (2881.25)
Meal_Snack		-272.21 (711.64)		-271.91 (708.70)		-203.32 (501.55)		-218.12 (495.55)		-295.24 (529.68)		-263.08 (523.10)
Meal_Burge r		-521.46 (687.82)		-530.66 (685.18)		-889.22 (473.96)		-1020.02* (468.29)		-669.45 (495.43)		-713.16 (489.28)
Meal_Soup		-435.45 (735.18)		-456.31 (732.13)		-812.01 (516.24)		-838.06 (510.06)		-832.00 (527.79)		743.71 (521.24)
Meal_Other		443.50 (2814.22)		285.87 (2802.90)		2445.04 (2161.35)		2345.43 (2135.50)		397.20 (2170.20)		173.87 (2143.25)
Meal_Lean		-885.52 (3211.15)		-229.25 (3198.26)		2580.29 (2663.52)		2413.26 (2631.67)		1010.74 (3166.99)		1140.78 (3127.66)
Ilpatio		684.34 (723.25)		623.78 (720.32)		652.62 (446.92)		686.78 (441.58)		648.13 (460.23)		695.40 (454.51)
Plansushi		554.23 (750.21)		435.81 (747.56)		379.55 (475.64)		381.99 (469.96)		378.43 (486.03)		415.71 (479.99)
Shikari		779.93 (770.57)		767.05 (767.40)		645.61 (481.93)		663.74 (476.16)		768.28 (496.81)		845.78 (490.64)
Tgifridays		978.56 (735.15)		909.11 (732.58)		1032.16* (457.17)		1092.18* (451.70)		1031.52* (471.14)		1088.30* (465.29)
AmBar		596.73 (907.90)		637.48 (904.65)		489.08 (606.88)		692.79 (599.62)		606.31 (613.59)		778.16 (605.97)
MamaRus		-515.93 (1988.31)		-334.16 (1980.02)		129.22 (1013.11)		304.76 (1001.00)		-154.57 (1617.14)		82.28 (1597.06)
PlanCoffee		6017.15** (2314.40)		6409.80** (2304.80)		-561.67 (959.94)		-303.06 (948.46)		-2051.28 (1862.89)		-1696.58 (1839.76)
Costa		298.18 (841.11)		233.57 (837.79)		-197.65 (541.18)		-190.44 (534.71)		-191.09 (553.70)		-171.86 (546.82)
Delivery		480.65 (306.77)		462.15 (305.55)		226.40 (215.82)		214.25 (213.24)		62.45 (224.88)		115.28 (222.09)

TakeAway		220.33 (502.01)		211.93 (500.10)		-114.22 (343.61)		-121.60 (339.50)		266.48 (336.64)		242.74 (332.46)
Intercept	2158.17 *** (57.65)	284.17 (885.19)	2025.03 *** (56.93)	-69.10 (884.12)	2158.17*** (42.72)	859.82 (570.19)	2028.61*** (41.83)	736.55 (563.37)	-330.17 *** (70.91)	847.83 (593.39)	-662.12*** (69.43)	659.26 (586.02)
N	2167	2167	2167	2167	2778	2778	2778	2778	2336	2336	2336	2336
$R^2_{adj.}$	0.0005	0.1404	-0.00	0.1291	0.00	0.0905	0.014	0.084	0.014	0.0902	0.008	0.08046
F-statistic	1.109	51.56	0.43	54.5	2.318	35.54	42.03	32.85	42.03	34.1	21.36	26.54
Prob (F-statistic)	0.2924	0	0.5115	0	0.128	0	0	0	0	0	0	0