Evaluating rewards in loyalty programmes – A novel approach to increase user retention

Abstract:

We study a novel loyalty program of a brick and mortar fast moving consumer goods retailer. Unlike most other loyalty programmes, it builds on immediate and delayed rewards. We study the impact of these reward mechanisms on customer retention using a logistic regression model. We observe that user retention is influenced by both the delayed and immediate reward form. Our results show that well designed rewards lead to significantly higher loyalty and user retention. We find evidence that reward activities applied during early stages of the customer relationship impact long-term retention. Our findings help retailers to design improved loyalty systems and provide guidance for implementing smarter and more efficient reward mechanisms that increase loyalty of customers.

Keywords:

loyalty programme, customer retention, reward redemption

Track:

Relationship Marketing

1 Introduction

Firms in fast moving consumer good (FMCG) markets spend a large amount of their marketing budget on price promotions. A recent study revealed that in 2014 18.3% of all sales in Germany, 33.4% in the UK, and even 36.7% in the US were sold on (price) promotion (Nielsen, 2014). Besides increasing short-term sales, the goal of such marketing efforts is to influence the consumers' mid- and long-term purchase behaviour (Van Heerde & Neslin, 2008). In addition, increasing competition and moderate market growth moved retailers to adopt loyalty card programmes (LP) in order to retain existing customers, increase customer loyalty and collect user-level data on the customers' shopping behaviour (Capizzi & Ferguson, 2005). LP customers typically receive rewards in exchange for points that are awarded based on the value of bought goods (Kivetz & Simonson, 2002).

Although existing LP have become increasingly ubiquitous, they suffer from a stunning lack of diversity in their rewards structure (Capizzi & Ferguson, 2005). In this paper we study a LP introduced in a large German city in 2015. While the system exhibits traits of traditional LP (e. g. loyalty points), the system uses an innovative retention mechanism. First, when redeeming collected points users receive free FMCG products instead of non-FMCG rewards (e.g. kitchen appliances). Second, transaction data collected within the system is used to derive individualised product recommendations in combination with individualised price discounts (Rossi, McCulloch, and Allenby, 1996). These tailor-made promotions are exclusively available to LP users. Both rewards, i.e. free products and exclusive price promotions, can be printed at in-store kiosk systems and are redeemed when the customers let the cashier scan their loyalty card at the checkout.

This paper analyses data of almost 15,000 customers collected during the launch of the LP. We quantify how the two mentioned reward mechanisms affect the probability that users are retained in the LP. We contribute to the theoretical understanding of user retention and provide valuable insights to marketing practitioners regarding the design and execution of LP.

The remainder of the paper is structured as follows: After presenting our hypotheses in section 2 we introduce the data and the research methods used in this analysis (section 3). In section 4 we describe and discuss our empirical results before summarising our findings and giving a brief outlook on potential avenues for future research (section 5).

2 Hypotheses

Literature on LP has shown that the reward structure has a significant impact on loyalty card usage (Keh & Lee, 2006; Kivetz & Simonson, 2002). Dowling and Uncles (1997), for example, propose a reward scheme that maximises a buyer's probability to make the next purchase. Taylor and Neslin (2005) find evidence of a "points pressure" and "rewarded behaviour" effect on sales for a retail frequency reward program. Keh and Lee (2006) show that direct rewards, i.e. products directly related to the value proposition of a firm's products or services, have a higher impact on customer loyalty than indirect rewards. Another important aspect of LP programs is the decision whether to use immediate rewards (i.e. experiencing the benefits at the time of the transaction) or delayed rewards. There is evidence that delayed rewards have a higher impact on loyalty for satisfied customers (Keh & Lee, 2006). In the LP analysed in this study, loyalty points are collected and redeemed at a later time (delayed reward) for free FMCG products (direct reward). Whether the perceived value of these free products is high enough to retain users in the LP is not obvious because FMCG products are much cheaper than non-FMCG rewards known from other LP. Hence, the first hypothesis is:

H1: *Delayed (direct) rewards have a positive impact on retention.*

Kumar and Shah (2004) propose a conceptual framework for understanding the evolving logic of LP. They provide a two tier reward structure for building and cultivating behavioural and attitudinal loyalty. They argue that by leveraging customer specific data through analytics, companies can design rewards that are relevant and perceived as high value by the customers. In accordance with this, greater individualisation was shown to increase user satisfaction (Liang, Lai, and Ku, 2007), service relevance and customer adoption (Tam & Ho, 2006). Since behavioural intention and retention highly correlate with satisfaction (Gupta & Zeithaml, 2006) LP with individualised rewarding schemes may yield additional benefits to customers. In the new LP product, recommendation in combination with individualised price discounts are used as reward. The rationale for the second pillar follows the "rewarded behaviour" effect (Taylor & Neslin, 2005), i.e. user behaviour is rewarded with price discounts which are generally perceived valuable by consumers (Chapmann 1993) and have been shown to have significant effects on consumer decisions, especially when individualised (Rossi et al., 1996). However, because these discounts are even smaller in value than the free products of the first reward pillar, we aim to test the impact of the second part of the reward mechanism and propose:

H2: *Immediate and individualised (direct) rewards have a positive impact on retention.*

3 Method and data

3.1 Retailer setup and data

To test the hypotheses outlined above, we conduct an empirical study at an FMCG retailer in a large German city. Customers can print *rewards*, i.e. coupons for free products and individualised promotions at in-store kiosk terminals located at the store entrance. We call the promotion printout *handbill*. Promotions are redeemed when the customers let the cashier scan their loyalty card at the checkout. The scan of the loyalty card at the checkout allows to associate users with shopping baskets. In this study we have access to transaction and handbill data for almost 15,000 customers who joined the LP in the seven months after the roll-out. From this data we derive the dependent and explanatory variables for the retention analysis.[1]

We measure user retention by the users' handbill printing activity. Focusing on printouts is reasonable for two reasons. First, price promotions on the handbills are a central feature of the LP and can only be activated by printing a handbill. Second, loyalty points are used by redeeming a free product promotion that is printed on the users' handbills. Therefore, customers can only benefit from the LP's reward pillars if they print promotions. We derive the retention criteria based on the average system usage. Users are classified *retained* (binary variable print after two months `P2M` equals one) if they printed a handbill at least once two months after joining the system, defined by the first printout. To measure retention without bias, we need to allow sufficient time after a user's first print. Since the average time between prints is 17.4 days and 86% of all users have an average time between prints of less than 31 days, we only consider users in the analysis who printed their first handbill three months ago or earlier.

The explanatory variables are the number of campaigns a user redeemed from the first handbill (`#RED`), the number of free products redeemed within the first month (`#FP`), the average time (in days) between a user's two prints within the four weeks after the first handbill printout (print frequency, `PF`), the user's average unit sales per basket (`AUS`), the user's sales

[1] Although the company that provided the data API and the retailer chose to remain anonymous, we thank them for their cooperation and support.

value for the basket following the first handbill print (promotion basket value sales, `PBVS`), and fixed effects for each year week (`YW`) and store (`ST`). `#RED` and `#FP` are used to test the hypotheses, the other variables control for user characteristics that could bias the measurement of the reward mechanism's impact on user retention, if omitted.

3.2 Method

To get a better understanding of the data, we start with a descriptive analysis. We calculate the mean and standard deviation for our main variables and correlations with `P2M`, `#FP`, and `#RED` (Pearson or biserial correlation depending on the level of measurement). Next, we split the data into two cohorts based on values of the variables `#RED` and `#FP` (none, at least one) and compare retention rates between these cohorts. In particular, we assume that `P2M` is binomially distributed with a flat prior. The posterior distribution of the retention rate is then beta-distributed and we can compute cohort-specific modes and 95%-HDIs, a measure of uncertainty, using 1,000 draws from posterior distribution.

In order to analyse the impact of several explanatory variables simultaneously and to add control variables, we use a Logistic Regression for modelling the binary `P2M`-variable (Blattberg, Kim, and Neslin, 2008):

$$P(\mathtt{P2M}_i = 1) = \frac{1}{1 + \exp\{-(\beta_{\mathtt{\#RED}} \cdot \mathtt{\#RED}_i + \beta_{\mathtt{\#FP}} \cdot \mathtt{\#FP}_i + \beta_{\mathtt{PF}} \cdot \mathtt{PF}_i + \beta_{\mathtt{AUS}} \cdot \mathtt{AUS}_i + \beta_{\mathtt{PBVS}} \cdot \mathtt{PBVS}_i + \beta_{\mathtt{YW}} \cdot \mathtt{YW}_i + \beta_{\mathtt{ST}} \cdot \mathtt{ST}_i)\}}. \quad (1)$$

$P(\mathtt{P2M}_i = 1)$ is the probability that LC user i is retained and β are parameters (to be estimated using Maximum Likelihood). As measure of model fit we use the Log-Likelihood value and the Gini coefficient (Blattberg et al., 2008).

4 Results

	Mean	SD	Cor `P2M`	Cor `#RED`	Cor `#FP`
`P2M`	0.67	-	-	$0.12^{\dagger}$	$0.31^{\dagger}$
`#RED`	0.60	0.89	$0.12^{\dagger}$	-	0.10
`#FP`	3.41	2.82	$0.31^{\dagger}$	0.10	-
`PF`	14.97	9.49	$-0.35^{\dagger}$	-0.09	-0.68
`AUS`	9.33	6.50	$0.04^{\dagger}$	0.19	0.05
`PBVS`	18.92	21.74	$0.04^{\dagger}$	0.18	0.03

Note: †: biserial correlation

Table 1: Descriptive statistics

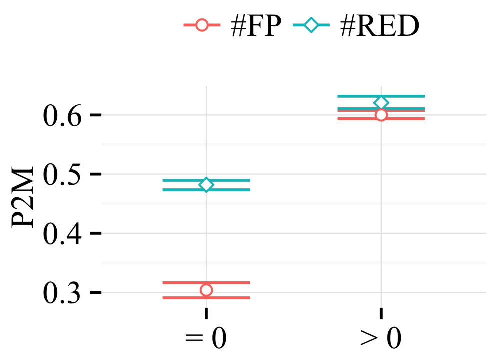

Figure 1: `P2M` by rewards and cohorts

Table 1 contains a description of the main variables used in the analysis. Besides the variables' means and standard deviations, the correlations with `P2M`, `#RED`, and `#FP` are provided. The overview shows that 2/3 of the 14,967 users in the analysis print at least once after two months and are considered retained. On average each user redeemed 0.60 promotions on their first handbill print and received 3.41 free products for collected loyalty points within the first four weeks. Both `#RED` and `#FP` are positively correlated with `P2M` which supports our proposed relationship between the reward mechanisms and user retention. Also, the positive correlation between `#RED` and `#FP` suggests that the correlation might overestimate the influence of `#RED` and `#FP` on `P2M`. Furthermore, `#FP` has negative correlation with `P2M`. Hence, users that printed less often within the first month (c. p. high values for `#FP`) are less likely to be retained.

The results of the cohort analysis for the variables `#RED` and `#FP` are visualised in figure 1. The graph shows the modes and the 95% HDI (indicated by the error bars) of the retention rates for all cohorts. `P2M` is on average much higher when `#FP` or `#RED` are greater than zero. Due to the pronounced differences in retention rates as well as the narrow and non-overlapping HDIs, it is very certain that the analysed rewards schemes increase retention.

Due to the fact that the analysis was not conducted in a (randomised) experimental setting, we have to control for user specific variables that can explain a potential proneness of customers for using the LP. Neglecting this would most likely lead to an overestimation of the positive effect of rewards on retention. Therefore, our findings were further scrutinised by modelling user retention using the logistic regression outlined in 3.2. Table 2 shows the results for seven different model specifications.

`M1` is the base model that only contains the two variables that were included in the model to test the hypotheses defined in the outset, i.e. `#RED` and `#FP`, and an additional constant. All three parameters are highly significant. The coefficients for both `#RED` and `#FP` are positive, supporting the findings of the descriptive analysis. The base model already fits the data well.

	M1	M2	M3	M4	M5	M6	M7
#RED	**0.191**	**0.179**	**0.187**	**0.197**	-	-	**0.203**
	(0.022)	(0.023)	(0.023)	(0.024)			(0.024)
#FP	**0.247**	**0.129**	**0.129**	**0.130**	-	**0.132**	-
	(0.009)	(0.012)	(0.012)	(0.012)		(0.012)	
PF	-	**−0.038**	**−0.037**	**−0.039**	**−0.062**	**−0.040**	**−0.061**
		(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)
AUS	-	0.0004	0.0003	0.002	0.009	0.005	*0.007*
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
PBVS	-	0.003	*0.002*	0.0003	0.002	0.001	0.001
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	**−0.173**	**0.740**	**1.046**	0.520	**1.339**	*0.623*	**1.218**
	(0.032)	(0.074)	(0.106)	(0.340)	(0.333)	(0.340)	(0.333)
ST/YW	No/No	No/No	No/Yes	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes
Gini	0.337	0.358	0.369	0.400	0.380	0.392	0.387
LL	−8,967	−8,866	−8,823	−8,686	−8,792	−8,722	−8,753

Std. error in parentheses; sign. levels: underline p<0.10, italic p<0.05, bold p<0.01

Table 2: Estimation Results

In `M2`, three control variables, namely `#FP`, `AUS`, and `PBVS` were added. Despite the newly introduced control variables, the estimate for `#RED` is fairly stable, whereas the estimate for `#FP` is almost halved. `PF` has a significant negative effect on user retention and this underlines the importance to control for the general print behaviour of users, to prevent overestimation of the reward effects. Both `AUS` and `PBVS` have a positive but small effect on `P2M` which is plausible since users who have larger baskets and spend more might have higher retention probabilities. The control variable slightly increases the model fit (Gini: +6.2%).

Adding spatio and temporal fixed effects (M3 and M4) do not change the results significantly, but further increases model fit (Gini: +9.5% and +18.7% respectively). This stability and robustness confirms our confidence in the validity of the results. M4 is considered to be the full and final model. The odd ratios for M4 show that one redemption increases the retention probability by 21.77% while one free product increases the retention probability by 13.88%. In terms of retention elasticity we have values of 0.032 for #RED and 0.105 for #FP.

Models M5, M6, and M7 were added to evaluate the explanatory power of the main variables (#RED and #FP). Adding only #RED increases the model Gini by 1.84% while using #FP leads to an improvement by 3.16%. Adding both (M4) variables improves the Gini by 5.26%. It is interesting to observe that the individual effects for #FP (M6) and #RED (M7) are higher than the respective effects in M4. This supports that bivariate analyses overestimate the effect on P2M and that the effects of both reward pillars should be measured simultaneously.

5 Discussion and conclusion

Retaining customers is an important topic (Reinartz, Thomas, and Kumar, 2005). Our findings provide valuable insights for researchers and practitioners alike. In particular, designing more holistic LP (Kumar & Shah, 2004) can increase loyalty and user satisfaction thereby driving customer lifetime value and profitability (Gupta & Zeithaml, 2006).

We have provided elasticity estimates for two novel retention mechanisms in a LP and thereby contribute to a better understanding of customer retention. The magnitudes of the elasticities illustrate the managerial importance for cultivating supporting conditions for customer retention. Our results show that delayed direct rewards as well as immediate and individualised direct rewards have a positive impact on user retention in the FMCG industry (compare Keh and Lee, 2006). Using rewards in form of free product rewards can be desirable for retailers in order to save cost (e. g. supply chain, promotional material). Furthermore, unlike classical, unrelated rewards in the FMCG industry (i.e. kitchen appliances) these products tend to be attractive to customers and hence can be used to increase customer satisfaction (Keh & Lee, 2006), which is directly linked to customer retention (Gupta & Zeithaml, 2006). The analysis further revealed that access to targeted promotions can be used as a driver for customer retention. The fact that LP users have exclusive access to price discounts can be viewed as a direct and immediate reward for LP usage (Keh & Lee, 2006). This insight is interesting for marketing practitioners as it might change the way the retail industry views price promotions. Beyond increasing store traffic, sales, and redemptions (Venkatesan & Farris, 2012), price promotions can have an innovative use case for retailers in increasing LP user retention.

This paper is only a first step towards a better understanding of the analysed LP. We have isolated the effects of the reward pillars on retention by incorporating control variables to account for endogeneity of reward redemptions. However, it is worth conducting an experiment to validate our findings in a more controlled setting. A question that should be addressed is the well known cold-start problem (Ansari, Essegaier and Kohli, 2000). Although a personalisation has clear advantages, an alternative for individualised promotions is needed if no data is available when users print their first handbill. This topic is closely related to the question how strongly the quality of recommendations (or the lack thereof) affects user retention and we plan to further investigate the impact of first usage patterns on user retention. Finally, it would be beneficial to model the impact of free products and individualised promotions on print frequency (possibly through mediation analysis). These avenues for further research will help to design new and improve existing LP in FMCG markets.

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