



# Short-term Impact of Item-based Loyalty Program on Customer Purchase Behaviors

Bo Wu<sup>1</sup> · Yi Sun<sup>2</sup> · Katsutoshi Yada<sup>3</sup>

Received: 27 February 2020 / Accepted: 2 July 2020 / Published online: 10 August 2020  
© The Author(s) 2020

## Abstract

Studies based on the analysis of a new design of loyalty program, *item-based loyalty programs* (IBLPs), indicate that customers are more interested in item-based reward points than in traditional price discounts. However, we are still unaware of customer responses to the different point settings on IBLP items. This study investigates an analysis with Tobit II to explore IBLPs' short-term (4 months) impact on customers' purchase behaviors using data from two newly opened Japanese supermarket chains that have implemented this new IBLP program from the beginning. The results showed that different types of customers are differently affected by IBLPs, and that heavy customers are more inclined to purchase more items with more spending money than others. The results also indicated that customers' purchase behaviors are affected by IBLPs' different point levels. Moreover, to an IBLP with different points, the responses from different types of customers are different. The findings of this study have important guiding significance in IBLP design and marketing management.

**Keywords** Loyalty program · IBLP · Customer purchase behavior · Short-term impact analysis

---

✉ Bo Wu  
wubo@aoni.waseda.jp

Yi Sun  
sun-yi650@g.ecc.u-tokyo.ac.jp

Katsutoshi Yada  
yada@kansai-u.ac.jp

<sup>1</sup> Faculty of Human Sciences, Waseda University, Tokorozawa, Japan

<sup>2</sup> Department of Systems Innovation, School of Engineering, The University of Tokyo, Tokyo, Japan

<sup>3</sup> Graduate School of Business and Commerce, Kansai University, Osaka, Japan

## 1 Introduction

To attract and retain more customers, as part of customer relationship management strategy, various industries use loyalty programs (e.g., issue points) to make more profits. The total points issued by companies in Japan were at least worth nearly 85 billion yen in 2014, and this number may increase to 1.1 trillion yen in 2022. The loyalty programs are used by industries such as airlines and grocery stores to increase their marketing promotions by identifying customers' performances [1]. By involving the loyalty programs, companies collect more data to enhance their targeted promotions and can further gain more repeated business [2]. Correspondingly, customers can earn reward points by their purchase rates that can help their closer to the redemption thresholds [2–4].

Some of the researches done on loyalty program suggest that it can successfully foster customer's loyalty [2, 3, 5, 6]. However, as a loyalty program is widely used in the current marketplace, it can also become a redundant resource in businesses [4]. According to some studies, the design of loyalty program is directly related to its effectiveness [1, 4, 5, 7], which means that new designs for loyalty program are important and worth studying.

For instance, a new design of loyalty program “item-based loyalty program (IBLP)” is proposed by Zhang et al. [7]. The difference between an IBLP and a conventional loyalty program is that the price discounts for each item are replaced by reward points in the former, which means that customers can earn extra points when purchasing specific items. Zhang et al.'s findings indicate that the customers showed more interest toward the item-based reward points than toward traditional price discount. However, in the study, they only explored the difference between non-members and members. As some researchers suggest that comparing the behavior of members with non-members cannot conclusively establish the causal relationship [3], it is important to further indicate the different responses to the IBLP from other types of member classification.

Therefore, in this study, we focus on a new IBLP-based design that assigns different points to different products, and try to explore this IBLP's short-term (4 months) impact on customers' purchase behaviors using Tobit II. The data we used were from two newly opened Japanese supermarket chains (belonging to the same company named Hankyu Oasis) that have this new IBLP program in practice since the beginning. To identify the effects of the new IBLP on customers' purchase behaviors, the research findings and conclusion of this study have important guiding significance in IBLP design and marketing management.

This paper is an extended version of our previous conference papers [8]. The remainder of this paper is organized as follows: an overview of related studies is provided in Sect. 2 with related empirical hypotheses. In Sect. 3, the target customer, related data set, and model are given. The analysis model and results that we used are provided in Sects. 4 and 5. Finally, we summarize the research results and provide our perspective regarding promising future research in Sect. 6.

## 2 Overview of Related Studies and Hypothesis Development

Many studies have been conducted to investigate the effects of IBLPs on customers' purchase behaviors. In this study, based on our case study of a supermarket in Japan (Hankyu Oasis), we define an IBLP as a design in which member customers can earn different points as rewards for purchase of different items. According to the prior researches and our purpose mentioned above, in this study, we try to solve three questions by testing the corresponding hypotheses.

### 2.1 The Effect of IBLP on Different Types of Customers

Findings from Zhang et al.'s [7] IBLP study, which examined the differences in responses between non-members and members, indicate that IBLPs may lead to an increase in non-members' total spending, but, at the same time, may also lead to a decrease in members' spending [7]. However, in this study, they did not consider the different types of members, which also lead to different responses [3]. Therefore, for the IBLP data we have, our first hypothesis will be:

**H1** Different types of customers respond differently to Oasis's IBLP.

According to the prior studies, customers can be classified into different types based on their basic demographic information [5], their attitude or behaviors to the firm, and so on [3, 4, 9, 10], which may better predict customer responses [4]. Therefore, drawing on the previous study [3], in this study, we use the spending level (heavy, moderate, light) to classify customers. Thus, to prove that the difference exists between the levels we used, as the first step, sub-hypothesis **H1a** will be:

**H1a** Oasis's IBLP affects light, moderate, and heavy customers' purchase behaviors differently.

Moreover, according to Lal et al.'s study [3], in this study, we use customers' purchase incidence and weekly spending to represent their purchase behavior. As heavy and light customers may be less concerned with the items' additional reward points, sub-hypothesis **H1b** for customers' purchase behaviors will be:

**H1b** Oasis's IBLP affects moderate customers' purchase behavior more than heavy and light customers' purchase behavior.

### 2.2 The Effect of Different Points on Customers' Purchase Behaviors

A few studies focus on the effect of IBLPs' different point levels on customers' purchase behaviors. Kumar et al. [11] pay attention to the effect of different values of coupons on their coupon elasticity. Their finding indicates that for the same brand, a higher value of coupon has a higher effect on the coupon elasticity. Therefore, as coupon values are similar to IBLP points, hypothesis **H2** will be:

**H2** Different points in Oasis's IBLP affect customers' purchase behavior differently.

Similar to H1, to prove that the difference exists between the groups classified by different points in customer purchase behaviors, sub-hypothesis **H2a** will be:

**H2a** Different points in Oasis's IBLP have different effects on customers' purchase behavior.

Moreover, according to the results of a coupon elasticity study [11], the higher point group may have a greater influence on customers' behaviors. Thus, sub-hypothesis **H2b** will be:

**H2b** Customers' purchase behavior is more affected by higher point items than lower point items.

### **2.3 How Customers with Different Characteristics Respond Differently to an IBLP with Different Points**

Lal et al. [3] suggest that grocery retailing is one of the least profitable industries and the competition for a shopper is fierce. To improve its competitiveness, a firm needs to increase customers' switching cost by constantly reminding customers about special benefits they can earn only in their store [5, 7]. However, given that most firms are offering loyalty programs now, it is very difficult for firms to create differences to attract customers by operating a conventional loyalty program. Zhang et al. [7] find that the IBLP they designed successfully reduced customers' responsiveness to competitors' promotions, which means this new design does differentiate their program from other competitors. Nevertheless, to further improve the IBLP effects, many topics still need to be explored.

Therefore, based on Liu [3] and Zhang et al.'s [7] results, this study analyzes the details of an IBLP. In our third hypothesis, we examine how different points in IBLPs affect different types of customers differently. The result of this hypothesis may provide us an opportunity to improve the effect of Oasis's IBLP by making the IBLP design more precise.

**H3** Different types of customers respond differently to IBLPs with different points.

If H1 and H2 are supported, we can draw a conclusion that different types of customers respond differently to Oasis's IBLP. Thus, we need to examine which kind of customers are more affected by which kind of points in the IBLP. Similar to what we do in H1b and H2b, we bring up the following sub-hypothesis:

**H3a** Higher point items affect moderate customers' purchase behavior more than they do heavy and light customers' purchase behavior.

### 3 Details of Data

#### 3.1 Data Set from Oasis’s IBLP

As mentioned above, to avoid the learning effect, the data set are selected from two newly opened Japanese supermarket chains (Oasis) that have been using the new IBLP program since the beginning. In their normal design, the member customers can earn one reward point for their each 200 yen spending in the store. Based on this basic design, an advance IBLP design called point plus is used to allow the member customers gain more points (ten levels from 5 to 100 points) according to their purchase items’ monthly changing classification.

As shown in Fig. 1, based on the whole data we have, a store selection period is used to estimate the open date of the stores; based on their open day, the data collection period is selected for analysis. In detail, as the prior studies indicate that customers’ behavioral loyalty is related more to the short-term period, we used the data from a 4-month period (2016.1.1 to 2016.4.30) and classified the data collection period into two parts: initialization period to classify customers and analysis period to estimate the model.

#### 3.2 Target Customers

In this study, to rule out the self-selection effect, we use three criteria to identify our target customers: date of membership, visit frequency, and last visit date. In other words, our target customers are the customers who have the data of purchase behaviors more than one at the beginning to the end of our research period. Therefore, the customers who joined the membership early, have more than one time of store visit history, and visited the store at least in the last month (April) are selected for analysis.

Based on our classification of customers and spending level mentioned in Sect. 2, 1245 target customers are picked for analysis, including 416 of light, 415 of moderate, and 414 of heavy spending category. Figure 2 shows the proportion of different

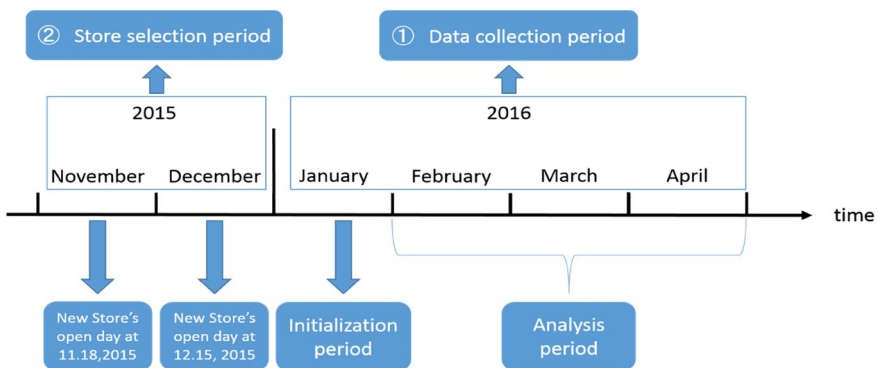


Fig. 1 The time periods we set

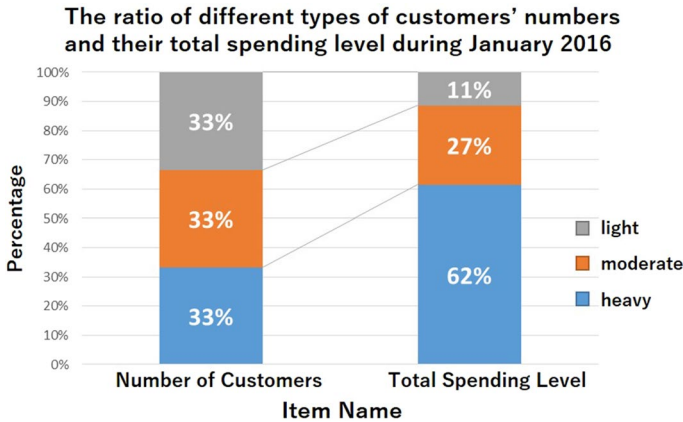


Fig. 2 The proportion of different customer types and their corresponding spending levels

customer types and their corresponding spending levels in January 2016. Of the total spending, 62% has been done by the heavy types, which is two times than that by the moderate, and six times than that by the light customers. The details of basic statistics of customers with different types are shown in Table 1.

### 3.3 IBLP Items

Based on Oasis’s IBLP design, ten levels of points including 5, 10, 15, 20, 25, 30, 35, 40, 50, and 100 point are used to bind the items with different price, which indicate that the items with higher price usually have a higher level of point setting. In addition, the 5- and 10-point levels have the most item categories, and the levels of 25 and 100 only have two.

## 4 Tobit II Model

Prior studies have used many methods such as a hierarchical linear model (HLM) that do not require independent observations and can accommodate individual heterogeneity to model customers’ reaction to loyalty program [3]. However, using an HLM to model purchase frequency and transaction size separately can lead to

Table 1 Descriptive statistics of each customer’s total spending level

Classification	Minimum	Median	Mean	Maximum	Standard deviation
Heavy	13,150	19,340	21,982	68,470	1670
Moderate	6700	9470	9640	13,100	1865
Light	450	4150	4050	6670	8834

inefficient and biased model estimates. To avoid this disadvantage, we focus on the model named Tobit II [12] that does not require the normality assumption and is usually used to measure customers’ purchase behavior [6, 10]. Therefore, to test the effect of different IBLP items on customers’ purchase behavior (purchases decision and weekly spending), the Tobit II model is involved in our analysis. The Tobit II model has two steps as follows:

### 4.1 Profit Model (Purchase Incidence)

To predict IBLP items’ purchase incidence, we assume that customer  $i$  purchases the IBLP items from Oasis’s store in week  $t$  ( $Z_{it}$ ), when the utility of doing so ( $Z_{it}^*$ ) is positive. Therefore,

$$Z_{it} = \begin{cases} 1 & \text{(Purchase) if } Z_{it}^* > 0 \\ 0 & \text{(No purchase) otherwise} \end{cases} \tag{1}$$

Equation 1 means that when customer  $i$  purchases in the store in week  $t$ , the value of  $Z_{it}$  will be 1, else it will be 0.  $Z_{it}^*$  represents the utility of customer  $i$ ’s purchase in week  $t$ , which can be calculated as:

$$Z_{it}^* = \alpha_0 + \delta_{\text{freq}} \text{Freq}_{it} + \delta_{\text{trend}} \log(t) + \varepsilon_{it} \tag{2}$$

In Eq. 2,  $\alpha_0$  represents the baseline IBLP items’ purchase incidence.  $\text{Freq}_{it}$  represents customer  $i$ ’s shop visit frequency in week  $t$ ,  $\log(t)$  represents the time trends.  $\varepsilon_{it}$  is the random error. To ensure the distribution closer to normal, the variables of independent and dependent are all log-transformed [7, 10].

### 4.2 OLS Regression Model (Weekly Spending)

Therefore, based on the Step 1, when the customer  $i$  has made a purchase in week  $t$  ( $Z_{it} = 1$ ), the logarithm of weekly spending of customer  $i$  in week  $t$  (Japanese yen)  $y_{it}$  will be:

$$y_{it} = \gamma_0 + \left[ \begin{matrix} \beta_{5p} \log(\text{Point}_{5it}) + \dots \\ + \beta_{100p} \log(\text{Point}_{100it}) \end{matrix} \right] + \beta_{\text{trend}} \log(t) + \sigma_{it} \tag{3}$$

In Eq. 3,  $\gamma_0$  represents the baseline weekly spending, and a set of point-related variables (a total of ten, e.g.,  $\text{Point}_{5it}$ ) is used to represent the spending on corresponding items (e.g., 5-point).  $\log(t)$  represents the time trends.  $\sigma_{it}$  is the random error.

These two models are used to perform analysis on all types of customers.

**Table 2** Results of IBLP items' purchase incidence

Variables	Heavy customers	Moderate customers	Light customers
$\alpha_0$	-0.693**	-0.912**	-1.142**
Shop visit frequency ( $Freq_{it}$ )	0.175**	0.209**	0.169**
Time trend [ $\log(t)$ ]	-0.203**	-0.212**	-0.108 <sup>n.s</sup>

\*\* $p$  value < 0.01; *n.s.* not statistically significant

**Table 3** Results of weekly spending on IBLP items

Variables	Heavy customers	Moderate customers	Light customers
$\gamma_0$	1.883**	1.752**	1.711**
5-point items	0.570**	0.591**	0.586**
10-point items	0.423**	0.404**	0.484**
15-point items	0.315**	0.443**	0.537**
20-point items	0.482**	0.473**	0.522**
25-point items	0.670**	0.780**	Omitted
30-point items	0.532**	0.545**	0.576**
35-point items	0.282**	Omitted	Omitted
40-point items	0.372**	0.438**	Omitted
50-point items	0.446**	Omitted	0.486**
100-point items	0.471**	0.625**	0.547**
Time trend [ $\log(t)$ ]	-0.014 <sup>n.s</sup>	-0.072**	-0.006 <sup>n.s</sup>

\*\* $p$  value < 0.01; *n.s.* not statistically significant

## 5 Results and Hypothesis Testing

In this study, the Tobit II model is used to test the effect of IBLP point levels on the purchase behaviors with different customer types.

As shown in Tables 2 and 3, for IBLP items' purchase incidence and weekly spending, the results indicate that all the tested variables in our model are significant. Moreover, customers did not have a significant upward trend in their IBLP items-based purchase behaviors.

Therefore, based on the analysis results, the hypotheses are tested as follows:

### 5.1 Test of Hypotheses 1

To test H1, two steps are used to test H1a and H1b.

At first, based on the basic statistics that show that the heavy customers have spent more money on the IBLP items, the analysis of variance analysis and Z-test are used to test H1a. As shown in Tables 4 and 5, the results of variance analysis and Z-test indicate that a significant difference exists among the three types of



**Table 4** Variance analysis for heavy, moderate, and light customers’ purchase behavior

Variance analysis	<i>p</i> value
Purchase incidence	0**
Total spending	2.36E – 10**

\*\**p* value < 0.01; *n.s.* not statistically significant

**Table 5** Z-test among heavy, moderate, and light customers’ purchase behaviors

Z-test ( <i>p</i> value)	Heavy and moderate	Moderate and light
Purchase incidence	7.62E – 12**	1.1E – 10**
Total spending	2.0542E – 06**	0.04**

\*\**p* value < 0.01; *n.s.* not statistically significant

**Table 6** Variance analysis for customers’ spending on 20-, 10-, and 5-point item

Variance analysis	<i>p</i> value
20, 10 and 5-point	0**

\*\**p* value < 0.01; *n.s.* not statistically significant

**Table 7** Z-test among customers’ spending on 20-, 10-, and 5-point items

Z-test ( <i>p</i> value)	2 and 10-point	10 and 5-point
Customers’ average spending	2.69E – 06**	0.07 <sup>n.s.</sup>

\*\**p* value < 0.01; *n.s.* not statistically significant

customers’ purchase incidence and weekly spending on IBLP items ( $p < 0.05$ ). H1a is supported.

In contrast, based on the results of the Tobit II model as shown in Table 2, a higher value in heavy customers is observed in the parameter of purchase probability baseline  $\alpha_0$ , which means that the heavy customers have a higher probability to purchase more IBLP items. Moreover, as shown in Table 3, the heavy customers also have the largest value in the parameter of purchase probability baseline  $\gamma_0$ . It means that the heavy customers spent more money on the IBLP items initially. However, except the beginning, the heavy customers not always the highest purchasers, therefore, H1b is partly supported. The heavy customers’ purchase behavior is most affected by Oasis’s IBLP initially.

### 5.2 Test of Hypotheses 2

Similarly, to test H2, two steps are used to test H2a and H2b.

For H2a, the analysis of variance analysis and Z-test are used. According to the large sample distribution theory [12], only the variables that have enough samples

**Table 8** Model estimation results for IBLP items' purchase incidence

Variables	Customers
$\alpha_0$	-0.900**
Shop visit frequency ( $Freq_{it}$ )	0.197**
Time trend [ $\log(t)$ ]	-0.203**

\*\* $p$  value < 0.01; *n.s.* not statistically significant

**Table 9** Model results for weekly spending on IBLP items

Variables	Customers
$\gamma_0$	1.831**
5-point items	0.576**
10-point items	0.428**
15-point items	0.374**
20-point items	0.488**
25-point items	0.741**
30-point items	0.545**
35-point items	0.300**
40-point items	0.406**
50-point items	0.459**
100-point items	0.538**
Time trend [ $\log(t)$ ]	-0.032**

\*\* $p$  value < 0.01; *n.s.* not statistically significant

can use the method of Z-test. Therefore, in this study, we select the points 5, 10, and 20 for analysis as they have more than 100 samples.

As shown in Tables 6 and 7, the results of variance analysis among total spending are significant ( $p < 0.05$ ), but the result of their Z-test is not significant ( $p > 0.05$ ), which indicates that to some extent, the customers do have different reactions to different point levels. H2a is partly supported.

In contrast, for H2b, the results for all customers' purchase behaviors are given in Tables 8 and 9. All of the variables are significant, and for the different point levels, the highest is the level of 25, which means that a higher point does not have a higher effect on customers. H2b is not supported.

### 5.3 Test of Hypotheses 3

To test H3a, as the coefficients of different points for heavy, moderate, and light customers are all significant, we try to explore H3 based on the results shown in Tables 2 and 3. Based on the results, the top three coefficients for heavy customers are 25-, 5-, and 30-point items, which are 0.670, 0.570, and 0.532. As for moderate customers, the coefficients of 25-, 100-, and 5-point items, 0.780, 0.625, and 0.591, are higher than other points. Finally, 5-, 30-, and 100-point items' coefficients for light customers are 0.586, 0.576, and 0.547. Among all these points, the 25-point

level items for moderate customer have the highest value. These results confirm that responses from different types of customers to an IBLP with different points are different.

Furthermore, moderate customers' weekly spending is more affected by 100-, 40-, 25-, and 5-point items, and light customers spend more money on 50-, 30-, 20-, 15-, and 10-point items than other customers. These results suggest that higher point items may have more effect on the moderate customers. Nevertheless, the purchase behaviors of light customers are more affected by the high-level point items. Moreover, the heavy customers are less sensitive to high-point items than others. Thus, H3a is partly supported.

This result indicates that heavy customers are also concerned about how to accumulate more points and maximize their benefits faster by purchasing items in IBLPs. However, heavy customers are less sensitive to the difference among points in IBLPs. In contrast, although moderate and light customers spend less money on IBLP items than heavy customers, they are more affected by certain points in IBLPs. It suggests that all customers pay attention to IBLPs, and, moderate and light customers choose more efficient ways to get more points.

## 6 Conclusion

This study focuses on the IBLP-based design that assigns different points to different products, based on the data from two newly opened Japanese supermarket chains (Oasis) that have used this new IBLP program since the beginning. The Tobit II model is used to explore an IBLP's short-term (4 months) impact on customers' purchase behaviors. In detail, the effects of IBLPs' different point levels (5–100, total ten levels) on different types (light, moderate, heavy) of customers' purchase incidence and weekly spending are analyzed.

The analysis results showed that all different types of customers are differently affected by the IBLP. In contrast to prior studies [2, 3], our results indicated that the heavy customers are more inclined to purchase more IBLP items with more spending money than others. Moreover, the results also indicated that customers' purchase behaviors are affected by the IBLP's different point levels. The behaviors of customers are affected by the items with a higher point level, but the highest effect belongs to the 25-point level. At the end, we also find that for the IBLP with different points, the responses from different types of customers are different. For example, a higher point item may have more effect on the moderate customers. This finding can help managers to improve the effect of IBLPs by arranging more targeted items to different types of customers.

This study only considers the effects of IBLPs in the short term. As the stores usually use multiple programs to promote sales, it would be useful to involve other programs' influences in future studies.

**Acknowledgements** This work was supported by JSPS KAKENHI Grant-in-Aid for Scientific Research(A) Number 16H02034.

## Compliance with ethical standards

**Conflict of interest** On behalf of all authors, the corresponding author states that there is no conflict of interest.

**Open Access** This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by/4.0/>.

## Reference

1. Bijmolt, T. H. A. (2011). Loyalty programs: Generalizations on their adoption, effectiveness and design. *Foundations and Trends in Marketing*, 5(4), 197–258.
2. Liu, Y. (2007). The long-term effect of loyalty programs on consumer purchase behavior and loyalty. *Journal of Marketing*, 71(4), 19–35.
3. Lal, R. D., & Bell, E. (2003). The effect of frequent shopper programs in grocery retailing. *Quantitative Marketing and Economics*, 1, 179–202.
4. Liu, Y. P., & Rong, Y. (2009). Competing loyalty programs: Effect of market saturation, market share, and category expandability. *Journal of Marketing*, 73(1), 93–108.
5. Leenheer, J., Harald, J. H., Tammo, H. A. B., & Ale, S. (2007). Do loyalty programs really enhance behavioral loyalty? An empirical analysis accounting for self-selecting members. *International Journal of Research in Marketing*, 24(1), 31–47.
6. Sharp, B., & Sharp, A. (1997). Loyalty programs and their effect on repeat-purchase loyalty patterns. *International Journal of Research in Marketing*, 14(5), 473–486.
7. Zhang, J., & Breugelmans, E. (2012). The effect of an item-based loyalty program on consumer purchase behavior. *Journal of Marketing Research*, 49(1), 50–65.
8. Wu, B., Sun, Y., Yada, K. (2018). The short-term impact of an item-based loyalty program. In: *2018 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, Miyazaki, Japan, pp1846–1851.
9. Zhang, Z. J., Aradhna, K., & Sanjay, K. D. (2000). The optimal choice of promotional vehicles: Front-loaded or rear-loaded incentives? *Management Science*, 46(3), 348–362.
10. Breugelmans, E., & Liu, Y. T. (2017). The effect of loyalty program expiration policy on consumer behavior. *Marketing Letters*, 28(4), 537–550.
11. Kumar, V., & Swaminathan, S. (2005). The different faces of coupon elasticity. *Journal of Retailing*, 81(1), 1–13.
12. Greene, W. W. H. (2012). *Econometric analysis* (Vol. 97). Upper Saddle River: Prentice Hall.

**Publisher's Note** Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.