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The role of marketing channels in consumers' promotional point redemption decisions

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ABSTRACT

Organizations employ loyalty programs to entice customers to repurchase their products and services. One popular promotional tool is the award of loyalty points. For this promotion to be effective, customers need to redeem these points. Currently, researchers opine that customers tend to stockpile these points. This study investigates customers' point redemption behavior in an omni-channel environment and posits that point redemption is a two-stage decision: whether to redeem and how many points to redeem. In the first stage, the results show that purchasing through PC channel positively impacts the probability of redeeming the points. However, in the second stage, purchasing through the mobile channel has a positive effect on the number of points redeemed. In an omni-channel world, different channels complement each other by enhancing the effectiveness of various marketing activities. Findings of this research highlight the role played by the online channels in encouraging customers' point redemption behavior.

1. Introduction

Many companies in industries ranging from hotels to airlines use loyalty programs to entice customers to repurchase (Septianto, An, Chiew, Paramita, & Tanudharma, 2019). One such commonly practiced loyalty program is the award of promotional points. Previous studies have shown multiple benefits of point redemptions for retailers. For example, reward redemptions improve customers' attitudes toward the retailer and extend their loyalty relationship (Smith & Sparks, 2009). Redemptions also increase customers' spending in post-redemption periods (Taylor & Neslin, 2005) and help customers form habits that significantly increase the frequency of purchase (Henderson, Beck, & Palmatier, 2011). However, these benefits are conditional on customers redeeming the promotional points earned by them. Yet, many customers tend to stockpile points in their loyalty program accounts. According to a recent estimation, customers do not redeem at least one-third of the $48 billion reward points issued annually (Radia, 2019). This point stockpiling behavior limits the benefits retailers would have received from their loyalty programs. The unredeemed points by customers merit special attention by retailers. Retailers are required by the Financial Accounting Standards Board (FASB) to make provisions for the unredeemed points in their financial statements (ASC topic 606/IFRS 15). This requirement has forced Delta airlines to increase its point liabilities from $410 million to $2.4 billion (Chun, Iancu, & Trichakis, 2020).

To encourage point redemption behavior, marketers use different types of promotions. These include point-plus-cash promotions, which allow customers to combine their points with cash (Montoya & Flores, 2019), and linear loyalty programs, which do not require a minimum amount in point redemption (Stourm, Bradlow, & Fader, 2015). Stockpiling the points in these loyalty programs is not rewarding, as customers forgo the time value of money for any delayed redemptions. However, points accumulation persists in these programs (Stourm et al., 2015). Prior research suggests that customers' point redemptions are mostly driven by product type (Kivetz & Simonson, 2002) and cognitive and psychological factors, such as non-monetary transaction costs and mental accounting for cash versus points (Stourm et al., 2015). In this research, we extend this literature by examining the role of marketing channels in customers' point redemption decisions.

With the growth of various types of marketing channels, retailers are able to influence consumer behavior seamlessly. In the past decade, marketers have witnessed a movement away from a multi-channel world, in which the personal computer (PC) channel complemented the traditional offline channel (e.g., physical store), to an omni-channel retailing environment. In the omni-channel environment, the mobile

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channel, the brick-and-mortar (BM) channel, and the PC channel all work in unison (Brynjolfsson, Hu, & Rahman, 2013). A rich literature discusses the complementarity between the PC and BM channels (e.g., Avery, Steenburgh, Deighton, & Caravella, 2012; Pauwels & Neslin, 2015) and the effect of mobile channel on consumer behavior in the retail context (e.g., Wang, Malthouse, & Krishnamurthi, 2015). However, customers' point redemption behavior when all the three channels are available has received scant attention in the marketing literature. Hwang, Chung, Kim, Lee, and Yoo (2016) is a seminal study in addressing the relationship between transaction channel and point redemption. Hwang et al. (2016) discuss the correlates of customers' point redemption likelihood. Their research finds that purchases through online channels are more likely to involve point redemption. They argue that online channels create a homogeneous transaction platform for customers, which mitigates the demographic effect (income, age, and gender) on point redemption. However, their research falls short on two dimensions. First, in their research, they do not distinguish the different types of online channels (PC and mobile channels). This distinction is important, as consumers tend to behave differently in these two channels while seeking information and making transactions (De Haan, Kannan, Verhoef, & Wiesel, 2018). Further, retailers are also interested in understanding the number of points redeemed by the customers for marketing and financial liability requirements discussed above. Hwang et al. (2016) do not address this issue.

This research extends Hwang et al. (2016) and other studies on loyalty point redemptions in three ways. First, previous research on point redemption has explored the first stage of point redemption decisions, that is, the probability of redeeming. In this study, we incorporate how many points to redeem as the second stage of the redemption decision. This extension is crucial because provisions have to be made to account for the cash value of unredeemed points according to the recent accounting rule change on loyalty points (ASC topic 606/IFRS 15). Second, we acknowledge the inherent differences between two types of online channels (the PC and mobile channels) due to their differences in perceived risk (De Haan et al., 2018) and perceived convenience (Emrich, Paul, & Rudolph, 2015). Whereas Hwang et al. (2016) treat all online channels the same, we posit that these differences are likely to have a differential impact on customers' point redemption decisions. Third, we correct the endogeneity bias that arises from the correlation of customers' channel decisions with unobserved customer factors in point redemptions. Doing so allows us to identify the causal effect of marketing channels on point redemption decisions. The correction for endogeneity bias is important in a practical sense. As we will later show, ignoring the endogeneity in customers' channel choice can be misleading to firms. While Hwang et al. (2016) do not address this issue, this research complements them by proposing a set of instrumental variables.

The structure of this paper is as follows: in Section 2, we provide a literature review on multi-channel and omni-channel retailing, customers' channel choices, the difference between PC channel and mobile channel, and point redemption behavior. In Section 3, we first describe the structure and characteristics of the dataset employed and then explain the empirical model, the identification strategy, and the estimation procedure of the model. In Section 4, we interpret the estimation results from the model. In Section 5, we provide a discussion for the results and the managerial implications. In Section 6, we discuss the study's limitations and avenues for future research.

2. Theoretical background

2.1. From multi-channel to omni-channel retailing

Neslin et al. (2006, p. 96) define multi-channel customer management as "the design, deployment, coordination, and evaluation of channels to enhance customer value through effective customer acquisition, retention, and development." Traditionally, multi-channel marketing involves a combination of BM, PC, and direct marketing channels (e.g., catalogs). Driven by the growth of the PC channel, early studies in multi-channel retailing focused on three streams of research (Verhoef, Kannan, & Inman, 2015): (1) the influence of channel adoption on firm performance (Ansari, Mela, & Neslin, 2008; Avery et al., 2012; Pauwels, Leeflang, Teerling, & Huizingh, 2011; Pauwels & Neslin, 2015), (2) shopper behavior across channels (Konuş, Verhoef, & Neslin, 2008; Venkatesan, Kumar, & Ravishanker, 2007; Verhoef, Neslin, & Vroomen, 2007), and (3) retail mix across channels (Emrich et al., 2015; Herhausen, Binder, Schoegel, & Herrmann, 2015). A consistent finding across the studies in the first stream is that adding the PC channel to the BM channel (or the other way around) increases the sales of both channels but cannibalizes the sales of the catalog channel. The second stream of research investigates customers' use of these channels interchangeably. Researchers in this stream find that customers routinely employ the "research shopping" strategy, in which they search in one channel (e.g., PC) and purchase in another (e.g., BM stores). Researchers in this stream also find that customers have different shopping patterns—some customers are enthusiastic about cross-channel shopping, while others concentrate their purchases on a single channel. The third stream of research emphasizes the integration effect of the retail mix across channels. Studies in this stream examine the overall impact of channel integration on customers' purchase intention. Researchers have identified several mediators through which channel integration may influence customer purchase, including perceived risk, perceived variety, and perceived convenience (Emrich et al., 2015).

With the advent of the mobile channel, retailers have realized the need to provide a seamless experience to customers (Verhoef et al., 2015). Customer relationship management practices that integrate customer data across the different channels are a central part of designing systems that provide this seamless experience. In this system, the mobile channel plays a crucial role. On the one hand, mobile devices are similar to moving PCs, in which customers can finalize their purchases immediately after their search in the store (showrooming). On the other hand, shoppers may gather information from the mobile channel and make purchases in the store (webrooming). Recent studies on omni-channel retailing have found that adding a mobile channel increases the purchase volume; however, the mobile channel is more commonly used for routine purchases than new products (Kim, Wang, & Malthouse, 2015; Wang et al., 2015). In this research, we extend understanding of shoppers' point redemption behavior in an omni-channel world in which retailers employ the BM, PC, and mobile channels.

2.2. Customers' channel choice in different shopping stages

Previous research has discussed why customers choose a particular channel in their shopping journey. For example, Verhoef et al. (2007) separate customers' shopping journey into two stages: search and purchase. Customers have different shopping foci across the two stages, and they choose the channel that fits the most with their focus in each stage. In the search stage, customers evaluate the channels on the basis of search benefits and search costs. The search benefits include the accessibility of information, the ability to compare alternatives, and the perceived ease with which consumers can gather information. The search costs include the required time and perceived difficulty in the information gathering process. With their lower search costs and maximum product information access (Bakos, 1997), online channels are often more advantageous than the BM channel in the search stage.

In the purchase stage, customers appraise channels on the basis of their benefits and costs when purchasing. Two channel attributes are important in this stage: perceived risk and perceived convenience (Emrich et al., 2015; Verhoef et al., 2007). Perceived risk consists of four components: product performance, financial, social, and psychological (Forsythe & Shi, 2003). Among these components, product performance risk and financial risk are directly linked to customers' decisions in the purchase stage. Product performance risk refers to the loss incurred when a brand or product does not perform as expected. Financial risk reflects the loss of money and personal information from possible leakage of credit card and other personal information. Forsythe and Shi (2003) find that online channels have higher perceived risks than the BM channel in both components. First, as the online channels prevent customers from touching and trying the product, customers' ability to judge the quality of a product is restricted. Therefore, when shopping online, customers are more likely to make purchases without sufficient information on some of the product attributes, a limitation that leads to product performance risk. Second, customers may feel a lack of control over the access others may have to their credit card information during the online navigation process (Hoffman, Novak, & Peralta, 1999), which leads to financial risk. Perceived convenience captures the perceived savings of time and effort during the purchase process (Emrich et al., 2015). Perceived convenience is determined by location, operating hours, and the time spent in queues (Keaveney, 1995; Seiders, Voss, Godfrey, & Grewal, 2007), all factors in which online channels have clear advantages over the BM channel. Overall, each of these channels has different advantages and disadvantages.

Point redemptions occur along with customers' decision to purchase the product. Therefore, we position our research in the purchase stage of customers' shopping journey. For loyalty programs with point awards, we propose two sub-stages within the purchase stage. In the first sub-stage, customers decide whether to redeem points for the purchase. In the second, conditional on their decision to redeem points in the first stage, customers consider how many points to redeem. For example, for a product that sells for $10, customers have the option to pay only with points or a combination of cash and points. The two-stage process in a loyalty program is different from the regular setting in the purchase stage, in which the decision to purchase and payment take place simultaneously. The unique setting in a loyalty program may help disentangle the influences of perceived risk and perceived convenience in the purchase stage. We posit that customers focus more on the perceived risk in the first stage. As the points are valuable, customers want to minimize the risk of redeeming points on a sub-optimal product. The decision of whether to redeem points from a particular channel determines the level of risk in customers' wealth (i.e., points). Therefore, customers are more concerned with the perceived risk than the perceived convenience of a channel. In the second stage, as customers have decided to redeem points (i.e., decided to take the perceived risks from a particular channel), perceived risk is not as important as in the first stage. Instead, customers' main objective is to find the channel with the greatest perceived convenience (i.e., the channel that will facilitate the redemption transaction). Therefore, we expect customers to choose channels with lower perceived risk in the first stage of their redemption decision and select channels with greater perceived convenience in the second stage.

The relationship of perceived risk and perceived convenience with customers' channel choice also depends on the characteristics of the product. Previous studies on this relationship (Bang, Lee, Han, Hwang, & Ahn, 2013; De Haan et al., 2018) have identified three product characteristics: privacy and safety risk, time criticality of transactions, and intensity of product information. A product with high privacy and safety risk contains important privacy and safety information for the customer. For these types of products, customers will tend to focus on evaluating the perceived risk of a channel for their purchase. A product with high time criticality of transactions is characterized by strong time constraints for purchase. Products for which demand is concentrated around a specific time (e.g., Christmas holiday) or personal events (e.g., anniversary) are time critical. The strict time constraint of purchase and consumption is likely to cause customers to focus more on the perceived convenience in their channel choice. Products with strong information intensity require customers to process a large amount of information (e.g., product descriptions, customer reviews) before purchasing. For these products, the perceived risk is higher if customers do not acquire sufficient information. Therefore, customers will tend to prefer the channel with lower perceived risk under high product information intensity.

2.3. Difference between PC channel and mobile channel

The two types of online channels (i.e., PC and mobile) have important differences, and recent omni-channel retailing studies have emphasized the need to distinguish between them. Bang et al. (2013) identify two dimensions to distinguish these channels: access and search capabilities. We posit that both dimensions are related to perceived risk and perceived convenience. Compared with using the PC channel, using the mobile channel gives customers access to e-tailers wherever and whenever they want. Therefore, the mobile channel is more competitive than the PC channel in perceived convenience. In turn, this suggests that the mobile channel will be more popular when the transaction of the product is time critical. Compared with the mobile channel, the PC channel is likely to score high on the ease of searching because of its larger screen. In particular, we expect that the screen-size advantage in the PC channel will be more pronounced when the product is more information intensive.

In the context of our research, in which both the PC channel and the mobile channel are available, customers are free to switch between the two channels in their shopping journey. When customers decide to purchase a product, they often want to take more time to check the details of a purchase and compare competitive offerings. Therefore, in the first stage, when customers decide whether to redeem points, we expect the PC channel to be more popular than the mobile channel. After customers decide to redeem points in their transaction, they enter the second stage in which they consider the number of points to redeem. In this stage, perceived risk is no longer a concern, as customers have decided to purchase the product and take the risks. Therefore, the impact of the channel on customers' redemption behavior in the second stage should be different from that in the first stage. As the mobile channel has higher perceived convenience than the PC channel, we expect customers to prefer the mobile channel to the PC channel in this stage.

2.4. Point redemptions in the loyalty program

Prior studies on point redemption behavior in loyalty programs focus on four streams of research: (1) the drivers of point redemptions (2) the role of promotional points in customer engagement with the loyalty program (3) the influence of point redemption on sales, and (4) the reason why customers tend to stockpile instead of redeeming points. The first stream focuses on the psychological motivation of point redemption behavior beyond its economic benefits. The motives to redeem points range from self-gifting (Smith & Sparks, 2009) to reducing the guilty feelings associated with luxury goods consumption (Kivetz & Simonson, 2002). The second stream investigates the impact of promotional points program on customer engagement. The design of the loyalty program plays a role in the evaluation (Ashley, Gillespie, & Noble, 2016) and customer commitment to the loyalty program (Noble, Esmark, & Noble, 2014). Also, a measurement scale for customers' loyalty program engagement is developed by Bruneau, Swaen, and Zidda (2018).

The third stream of research finds a positive impact of point redemption on sales. Researchers have identified several mechanisms on how redeeming points increase sales before and after the redemption. Thematic interviews by Smith and Sparks (2009) reveal that redemptions improve consumers' favorable evaluation of the loyalty program. Enrollment in the loyalty program has a dual effect. On the one hand, it produces switching costs. On the other hand, it creates pressure to purchase from the retailer to meet the point targets (Dorotic, Verhoef, Fok, & Bijmolt, 2014; Kopalle, Sun, Neslin, Sun, & Swaminathan, 2012; Taylor & Neslin, 2005). The other positive impacts of point redemptions include a) customers' enhanced gratitude and attitudinal loyalty

(Steinhoff & Palmatier, 2016), b) habit formation resulting in automatic and effortless repurchase (Henderson et al., 2011), and c) customers' strengthened self-efficacy that leads to more post-redemption purchases (Drèze & Nunes, 2011).

The fourth stream aims to explain the point stockpiling behavior in loyalty programs; researchers have identified three types of motivations: economic, cognitive, and psychological (Stourm et al., 2015). The economic motivation stems from the design of the loyalty program. Some loyalty programs require customers to stockpile points to earn specific rewards (e.g., reach 100,000 points to receive one free night in a hotel). For these programs, as the stock of points increases, the value of each point increases non-linearly. Therefore, stockpiling points in a certain range is optimal for customers. Other programs do not require a minimum amount for customers to redeem points. For these programs, the redeemable value of each point does not increase with point accumulation. However, some of these programs do not allow customers to earn points on the transactions with point redemptions. Because customers forgo the opportunity to earn points in these transactions, they choose not to redeem points in some transactions (Stourm et al., 2015). The cognitive motivation derives from the non-monetary cost incurred by the redemption behavior, such as spending cognitive resources to find the items to redeem or putting effort into considering how many points to redeem. These non-monetary costs prevent customers from redeeming often. The psychological motivation includes several aspects, such as separate mental accounting for cash and points (Drèze & Nunes, 2004; Stourm et al., 2015) and gaining a sense of achievement through point accumulation (Zhang & Gao, 2016). We summarize the findings of seminal articles in Table 1. We contribute to the literature by examining customers' choice to redeem points and the number of points to redeem across the channels.

3. Research methods

3.1. Data source

Our data come from a large multi-industry company based in South Korea that manufactures and retails food ingredients and pharmaceuticals and provides entertainment and media services. The company

Table 1
Summary of research findings on point redemptions.

Research focus	Representative studies	Channels involved	Data source	Key findings
Drivers of point redemption	Smith and Sparks (2009)	NA	A single-vendor loyalty program operated by a health and beauty retailer in the UK Qualitative interviews	The motivations of redemptions focus on self-gifting and therapy purposes.
	Kivetz and Simonson (2002)	NA	Experimental data from travelers	Consumers tend to redeem points on luxury than necessity items.
Role of points in customer engagement with loyalty program	Ashley et al. (2016)	NA	Experimental data from students and online survey	The complexity of the point accrual system moderates the impact of program fees on customers' likelihood to join the program.
	Noble et al. (2014)	NA	Experimental data from students	Loyalty program types moderate the impact of redemption control policy on customers' continuance commitment to the program.
	Bruneau et al. (2018)	NA	Data from in-depth interviews and surveys	Customers' engagement in loyalty program is categorized into six types based on their point redemption, purchase, information seeking, and word of mouth behaviors.
Influence of point redemption on sales	Smith and Sparks (2009)	NA	A single-vendor loyalty program operated by a health and beauty retailer in the UK Qualitative interviews	Redemption activities have a positive impact on consumer perceptions of the loyalty program.
	Taylor and Neslin (2005)	BM	An annually held single-vendor loyalty program operated by a retail store	• Loyalty program members tend to purchase more before the expiry of the reward program. • Loyalty program members' baseline purchases are higher after they receive the reward.
	Dorotic et al. (2014)	PC, BM	A coalition loyalty program in the Netherlands	The mere decision to redeem a reward significantly enhances purchase behavior before and after the redemption event.
	Drèze and Nunes (2011)	NA	Frequent-flier program of a major U.S.-based international airline	Reward redemption strengthens customers' self-efficacy, increasing post-redemption purchases.
	Steinhoff and Palmatier (2016)	NA	Experimental data from Mturk	Receiving a reward from firms elicits customers' gratitude, which improves customers' attitudinal loyalty.
	Henderson et al. (2011)	NA	Conceptual framework	Point redemption helps customers build shopping habit.
	Kopalle et al. (2012)	NA	The loyalty program of a major hotel chain	Promotional structure and customer-tiers jointly impact sales.
Drivers of point stockpiling behavior	Stourm et al. (2015)	BM	A single-vendor loyalty program operated by a supercenter chain that sells high-end product categories in Latin America	Customers' point stockpiling behavior contains three motivations: economic, cognitive, and psychological.
	Kwong, Soman, and Ho (2011)	NA	Experimental data from students	Consumers' decision to spend points is positively related to the ease of calculating the percentage of savings.
	Zhang and Gao (2016)	NA	Experimental data from students	Customers who receive rewards piece by piece are more motivated to acquire more rewards when compared to those who receive the same rewards in a lump sum.
Relationship between channel and point Redemption	Hwang et al. (2016)	PC, BM	A coalition loyalty program in South Korea	• Transactions through online channels exhibit a higher probability of point redemptions. • Transactions by younger customers exhibit a higher probability of point redemptions. • Online channels mitigate the impact of demographics on the probability of point redemption.
	This research	PC, BM, mobile	A coalition loyalty program in South Korea	• PC channel has a higher impact on customers' probability of redeeming points than the mobile channel. • Mobile channel has a higher impact on the number of points redeemed than PC and BM channels.

operates a popular loyalty program that rewards customers with points for purchases. The points in the program do not expire, and there is no minimum requirement for point redemption. Customers can collect and redeem points on any brand that participates in the program. They can also freely choose the combination of cash and points in any purchase. In the program, one point is equivalent to one South Korean won (₩). In other words, if a product sells for ₩10,000 and a customer decides to redeem 3,000 points for the transaction, he or she only needs to pay ₩7,000.

3.2. Sample description

In this research, we focus on the cinema chain brand, as this is the only brand in the program distributed through all three channels (i.e., BM, PC, and mobile). We chose only the customers who have made three or more purchases in the brand because this is the minimum number of purchases for customers to be able to choose all three channels. Our data contain the details of 8,798,645 transactions and 730,400 customers from 100 movie theaters. Among these transactions, 2,091,332 are through the PC channel, 4,620,476 through the BM channel, and 2,086,837 through the mobile channel. The average bill amount for transactions when points were redeemed is ₩17,652, with an SD of ₩8,517. The average number of points redeemed is 4,299, with an SD of 3,634. In the BM channel, customers typically purchase from a human being though there are kiosks available. The data capture mechanism does not distinguish between these two types of purchases. The mobile channels are app-based. Gift cards are available, but the dataset does not capture this information. The data include customer ID, date, cash payment, number of points redeemed for each transaction, the channel, and the store identification. Customers have access to concession stands in all three channels and can redeem points in them.

The two-stage decision process requires two sets of statistics (redemption probability in the first stage and the number of points redeemed in the second stage) to describe customers' redemption behavior. We show the two types of summary statistics in Table 2. For redemption probability, we compute the ratio of the number of redemptions to the number of all transactions in the focal brand for each customer (redemption–transaction ratio). A higher redemption–-transaction ratio indicates a higher chance of redemption for the customer in a particular transaction. For the number of points redeemed, we compute the mean and standard deviation of all redemption transactions. To compare the difference in the redemption–transaction ratio and the number of points redeemed across channels, we report the two statistics for each channel separately. We find variations in redemption probabilities and the number of points redeemed across channels.

3.3. Defining variables

In this research, the independent variables of interest are the three channels (BM, PC, and mobile), and the dependent variables are probability of point redemption and the number of points redeemed. The summary statistics in Table 2 reflect the marginal distribution of the two-stage redemption decision across channels. To estimate the impact of channels on point redemptions, we need to take into account the joint distribution of channels and other control variables. When modeling the impact of channels on point redemption decisions, we need to ensure that the channel variables are exogenous. However, in the current context, customers' channel decisions may correlate with the unobserved customer characteristics, and these characteristics may also affect customers' redemption decisions. Not correcting for this endogeneity would result in biased estimates of the impact of channels on point redemptions. Therefore, in the rest of the section, we specify the empirical model for the two-stage decisions, discuss the identification strategy, and provide the estimation method. We choose the PC channel as the baseline, so we define two dummy variables for the other two marketing channels: *BM*for the BM channel and *MO* for the mobile channel.

Table 2
Summary statistics for point redemption decisions.

Measure	Redemption probability		Number of points redeemed	
	M	SD	M	SD
Channel				
PC	0.3080	0.3548	4,251	3,468
BM	0.1174	0.1936	4,223	3,389
Mobile	0.2789	0.8287	4,474	4,148
Total	0.1762	0.1813	4,299	3,634

3.4. Empirical model

Our model covers the two stages in customers' point redemption behavior: whether to redeem points or not and how many points to redeem. Our key dependent variables in the two stages are (1) a binary variable that equals 1 if the customer in a transaction decides to redeem points and 0 otherwise and (2) a continuous variable for the number of points redeemed in the transaction. In line with our research questions, the key independent variables in both stages are the dummy variables for marketing channels, *BM* and *MO*. We provide notations and variable descriptions in Table 3.

3.4.1. First-stage decision: Whether to redeem or not

The customer's redemption decision in the first stage is whether to redeem points or not in a transaction. We model this decision with a probit model (Dorotic et al., 2014; Taylor & Neslin, 2005). We characterize the probit model as

$$RD^* = \beta_0 + \beta_1 BM + \beta_2 MO + \mathbf{Z}_1' \boldsymbol{\lambda} + \epsilon, \tag{1}$$

where $\mathbf{Z}_1$ is the vector of control variables, and ϵ $N(0,1)$. The relationship between the observed redemption decision (RD) and the latent redemption decision (RD^*) is

$$RD = \begin{cases} 1, if RD^* > 0 \\ 0, if RD^* \leq 0 \end{cases} \tag{2}$$

3.4.2. Second-stage decision: How many points to redeem

Conditional on customers' decision to redeem points, their decision in the second stage is the number of points to redeem. We propose a log-linear model to estimate the impact of the independent variables on the number of points redeemed. The log transformation is consistent with previous research's treatment of the number of points (Dorotic et al.,

Table 3
Notations and variable descriptions.

Variable	Descriptions
RD	Equals 1 if the number of points redeemed > 0 and 0 otherwise.
RD^*	Latent redemption decision.
RA	The number of points redeemed.
BM	Equals 1 if the transaction occurred through the BM channel.
MO	Equals 1 if the transaction occurred through the mobile channel.
$\mathbf{Z}_1$ [a]	A vector of control variables in the first-stage model (Eq. (1)).
$\mathbf{Z}_2$	A vector of control variables in the second-stage model (Eq. (3)).
$\mathbf{Z}_3$	A vector of control variables in the reduced-form equation (Eq. (5)), viz., month dummies and store dummies.
IV_BM	Instrumental variable for the endogenous variable *BM*, defined as the proportion of transactions from the BM channel on the same store-date, excluding all transactions of the focal customer.
IV_MO	Instrumental variable for the endogenous variable *MO*, defined as the proportion of transactions from the mobile channel on the same store-date, excluding all transactions of the focal customer.

[a] We use bold fonts to express vectors in this paper.

2014),

$$log(RA) = \gamma_0 + \gamma_1 BM + \gamma_2 MO + \mathbf{Z}_2^{'}\boldsymbol{\kappa} + \eta \tag{3}$$

where $\mathbf{Z}_2$ is the vector of control variables, and η $N(0, \sigma_\eta^2)$.

3.5. Identification strategy

Many factors unobservable to marketers could influence customers' channel decisions. Moreover, these factors may affect customers' redemption decisions, which creates an endogeneity problem when we estimate the effect of channel on point redemptions. For example, customers could be busier when they are in the BM store (otherwise, they would have bought the ticket using PC or mobile channel ahead of time). The degree of busyness may also correlate with customers' redemption decisions. When customers are occupied, they are less likely to spend time thinking about whether they want to redeem points and how many points to redeem. Therefore, we may observe a negative correlation of BM channel choice with redemption probability and the number of points redeemed. The negative correlation arises because the independent variable (BM channel choice) and dependent variable (redemption probability) are correlated with a common omitted variable (e.g., the degree of busyness), not because the BM channel itself affects customers' point redemption decisions.

To correct the endogeneity bias from the channel decision, we employ instrumental variables (IVs) for the endogenous regressors *BM* and *MO*. We construct the IVs as follows: for each transaction, we extract the information on the transaction date and the ordering store. Then, we calculate the proportion of transactions completed through the BM and mobile channels by other customers in the same store on the same day and use the proportions as the IVs. The IVs are strong because the focal transaction and other customers' transactions occurred in the same store on the same day, so they are likely to be influenced by the same actions from the store side and should significantly correlate with each other. The IVs are not likely to be correlated with the unobserved customer characteristics of the focal customer because we construct them using other customers' channel choices. The identifying assumption is that within the same month (controlled by month dummies), the unobserved characteristics of the focal customer that affect point redemption are independent of the store actions that influence customers' channel decisions. The identification assumption will not hold when a nation-wide demand shock related to the unobserved customer characteristics occurs (e.g., holiday seasons). As the aggregate shock to the demand is captured by the time dummy variables, the IVs generate exogenous variations to the endogenous variables.

3.6. Estimation

3.6.1. Estimation for first-stage decisions

In the first stage, we model the redemption probability using Eq. (1). Because we have binary endogenous regressors in a non-linear (probit) model, standard two-stage least squares estimation procedures are forbidden (Wooldridge, 2010, p. 267). Instead, we apply the estimation method from the bivariate probit model (see Wooldridge, 2010, pp. 595–597; for the technical details of the bivariate model, also see Li, Poskitt, & Zhao, 2019). The bivariate probit model is characterized by a structural equation determining a binary outcome as a function of a binary treatment variable (Eq. (4)), and the binary treatment variables are further governed by a reduced-form equation (Eq. (5)). Each equation is a probit model, and we estimate both equations jointly with the maximum likelihood method using the Stata command *biprobit*.

The estimation procedure implemented in the bivariate probit model can only accommodate one endogenous regressor and one reduced-form equation for the endogenous regressor (Wooldridge, 2010, p. 594). However, in Eq. (1), we have two endogenous regressors: *BM*and *MO*. To accommodate these two regressors, we construct two bivariate probit models. In both models, transactions in the PC channel are the baseline. We first select all transactions through the PC and BM channels and estimate the model using Eqs. (4) and (5). Then, we select all transactions through the PC and mobile channels and estimate the second bivariate probit model. The second bivariate probit model has a similar structure to that in Eqs. (4) and (5), except that we replace the endogenous variable *BM* with *MO* and the corresponding latent decision variable BM^* with MO^*. As both models have an identical baseline group (transactions through PC), the average treatment effects (ATEs) from the two estimations are comparable. In addition, as the IVs in the reduced-form equations of the two bivariate probit models are identical, the exogenous variations generated by the IVs are also identical in the two models.

For simplicity, we explain the estimation of the bivariate probit model with PC and BM transactions:

$$RD^* = \mathbf{Z}_1^{'}\boldsymbol{\alpha} + \delta BM + \xi_1 \tag{4}$$

$$BM^* = \mathbf{Z}_3^{'}\boldsymbol{\pi} + \mathbf{IV}^{'}\boldsymbol{\psi} + \xi_2 \tag{5}$$

where

$$RD = \begin{cases} 1, if RD^* > 0 \\ 0, if RD^* \leq 0 \end{cases} \tag{6}$$

and

$$BM = \begin{cases} 1, if BM^* > 0 \\ 0, if BM^* \leq 0 \end{cases} \tag{7}$$

Here, $\mathbf{IV}$ is the vector of instruments; that is, $\mathbf{IV} = [IV\_BM, IV\_MO]'$; $\mathbf{Z}_1$ and $\mathbf{Z}_3$ are the vectors of control variables for the structural equation (Eq. (4)) and the reduced-form equation (Eq. (5)) respectively. We map the underlying continuous latent variables $RD^*$and BM^* onto the observed outcomes *RD* and *BM* via threshold crossing conditions (Eqs. (6) and (7)). The joint distribution of *RD* and *BM* conditional on $\mathbf{Z}_1$, $\mathbf{Z}_3$, and $\mathbf{IV}$, $P(RD = rd, BM = bm | \mathbf{Z}_1 = z_1, \mathbf{Z}_3 = z_3, \mathbf{IV} = \mathbf{iv})$ (for notational convenience, we abbreviate to $P_{rd,bm}$), has four elements:

$$\begin{aligned} P_{11} &= P(\xi_1 > -\mathbf{Z}_1^{'}\boldsymbol{\alpha} - \delta, \xi_2 > -\mathbf{Z}_3^{'}\boldsymbol{\pi} - \mathbf{IV}^{'}\boldsymbol{\psi}) \\ P_{10} &= P(\xi_1 > -\mathbf{Z}_1^{'}\boldsymbol{\alpha}, \xi_2 < -\mathbf{Z}_3^{'}\boldsymbol{\pi} - \mathbf{IV}^{'}\boldsymbol{\psi}) \\ P_{01} &= P(\xi_1 < -\mathbf{Z}_1^{'}\boldsymbol{\alpha} - \delta, \xi_2 > -\mathbf{Z}_3^{'}\boldsymbol{\pi} - \mathbf{IV}^{'}\boldsymbol{\psi}), \text{ and} \\ P_{00} &= P(\xi_1 < -\mathbf{Z}_1^{'}\boldsymbol{\alpha}, \xi_2 < -\mathbf{Z}_3^{'}\boldsymbol{\pi} - \mathbf{IV}^{'}\boldsymbol{\psi}) \end{aligned} \tag{8}$$

We assume that $(\xi_1, \xi_2)$is drawn from a standard bivariate normal distribution with zero means, unit variances, and correlation of coefficient ρ; that is,

$$\begin{pmatrix} \xi_1 \\ \xi_2 \end{pmatrix} N_2\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \right) \tag{9}$$

Given data consisting of *N* observations for $n = 1, \cdots, N$, the log-likelihood function for the bivariate probit model is

$$L = \sum_{n=1}^{N} [rd_n bm_n \ln P_{11_n} + rd_n(1 - bm_n)\ln P_{10_n} + (1 - rd_n)bm_n \ln P_{01_n} + (1 - rd_n)(1 - bm_n)\ln P_{00_n}] \tag{10}$$

3.6.2. Estimation for second-stage decisions

Because customers' point redemption decision in the second stage is a linear model (Eq. (3)) and the dependent variable (number of points redeemed) in the second-stage decision is continuous, we use the standard two-stage least squares procedure to estimate the system of equations (Eqs. (11)–(13)):

$$log(RA) = \gamma_0 + \gamma_1 BM + \gamma_2 MO + \mathbf{Z}_2^{'}\boldsymbol{\kappa} + \eta \tag{11}$$

$$BM = \theta_0 + \theta_1 IV\_BM + \theta_2 IV\_MO + \mathbf{Z}_2^{'}\boldsymbol{\iota} + \upsilon_1 \quad (12)$$

$$MO = \rho_0 + \rho_1 IV\_BM + \rho_2 IV\_MO + \mathbf{Z}_2^{'}\boldsymbol{\mu} + \upsilon_2 \quad (13)$$

where $\mathbf{Z}_2$is the vector of control variables, and $\eta\ N(0, \sigma_\eta^2)$, $\upsilon_1\ N(0, \sigma_{\upsilon_1}^2)$, and $\upsilon_2\ N(0, \sigma_{\upsilon_2}^2)$.

4. Results

4.1. Results of the first-stage decision estimations

To interpret the impact of channel on redemption probability in the probit model, we compute the ATE for each independent variable. The ATE measures the mean difference in redemption probabilities when all cases receive the treatment (i.e., $BM = 1$ or $MO = 1$, but not both) versus when all cases do not receive the treatment (i.e., $BM = 0$ and $MO = 0$), holding all other control variables constant. We incorporate 21 month dummies and 99 store dummies to control for the heterogeneity of redemption decisions across time and stores. Also, we incorporate the log of the stock of points in our models to control for the correlation between the available stock of points in customers' loyalty program account and customers' redemption decisions.[1]

The ATEs of BM and mobile channels in the bivariate probit models appear in Model 1 of Tables 4a and 4b. The ATEs reflect the impact of channel decision on redemption probability. We show that customers are less likely to redeem if the transactions occur in the BM and mobile channels than the PC channel. The redemption probability drops by 0.5402 if customers make purchases in the mobile channel when compared with the PC channel. The redemption probability from the BM channel is lower by 0.0642 than that from the PC channel.

To check the robustness of our result, we control for a few other factors that may confound the negative impact of mobile channel on redemptions. One potential factor is the heterogeneity of customers' redemption probability. Perhaps the customers who rarely redeem points usually purchase through the mobile or BM channel. The negative impact of the mobile and BM channels on redemption probability may largely come from the low redemption tendency of these customers. To control for this effect, we augment Model 1 of Tables 4a and 4b by adding the redemption–transaction ratio (defined as the number of transactions where points are redeemed to the total number of transactions) of each customer as an additional control variable. We present the ATEs in Model 2 of Tables 4a and 4b. Another factor is customers' product experience when they purchase through the mobile or BM channel. Customers are less likely to purchase when they have less product experience (De Haan et al., 2018), and most customers are likely to have little experience with a product initially. As such, if they predominantly purchase using the mobile or BM channel when they have little product experience, the negative impact of these channels may come from this product inexperience. To control for product inexperience, we further augment Model 2 by including the number of previous purchases for each transaction as a covariate. We report the ATEs in Model 3 of Tables 4a and 4b. The negative impact of mobile and BM channels on redemption probability (when compared to the PC channel) is consistent across the three models, which attests to the robustness of our findings.

Table 4a
First-stage decision: ATE of BM channel.

	Model 1	Model 2	Model 3
Channel impact			
BM (baseline = PC)	**−0.0642**	**−0.0313**	**−0.0300**
	(0.0012)	**(0.0011)**	**(0.0011)**
Control variables			
Log (stock of points)	**0.0618**	**0.0795**	**0.0810**
	(0.0001)	**(0.0001)**	**(0.0001)**
Month dummies	✓	✓	✓
Store dummies	✓	✓	✓
Redemption–transaction ratio		✓	✓
Number of previous purchases			✓

Notes: Bold means the ATE is significantly different from 0 at the 0.05 level. Standard errors are reported in the parentheses. The checkmarks indicate that these variables are included in the estimation of the structural equation. The estimates of the covariates are not reported for parsimony.

Table 4b
First-stage decision: ATE of mobile channel.

	Model 1	Model 2	Model 3
Channel impact			
Mobile (baseline = PC)	**−0.5402**	**−0.4545**	**−0.4522**
	(0.0003)	**(0.0010)**	**(0.0010)**
Control variables			
Log (stock of points)	**0.0233**	**0.0509**	**0.0522**
	(0.0001)	**(0.0002)**	**(0.0002)**
Month dummies	✓	✓	✓
Store dummies	✓	✓	✓
Redemption–transaction ratio		✓	✓
Number of previous purchases			✓

Notes: Bold means the ATE is significantly different from 0 at the 0.05 level. Standard errors are reported in the parentheses. The checkmarks indicate that these variables are included in the estimation of the structural equation. The estimates of the covariates are not reported for parsimony.

4.2. Results of the second-stage decision estimations

After customers decide to redeem points in the first stage, they enter the second stage of the point redemption decision. In this stage, they decide on the number of points to redeem. In this section, we investigate the impact of channel decisions on the number of points redeemed. Owing to the linearity of the model for the second-stage decision (Eq. (3)), the coefficient estimates are directly interpretable.

We report the coefficient estimates for the independent variables in Model 1 of Table 5. In this model, in addition to month and store fixed effects and the stock of available points,[2] we account for the

Table 5
Second-stage decision: coefficient estimates for channels.

	Model 1	Model 2
Channel impact		
BM	**−0.1209**	**−0.4127**
	(0.0146)	**(0.0289)**
Mobile	**0.5778**	**0.2297**
	(0.0133)	**(0.0175)**
Control variables		
Log (stock of points)	**0.4651**	**0.7687**
	(0.0016)	**(0.0034)**
Month dummies	✓	✓
Store dummies	✓	✓
Redemption–spending ratio	**1.1998**	
	(0.0044)	
Individual dummies		✓
Price of the product	**0.2816**	**0.0729**
	(0.0035)	**(0.0044)**

Notes: Bold means the coefficient is significantly different from 0 at the 0.05 level. The checkmarks indicate that these variables are included in the estimation. The estimates of some covariates are not reported for parsimony.

[1] We thank an anonymous reviewer for pointing this out.

[2] We thank an anonymous reviewer for his/her suggestion.

heterogeneity of customers' point redemption habits. In redemption transactions, some customers prefer using points to cover the product payment in its entirety (e.g., if a product sells for ₩10,000, the customers redeem points worth ₩10,000 for the payment), while other customers prefer using points to cover a fraction of the payment (e.g., if a product sells for ₩10,000, the customers redeem points worth ₩2,000 for the payment). This difference in redemption habits will result in a higher number of points redeemed for the former customer type. If customers of the former type also use the mobile channel for the transactions, the impact of this channel, if any, will be accentuated by their redemption habit. To control for this confounding effect, we add the redemption-spending ratio of each customer as a control variable. This ratio captures the cash value of the total number of points redeemed in all transactions of the focal brand from a customer to the total bill (cash value of points redeemed plus cash payments) in those transactions. We also control for the price of the product because the number of points redeemed in a transaction could depend on the price of the product for that particular transaction. For example, if a customer buys a low-priced product, he or she can only redeem a smaller number of points. Thus, adding the price of the product in each transaction controls for the possible correlation of the number of points redeemed with the price of the product. Model 1 of Table 5 implies that the mobile channel, BM channel, and PC channel have different impacts on the number of points redeemed. When using the mobile channel, customers redeem a higher number of points compared to the PC channel. Conversely, when using the BM channel, customers redeem a lower number of points compared to the PC channel.

As a robustness check, we add the individual dummies in Model 2 of Table 5. The vector of control variables ($\mathbf{Z}_2$) for Model 2 includes the month dummies, store dummies, logarithm of the stock of points, individual dummies, and the price of the product. The individual dummies subsume all heterogeneities across customers, so the redemption-spending ratio is dropped to avoid the multicollinearity issue. We find that the estimates for the mobile and BM channels in Model 2 are consistent with the estimates in Model 1. The results in Tables 4a, 4b, and 5 show that customers are less likely to redeem points when purchasing in the mobile channel, but the mobile channel motivates customers to redeem more points than the PC channel once they decide to redeem.

5. Discussion

The lack of point redemptions in some loyalty programs prevents retailers from maintaining customer loyalty and reaping profits in the future. Currently, point redemption literature (e.g., Stourm et al., 2015) has identified point stockpiling factors, such as economic, cognitive, and psychological, from the consumer side. We contribute to the literature by examining the impact of channels on point redemptions. Building on the work of Hwang et al. (2016), who investigate the impact of BM and online channels on point redemption probability, our research extends the knowledge of point redemption in three major ways. First, we identify the impact of the three most popular marketing channels (BM, PC, and mobile) on customers' redemption decisions. Second, we expand the discussion of point redemption decisions from redemption probability to the number of points redeemed. Third, we use the IV method to correct for the endogeneity bias in customers' channel choice. We find that (1) customers are least likely to redeem points when they purchase in the mobile channel; and (2) once they decide to redeem, they redeem more points in the mobile channel than in the PC and BM channels.

We observe a discrepancy in the performance of the two types of online channels (PC and mobile) in the two stages of point redemption. The differential impacts of these channels across the stages reflect a shift in customers' focus in their shopping journey. In the first stage, customers consider whether the value of a product is worth spending points. Compared with the PC channel, the mobile channel is disadvantageous in obtaining detailed product information and thus has a higher perceived risk for customers. Therefore, customers are hesitant to spend points through the mobile channel, which results in a lower redemption probability in the channel. In the second stage, customers have decided to redeem points (i.e., they believe the value of the product matches the spending of points), so perceived risk is no longer a concern in the channel choice. Instead, their focus shifts to the perceived convenience of the channel. In this stage, the mobile channel has an unparalleled advantage over other channels due to its ubiquitous access. The enhanced perceived convenience in the mobile channel reinforces customers' psychological and experiential state of being in a relationship with the firm (Wang et al., 2015). In turn, this elevated relationship state motivates customers to redeem more points in the transactions.

Our findings suggest three broad recommendations to managers. First, the mobile channel is a compelling transaction channel in the loyalty program. In the omni-channel retailing context, practitioners usually consider the mobile devices as the avenue for early stages of product search (De Haan et al., 2018) or in-store product comparison (Rapp, Baker, Bachrach, Ogilvie, & Beitelspacher, 2015). Managers are advised not to be too concerned with the low conversion rate on the mobile channel (De Haan et al., 2018). Our findings imply that managers should consider the mobile channel as an essential transaction channel to maximize the number of points redeemed and thus increase firm profits. Second, PC and mobile channels have different roles in motivating point redemption behavior. PC channel is more effective in motivating the redemption decision, while the mobile channel is more efficient in maximizing the number of points redeemed. Therefore, firms should have both channels available in their online channel portfolio when running a loyalty program. Third, to exploit the strengths of PC and mobile channels, firms should differentiate the interfaces of their website and mobile app. In the PC channel, firms should make point redemption more accessible by providing eye-catching messages or figures that motivate point redemption decisions. For example, they can provide a call-to-action button for redemption, which accurately states what clicking will do, such as "Redeem Now" as opposed to "Learn More." In the mobile channel, firms should highlight the balance of points, which positively correlates with the number of points redeemed. They could also offer additional benefits to customers when they redeem a higher fraction of their point balance. In rare cases where customers never redeem points, it might be advantageous for retailers to have unredeemed points. This assumes that customers continue the relationship without the point redemptions.[3]

6. Limitations

Data and model availability issues suggest that some caution is warranted in our results or speculations. First, we model the two stages of point redemption decisions separately. In particular, the estimates in the second stage are conditional on consumers' positive point redemption decisions in the first stage, not on the entire sample. Therefore, the estimation result from the second stage is to be interpreted only for the customers who redeem. A two-part model would have been ideal to understand the impact of channel on the number of points redeemed for the entire sample.[4] However, the two-part model does not accommodate the endogeneity problem of its regressors, which we believe is a critical issue in our case. Future research might consider providing new econometric models that combine the two stages and deal with the endogeneity issue simultaneously. Second, the lack of data on customers' demographic information or other characteristics prevented us from investigating the relationship of these variables with point redemption decisions. Third, behavioral research exploring the underlying psychological process of customers' shift in focus across the two

[3] We thank an anonymous reviewer for pointing this out.

[4] For details of the two-part model, see Chapter 17.6 in Wooldridge (2010).

stages is necessary to complete the whole picture. Last, this research focuses on customers' point redemption in an omni-channel world in one category. When customers purchase in different categories, the decision to redeem points is likely to be more complicated. Some customers might accumulate points when they purchase in a low-value category and redeem them in a high-value category. Some customers might accumulate points in utilitarian categories and might redeem them in hedonic categories. Some segments of customers might have separate mental accounts for the major categories and might accumulate and redeem points in those categories. Future researchers might want to evaluate the segment-wise point redemption behavior of customers.[5]

Notwithstanding these limitations, our analysis documents the effects of different marketing channels on customers' point redemption behavior. Further research could expand on this issue to examine how marketing channels affect customers in loyalty programs.

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