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E-market Consumer Responses to Platform Promotions: A Case of Korean E-marketplace

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A B S T R A C T

This study empirically investigates e-market consumers' responses to monthly platform discount coupons. Specifically, based on an archival data set obtained from a leading e-marketplace in Korea, our hidden Markov model reveals that there are two different types of consumers on the e-market, those who purchase relatively less but seek temporal seller discounts (Class 1) and those who buy relatively more but are less attracted by such discounts (Class 2). Class 1 consumers purchase products when platform coupons are available but are less likely to buy when platform coupons are all redeemed. On the other hand, Class 2 consumers are willing to purchase products even without platform coupons. Our latent groups demonstrate that the effect of platform promotion is not unidirectional but may depend on the consumer state and class. We discuss the theoretical contributions and managerial implications of our findings.

Keywords: Two-sided Market, Promotion, Hidden Markov Model, Consumer Heterogeneity, Transaction Intention

Ⅰ. Introduction

Promotions on an e-market platform are conducted at the platform and individual seller levels (Khouja and Liu, 2020). Amazon.com, for example, provides contests and sweepstakes to attract consumers, while individual sellers on the platform may cut down their prices at the same time. Such promotions may effectively increase short-term sales, keep existing consumers, and attract new consumers.

Platform promotions are different from individual seller promotions in nature. First, their objectives are different. Platforms are mainly interested in increasing their aggregate revenue facing competition from other platforms, while individual sellers maximize their sales by competing with other sellers within their platform. As such, platform promotion coupons typically apply to multiple sellers on the plat-

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form, whereas individual sellers only promote their products. Second, platform coupons allow consumers to choose the time and the product to redeem. In contrast, individual sellers provide temporal price discounts, which are unexpected to consumers.

In particular, matured e-markets such as Korean e-marketplaces face severe competition, pushing them to conduct frequent promotions to attract consumers. They subsidize consumers' transactions on their platform with discount coupons. Our focal e-marketplace in Korea regularly issued at least two monthly discount coupons to all signed-up consumers during our observation window. As such, consumers could make their purchase plan with platform coupons expected in the following month.

Many studies have revealed empirical evidence regarding sellers' promotion effects on sales. However, we have a limited understanding of the platform promotion effects. While sales promotions attract consumers and may cause a significant short-term sales spike, the effects of repeated regular promotions have been underexamined. Price promotions may lower consumers' reference prices (Bell and Lattin, 2000; Lowe and Barnes, 2012) or make them adjust their consumption according to promotions rather than increase their total consumption (Erdem et al., 2003; Song and Chintagunta, 2003; Sun et al., 2003). Such consumer learning would prevail in the e-marketplaces awash with regular promotion coupons. Upon receiving discount coupons the following month, consumers may split and postpone their purchase to maximize their overall discount.

Based on a transaction data set obtained from a leading Korean e-marketplace offering discount coupons every month to all its registered consumers, this study empirically investigates e-market consumers' heterogeneous responses to such platform promotions in their different classes and states. Consumers' coupon redemption may depend on the intensity of their transactional relationship with the platform, and such a relationship may change over time. To consider these dynamics, we adopt a hidden Markov model (HMM) to incorporate the changes in consumers' state-dependent behaviors. This model allows us to capture consumers' dynamic transaction intentions while simultaneously considering their spending and seller choice as indicators of the latent state of different customer segments.

Our analysis results show that two latent consumer groups exist in our focal e-market. One group purchases relatively less but relies more on temporal seller discounts (Class 1). The other group purchases relatively more but is less attracted by temporal seller discounts (Class 2). Class 1 consumers purchase products when platform coupons are available but are less likely to buy when platform coupons are all redeemed. On the other hand, class 2 consumers are willing to purchase products even without platform coupons.

Our findings provide significant theoretical contributions. Prior studies have often assumed a unidirectional effect of promotion. Our latent groups showing a heterogeneous response to platform promotions demonstrate that the promotion effect is not straightforward but may depend on the consumer state and class. Therefore, systematic errors may exist in a simple regression model that does not consider heterogeneity in consumer responses. For example, when most consumers belong to Class 1 and are low in transaction intention, the overall promotion effect may be positive and significant. However, when they are high in transaction intention, the same promotion may have an insignificant effect. Furthermore, the adverse profit effects of platform promotions may be found for Class 2 consumers because they would purchase products without platform coupons.

Our findings also cast meaningful managerial implications. Practitioners who conduct A/B tests to develop effective promotions should pay attention to their selection of consumer panels. Further, since Class 1 and Class 2 consumers react to platform promotions differently, e-marketplaces may develop an effective promotion campaign up to their proportions in the consumer base.

Ⅱ. Related Literature

Our research context is a two-sided platform involving an intermediary coordinating two (more) distinct groups (Evans, 2003). An e-commerce platform is a typical two-sided market platform that matches buyers and sellers. Considering that three entities (the platform and two sides) construct the two-sided platform, a great deal of effort has been devoted to understanding the relationship between these entities. Literature finds positive cross-network externalities between the two sides in various contexts, including CD titles and CD players (Gandal et al., 2000), the hardware and software industry (Nair et al., 2004), the automatic clearing house (ACH) baking industry (Ackerberg and Gowrisankaran, 2006) as well as the yellow page market (Rysman, 2004). A recent empirical study on e-market platforms shows that sellers' participation is affected by the number of available buyers and their purchasing power. Simultaneously, consumers' involvement also depends on the number of sellers and product variety (Chu and Manchanda, 2016).

Given the positive cross-network effects, platforms may intervene by charging or subsidizing one side to nurture both sides and enhance market efficiency. Theoretical papers show that usage- and membership-based externalities driven by a platform may improve market efficiency (Armstrong, 2006; Rochet and Tirole, 2003; Rochet and Tirole, 2006). Liu (2010) finds empirical evidence that firms' pricing strategy depends on network effects. Kim and Tse (2011) find that user-generated content characteristics affect platform-determined membership fees in the two-sided knowledge-sharing market. Platforms can also affect transactions between the two sides through non-price interventions. For example, platforms may send buyers signals to lower their uncertainty about seller quality (Subramanian and Rao, 2016). The platform may also reshape the competition among sellers by providing trend information (Kocas and Akkan, 2016; Pavlou and Dimoka, 2006).

To attract consumers (thus sellers, as well), South Korean e-marketplaces issue discount coupons competitively. Typical promotion effects on sales are positive. Promotions increase consumers' purchase intention, reduce search and decision costs, and enhance their self-perceptions about being savvy shoppers or generate joyful feelings (e.g., Chandon et al., 2000).

However, many studies have also found counter effects of promotions. Some claim that previous promotion activities mitigate consumers' sensitivity to promotions because such actions may lower their reference price (Bell and Lattin, 2000; Lowe and Barnes, 2012). Others show that purchases without promotions may lead to stronger brand loyalty and a higher chance of repurchasing (Allender and Richards, 2012; Guadagni and Little, 1983). Consumers' relationship with sellers also determines their intention to adopt promotions (Kim and Krishnan, 2019). Further, consumers may strategically allocate their purchases to each promotion schedule to maximize their benefits (Erdem et al., 2003; Song and Chintagunta, 2003; Sun et al., 2003).

In line with the above studies, various efforts have been dedicated to characterizing consumer segments in the e-marketplace showing their different reactions to promotions and shopping behaviors (e.g., Barnes et al., 2007; Kau et al., 2003; Liu et al., 2015; Rohm and Swaminathan, 2004). Promotion effects could be heterogeneous across consumers because they differ in choice preference, loss aversion, mindsets, and discount sensitivity (Bell and Lattin, 2000; Cheema and Patrick, 2008; Cosguner et al., 2017; Musalem et al., 2008). Thus, overall promotion effects may depend on the proportion of each segment reacting to such promotions differently. Most notably, Lichtenstein et al. (1997) reveal that there are 'deal prone' and 'deal insensitive' segments in an offline setting, where various promotion effects are more effective for the 'deal prone segment.' Similarly, DelVecchio (2005) sets two distinct groups of consumer segments, low and high in deal proneness, and shows when deal-prone consumers are sensitive to promotions.

We adopt a behaviourally grounded model to measure promotion effects with the transition probability between different transaction intention states. Contrary to the studies discovering only a unidirectional impact of promotions (by segments), regardless of consumer states, our method approximates the intention-induced behavior process using latent states and classes, which affords more flexibility in describing promotion effects than typical regression models.

Ⅲ. Empirical Approach

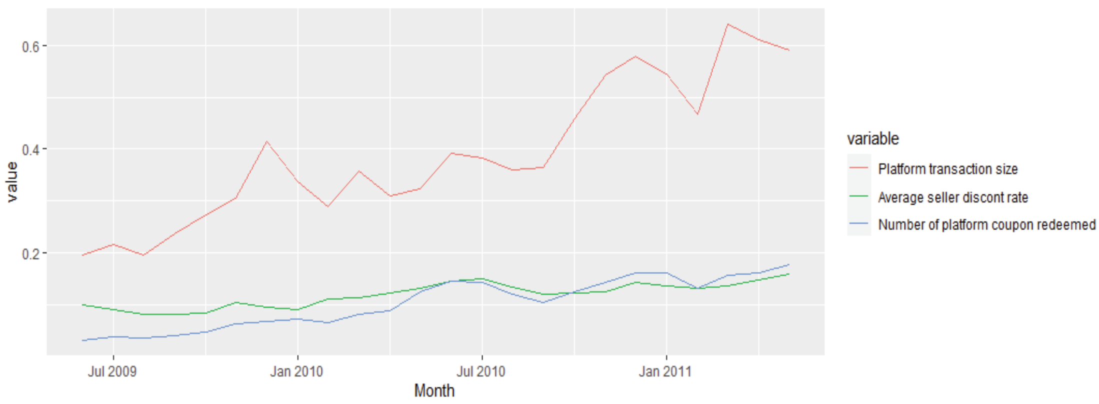
3.1. Data

We analyze a large transaction dataset from a leading e-commerce platform in Korea. Our dataset contains 2,451,943 transactions conducted by 37,470 sellers and 58,349 buyers from June 2009 to May 2011. During our observation period, 377,310 unique platform coupons were redeemed.

There were two different types of platform coupons: amount coupons (which deduct a monetary value from the order amount, e.g., a \$2 discount) and rate coupons (which deduct a fixed percentage value from the order amount but are limited to a fixed amount, e.g., a 5% discount, but up to \$2). Our dataset contains transactions discounted with 934,375 rate coupons and 793,997 amount coupons.[1)] The most popular coupon was redeemed 10,193 times, whereas the least popular ones were redeemed only once. Coupons were displayed in a salient position and could be easily applied with a few clicks before payment. The platform coupons were issued on the first day of each month and were valid only for that month. Consumers could use platform coupons for all product purchases except gift certificates. Platform coupon usage was restricted by a particular criterion, e.g., a minimum purchase amount; however, not limited to a specific seller. Meanwhile, individual sellers also provided price discounts. Seller discount rates varied from 0.5% to 99%.

<Figure 1> shows the number of platform discount coupons redeemed, the average seller discount rate per order, and the sales volume overtime on the platform. The red line represents the monthly transaction size on the platform (scaled down by 10 billion KRW). We see overall growth in sales with large fluctuations. The blue line shows the number of platform discount coupons used each month (scaled

1) All rate coupons have a maximum saving amount, while amount coupons have a minimum order amount, which makes the two types of coupons not differ too much in saving capabilities. In our sample, 95% of platform coupons were redeemed to save money by less than 3,650 KRW (around \$3).



<Figure 1> Promotions and Sales on the Platform

down by 1,000,000 units). The green line illustrates the average seller discount rate of the transactions, which moves between 8% and 16%.

<Table 1> shows our dataset's summary statistics of platform and seller promotions. <Table 2> provides correlations between variables used in our equations. The 1,864,383 transactions (out of 2,451,943, around 76%) enjoyed both platform and seller discounts. The 46,606 transactions (about 2%) involved a platform discount coupon only, while the 252,373 transactions (about 10%) were with a seller discount only. Lastly, the remaining 288,581 transactions (about 12%) were conducted without discounts. The average seller discount rate was 12.6%.

Transactions with a platform coupon have an average seller discount rate of approximately 15.2%, while transactions without a platform coupon have only 3.7%. Such a considerable difference in the average seller discount rate indicates that the redemption of platform coupons is positively associated with the choice of deals from sellers offering promotions. We consider this association in our formal model.

We need to set each consumer's initial transaction intention state for our model estimation. Given that consumers' sign-up is highly associated with their purchase in the e-market platform (Bang et al., 2013), we set their initial state as a high transaction intention for their first month of joining the platform. For others, we do not have any clue to assume their initial state. As such, we drop consumers from our sample who signed up for the platform before our observation window. Further, we focus

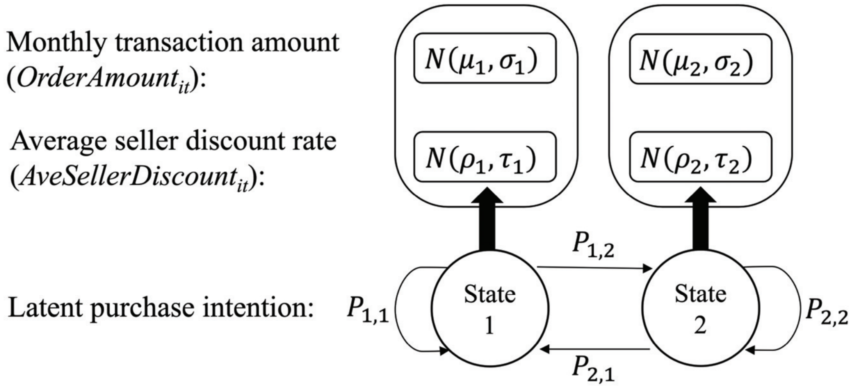
<Table 1> Summary Statistics on Transactions and Promotions

No. of Transactions	With Platform Discount	Without Platform Discount	Total
With Seller Discount	1,864,383	252,373	2,116,756
Without Seller Discount	46,606	288,581	335,187
Total	1,910,989	540,954	2,451,943
Average Seller Discount Rate	15.2%	3.7%	12.6%
Average Transaction Size (USD)	34.29	23.77	31.96

Note: 1 USD = 1,176.47 KRW (as of December 7, 2021)

<Table 2> Variables and Correlations

	Mean	Std	1	2	3	5	6	7	8	9	10
OrderAmount (1)	2.681	9.374	1.000								
AveSellerDiscount (2)	0.111	0.102	-0.024	1.000							
COrderRatio (3)	0.799	0.284	0.005	0.247	1.000						
Age (4)	33.315	9.110	0.070	-0.049	0.029	1.000					
Gender (5)	0.411	0.492	0.043	-0.051	0.013	0.046	1.000				
Mobile (6)	0.484	0.500	-0.014	0.030	-0.043	-0.213	0.019	1.000			
Email (7)	0.816	0.387	-0.002	0.039	0.018	-0.014	0.025	-0.028	1.000		
SMS (8)	0.498	0.500	-0.012	0.022	-0.037	0.043	-0.039	0.003	0.357	1.000	
Membership (9)	2.010	0.635	0.011	0.043	-0.044	-0.067	0.022	-0.015	-0.016	0.017	1.000



<Figure 2> Hidden Markov Model

on regular consumers who purchase at least one item each month and have purchase records on the platform for at least six months.[2] As a result, 1,081 consumers contributed to 117,289 transactions in our sample. They placed 8.8 orders each month on average.

2) The responses of non-regular consumers to platform coupons were insignificant due to their inactiveness on the platform (technically, the number of their purchases was not high enough to reveal their responses). Also, non-regular users might be unaware of the availability of platform coupons, which could be the reason for insignificant results. Thus, we focus on regular consumers for our analysis.

3.2. Empirical Method

We employ a Hidden Markov Model (HMM) to examine how platform promotions affect purchase intention <Figure 2>. For interpretation, we pre-set two consumer states in purchase intention: *high* and *low*.[3] The model captures the change in each consumer's purchase intention over time with two latent states and allows us to look into how platform promotions affect

3) We fix the number of latent consumer states to two based on previous findings (Lichtenstein et al.,1997; Park et al., 2018) while allowing for the free number of consumer classes.

consumers' transition probability between the states.

The HMM has several desirable properties over the traditional regression approach. First, the HMM allows for a flexible direction of state transitions, whereas a conventional regression allows only for a single orientation of transaction movement. The transactional relationship between sellers and consumers is stochastic, in that consumers can increase, decrease, or keep their transaction intention (Aaker et al., 2004; Netzer et al., 2008). The HMM is more suitable to describe the change in transaction intention, allowing all possible direction movement types among latent states with transition probability. Second, the HMM allows multiple observables as the latent transaction intention state indicators. These states determine the distribution of indicators with emission probabilities, which provide more flexibility in describing the transaction intention than a single dependent variable, such as spending amount. For example, the HMM can simultaneously capture a spending amount and a deal choice, given seller discounts. With the assumption of one-period dependence, the HMM simplifies history-dependent transactions and provides an affordable way of estimating parameters.

Our HMM has two latent states: low transaction intention state (State 1) and high transaction intention state (State 2). Purchase intention is closely associated with the actual purchase amount and the perception of the product price (Kytö et al., 2019; Satriawan and Setiawan, 2020). Therefore, we adopt the purchase amount and the average seller discount rate per transaction as the revealed indicators to identify such states. Also, each consumer's purchase amount ($OrderAmount_{it}$) is assumed to follow a normal distribution with the mean $\mu_{1|s,x}$ (which we scale down by 100,000 KRW). Likewise, each consumer's averaged seller discount rate per transaction ($AveSellerDiscount_{it}$) follows a normal distribution with the mean $\mu_{2|s,x}$. $\mu_{1|s,x}$ and $\mu_{2|s,x}$ are represented by state s and class x, as in Equations (1) and (2).[4]

$$\mu_{1|s,x} = \theta_0 + x_i'\theta_x + s_{it}'\theta_s, \tag{1}$$
$$\mu_{2|s,x} = \gamma_0 + x_i'\gamma_x + s_{it}'\gamma_s, \tag{2}$$

where $\mu_{1|s,x}$ is the monthly average purchase amount when the class x buyer is in the state s, $\mu_{2|s,x}$ is the monthly average seller discount rate per transaction when the class x buyer is in the state s, x_i is the vector of k dummy variables indicating the consumer i (=1 to k) class, $\boldsymbol{s}_{it}$ is the vector of two dummy variables indicating the consumer i state in month t, $\theta_x(\theta_s)$ is the coefficients of the monthly purchase amount for classes(states), $\gamma_x(\gamma_s)$ is the coefficients of the monthly seller discount rate per transaction for classes(states) and θ_0 and γ_0 are the intercepts. For identification, $\sum_{s=1}^{2}\theta_s = 0$, $\sum_{s=1}^{2}\gamma_s = 0$, $\sum_{x=1}^{k}\theta_x = 0$, and $\sum_{x=1}^{k}\gamma_x = 0$.

We model the initial state of consumer i (i.e., the probability of customer i in states 1 or 2 at time 0) with a standard logistic model. We assume that the initial state is affected by their first sign-up date, given that the first sign-up tends to be associated with high purchase intention (Bang et al., 2013) and class x, as in Equation (3).

$$log\frac{\mathbf{P}(s_{i0}=1|x)}{1\text{-}\mathbf{P}(s_{i0}=1|x)}=\alpha_0+LoginMonth_i'\boldsymbol{\alpha}_{1x}, \tag{3}$$

where $LoginMonth_i$ is a vector of the month dummies indicating the sign-up month of consumer i, $\boldsymbol{\alpha}_{1x}$ is the coefficients for the first log-in month, and α_0 is the intercept.

4) Consistent with the previous literature, the indicators are modeled with linear combinations of latent states and classes (e.g., Netzer et al., 2008; Xiao and Dong, 2015).

$$log\frac{\mathbf{P}(s_{it}=2|s_{i\,t-1}=1,\, x)}{\mathbf{P}(s_{it}=1|s_{i\,t-1}=1,\, x)}=\beta_{x0}+\beta_{x1}COrderRatio_{it}+\beta_{x2}UsageAge_{it}+\beta'_{x3}LoginMonth_i$$
$$+\beta_{x4}Age_i+\beta_{x5}Gender_i+\beta_{x6}Mobile_i+\beta_{x7}Email_i+\beta_{x8}SMS_i+\beta_{x9}Membership_i+\beta'_{x10}Month_{it}, \quad (4)$$

$$log\frac{\mathbf{P}(s_{it}=1|s_{i\,t-1}=2,\, x)}{\mathbf{P}(s_{it}=2|s_{i\,t-1}=2,\, x)}=\delta_{x0}+\delta_{x1}COrderRatio_{it}+\delta_{x2}UsageAge_{it}+\delta'_{x3}LoginMonth_i$$
$$+\delta_{x4}Age_i+\delta_{x5}Gender_i+\delta_{x6}Mobile_i+\delta_{x7}Email_i+\delta_{x8}SMS_i+\delta_{x9}Membership_i+\delta'_{x10}Month_{it}, \quad (5)$$

$$log\frac{\mathbf{P}(x_i=k)}{1-\mathbf{P}(x_i=k)}=\eta_{k0}+\eta'_{k1}LoginMonth_i+\eta_{k2}Age_i+\eta_{k3}Gender_i+\eta_{k4}Mobile_i$$
$$+\eta_{k5}Email_i+\eta_{k6}SMS_i+\eta_{k7}Membership_i, \quad (6)$$

$$f=\prod_{i=1}^{I}\sum_{x=1}^{K}\sum_{s_0=1}^{2}\sum_{s_1=1}^{2}\cdots\sum_{s_T=1}^{2}\mathbf{P}(x_i)\mathbf{P}(s_{i0}|x_i)\times$$
$$\prod_{t=1}^{T}\mathbf{P}(OrderAmount_{it},AveSellerDiscount_{it}|s_{it},x_i)\mathbf{P}(s_{it}|s_{it\text{-}1},x_i) \quad (7)$$

We also employ a transition logit model to model state transition probabilities. We model consumers' purchase intention to be affected by promotions and consumers' characteristics, such as their membership period, age, gender, or platform settings (Zhang et al., 2018). Our equations (4) and (5) describe the transition probability from State 1 to State 2 and from State 2 to State 1.

where $COrderRatio_{it}$ is the ratio of orders using the platform coupons for consumer i in month t, adapted from the Kim and Krishnan's construction (Chandon et al., 2000), $UsageAge_{it}$ is the elapsed months from the first log-in on the platform for consumer i in month t, $LoginMonth_i$ is a vector of the month dummies indicating the sign-up month of consumer i, Age_i is an integer variable measuring the age of consumer i, $Gender_i$ is a dummy variable indicating the gender of consumer i (1= male, 0=female), $Mobile_i$ is a dummy variable indicating whether the consumer i adopts the mobile channel, $Email_i$ is a dummy variable indicating whether the consumer i receives a notification email from the platform, SMS_i is a dummy variable indicating whether the consumer i receives a notification SMS from the platform, $Membership_i$ is an integer variable from 1 to 7 indicating customer membership status on the platform (1 is the highest, 7 is the lowest), and $Month_{it}$ is a vector of the month dummies for seller i in month t to account for month fixed effects.

We also construct the class prediction model, incorporating consumer heterogeneity. The probability of a customer belonging to class x is determined by a standard logistic model, as in Equation (6). Several time-invariant characteristics are employed to predict a consumer class x_i.

All parameters in Equations (1) to (6) are estimated by maximizing the likelihood function, as in Equation (7). The likelihood function has four sets of probabilities. P(x_i) is the class probability, depending on the time-constant consumer characteristics derived from Equation (5). P($s_{i0}|x$) indicates that the initial state could be any state with a certain

<Table 3> Model Comparison

HMM Statistics	LL	BIC	N_{par}
2-state-1-class	-16,975.88	34,838.95	127
2-state-2-class	-15,550.21	33,007.49	273
2-state-3-class	-15,048.95	33,024.88	419

probability, determined by Equation (3). $f(OrderAmount_{it}, AveSellerDiscount_{it} | s_{it}, x)$ is the probability of indicators, derived from the state-dependent distribution. The joint probability is merely the product of a two-occurrence probability given the state. $P(s_{it}|s_{it-1},x)$ is the transition probability related to the last state, the consumer class, and a series of independent variables, as in Equations (4) and (5).

Ⅳ. Analysis Results

We ran the same two-state models with increasing classes to decide the number of consumer classes.[5] The lowest BIC (33,007.49) was obtained from the two-class model <Table 3>. Thus, we constructed the two-class two-state HMM for our analysis.

<Table 4> presents the estimation results containing the estimated emission probabilities and transition probabilities. 76% (821 consumers) belong to Class 1, and 24% belong to Class 2 (260 consumers). The emission probability reflects the mean value of the distribution for the indicators in different states. The mean of the $OrderAmount_{it}$ distribution is 1.344 (-4.233 + 6.361 - 0.784) in State 1 and 9.810 (4.233 + 6.361 - 0.784) in State 2, respectively, for Class 1. More specifically, Class 1 consumers spend ₩134,400 (around $110) per month in a low transaction intention state, while they spend ₩981,000 (around $810) per month in a high transaction intention state on average. Similarly, the mean of the $OrderAmount_{it}$ distribution is 2.912 (-4.233 + 6.361 + 0.784) in State 1 and 11.378 (4.233 + 6.361 + 0.784) in State 2, respectively, for Class 2. The results show that State 1 (2) is the low (high) transaction intention state.

The estimation of Equation (2) shows that the mean of $AveSellerDiscount_{it}$ is 0.101 (-0.067 + 0.159 + 0.009) in State 1 and 0.235 (0.067 + 0.159 + 0.009) in State 2 for Class 1. Consumers with a low transaction intention enjoyed a 10.1% discount (on average) per order, while a 23.5% discount for consumers with a high transaction intention. Likewise, the mean of $AveSellerDiscount_{it}$ is 0.083 (-0.067 + 0.159 - 0.009) in State 1 and 0.217 (0.067 + 0.159 - 0.009) in State 2 for Class 2. The positive association between the transaction intention and the seller discount for both classes has two plausible explanations. One is that the seller's price discount encourages consumers to spend more. Another is that consumers are more likely to search for sellers offering discounts when spending more.

We also observe a difference in spending and the seller discount between consumer classes. On average, Class 1 consumers spend ₩156,800 (equivalent to $133.28) less than Class 2 buyers. However, Class 1 consumers enjoyed an additional 1.8% (0.0009+ 0.0009) seller discount over Class 2 consumers.

The estimation results of the transition probability

5) The model is estimated by the maximum likelihood method using the software LatentGold 6.0.

<Table 4> Analysis Results of the Two-class Two-state Hidden Markov Model

Emission Probability Estimation			
		$OrderAmount_{it}$	*$AveSellerDiscount_{it}$*
State 1		-4.233***	-0.067***
		(0.366)	(0.003)
State 2		4.233***	0.067***
		(0.366)	(0.003)
Class 1		-0.784***	0.009***
		(0.019)	(0.001)
Class 2		0.784***	-0.009***
		(0.019)	(0.001)
Intercept		6.361***	0.159***
		(0.367)	(0.003)
Transition Probability Estimation			
	State Transition	1→2	2→1
$COrderRatio_{it}$	Class 1	1.941***	-2.351***
		(0.288)	(0.699)
	Class 2	0.537	3.167***
		(0.374)	(0.864)
Wald chi-square test		$\chi^2(2) = 32.97^{***}$	

Note: $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

in Equations (4) and (5) show how the covariates affect the transition probability between states. The estimated coefficient of *$COrderRatio_{it}$* for the state transition probability from States 1 to 2 of Class 1 (1.941) is positive and significant, while Class 2 (0.537) is insignificant. The positive coefficient means that a higher proportion of orders with platform discounts is positively associated with the transition from low to high intention; specifically, a 1% increase in the proportion is associated with approximately 1.02 ($e^{1.941\times0.01}$) times higher transition logit. However, *$COrderRatio_{it}$* was not associated with Class 2 consumers' transition probability from low to high intention.

For the transition estimate from States 2 to 1, the coefficient of *$COrderRatio_{it}$* is negative and significant in Class 1 (-2.351) while positive and significant in Class 2 (3.167). The negative coefficient means that a higher proportion of orders with platform discounts is negatively associated with the probability of leaving the high intention state. The result shows that platform coupons keep the consumers' high transaction intention for Class 1 consumers when they are in a high intention state. However, for Class 2 consumers, a higher proportion is negatively associated with the probability of staying in the high transaction intention state. As *$COrderRatio_{it}$* refers to the ratio of orders with platform coupon redemption, additional transactions after consuming all available platform coupons lead to a lower *$COrderRatio_{it}$*. In sum, Class 1 consumers (who are more sensitive to seller discounts but spend less than

<Table 5> Transition Probability Estimation with an Alternate Independent Variable

	State Transition	1→2	2→1
AllRedeem$_{it}$	Class 1	1.306^{***}	-0.135^{***}
		(0.203)	(0.485)
	Class 2	0.781^{*}	-0.771
		(0.375)	(0.516)

Class 2 consumers) purchase products when platform coupons are available but are less likely to buy in the case when platform coupons are all redeemed. Class 2 consumers (less sensitive to seller discounts but spending more than Class 1 consumers) are willing to purchase products without platform coupons.

We replicate our analysis with an alternate independent variable, *AllRedeem*$_{it}$, which is a dummy variable indicating whether a consumer i has redeemed all platform coupons in month t (1 = all redeemed, 0 = otherwise) (<Table 5>). Regarding the transition estimate from States 1 to 2, the coefficient of *AllRedeem*$_{it}$ is positive and significant for Classes 1 and 2, suggesting that all redemption is associated with the transition from low to high intention for both classes. However, the coefficient size (in absolute terms) is substantially smaller for Class 2. Regarding the transition estimate from States 2 to 1, the coefficient of *AllRedeem*$_{it}$ is negative and significant for Class 1 but insignificant for Class 2. The results indicate that when Class 1 consumers redeem all coupons, they are more likely in State 2 (high intention state), but not for Class 2 consumers. Class 2 users are in State 2 even without discount coupons.

We further investigate whether Class 1 and Class 2 consumers differ in their coupon redemption across product types. Specifically, we compare coupon redemption of each class for search goods and experience goods. Experience goods have attributes that are difficult to evaluate before purchase (e.g., taste, flavor, touch feeling), whereas search goods have standardized attributes and thus are more comparable with their competing alternatives (Hong and Pavlou, 2014; Weathers et al., 2007).

<Table 6> contains the t-test results concerning the purchase behaviors (*COrderRatio*, *OrderAmount*, *AveSellerDiscount*). Class 1 and Class 2 consumers show a similar pattern in comparing order amount (*OrderAmount*) and seller discount (*AveSellerDiscount*) between the product types, where both have a higher monthly spending and a larger seller discount on experience goods than search goods. However, Class 1 consumers have a lower coupon consumption in search goods than experience goods (0.815 vs. 0.825, $p < 0.1$), different from Class 2 consumers (0.832 vs. 0.824, $p > 0.1$).

Why are platform coupon redemptions more prominent in experience goods than search goods for Class 1 consumers? Typically, consumers conduct easier trade-off decisions between product quality and price for search goods than experience goods (Park et al., 2020). Given that Class 1 consumers are more economy-minded than Class 2 consumers (note that Class 1 consumers are more sensitive to seller discounts but spend less), Class 1 consumers might have a stronger economic desire to justify their purchase. As such, Class 1 consumers might prefer to experience goods in their coupon redemption, which are harder to find Pareto efficient alternatives (Green et al., 1988; Krieger and Green, 1991). Although we provide our wild conjecture, further behavioral studies are re-

<Table 6> Comparison of Purchase Behehaviors (Search vs. Experience goods)

		Search	Experience	p - value
Average Number of Coupons Used Per Order				
Class 1 Users	Mean	0.815	0.825	0.050*
	Std. Err.	0.004	0.003	
Class 2 Users	Mean	0.832	0.824	0.194
	Std. Err.	0.005	0.004	
Average Monthly Spending (KRW)				
Class 1 Users	Mean	109,162	168,547	< 0.01***
	Std. Err.	4,222.3	11,230	
Class 2 Users	Mean	174,261	232,914	< 0.01***
	Std. Err.	9,775.1	5,462.4	
Average Seller Discount Per Order				
Class 1 Users	Mean	14.3%	16.3%	< 0.01***
	Std. Err.	0.002	0.002	
Class 2 Users	Mean	13.0%	14.8%	< 0.01***
	Std. Err.	0.003	0.002	

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$; Seach goods include PC parts and accessories, navigation and black box, laptop and desktop, monitor, printer, storage devices, stationery and office products, detergent, paper products, office appliances, car accessories, toys, kitchen products, tablets, and phones. Experience goods include health, diet, golf, fishing, fashion, fruits, perfume, beauty, hair, body, skincare, and maternity products.

quired to fully understand how consumers utilize limited platform coupons for their purchases.

Ⅴ. Conclusion

This paper empirically reveals consumers' heterogeneity in responding to regular platform coupons. Specifically, we find two latent groups of consumers responding to platform promotions differently. Our findings illustrate that the effect of platform promotion largely depends on the consumer segment. The availability of platform promotion coupons is positively associated with Class 1 consumers' transaction intention when their intention is low and may maintain their high transaction intention when their intention is high. That means Class 1 consumers consider the availability of platform coupons for their purchase decision. However, such platform promotion coupons may not encourage Class 2 consumers to buy when they are in a low transaction intention state. Furthermore, when Class 2 consumers are in a high transaction intention state, they are not restricted to the availability of platform coupons in their purchase decisions.

This study provides critical theoretical implications. This study is one of the first attempts to empirically examine e-market consumers' responses to the regularly issued platform promotions. Despite platform promotions being a common practice among e-marketplaces, little research has examined how they are related to consumer sales. Prior empirical studies concerning promotion effects focus on unexpected seller promotions to consumers. Consumers expect platform coupons the following month, so they may adjust their purchases to maximize their discounts. Class 1 consumers in our HMM analysis show such cherry-picking behaviors.

While prior studies have often assumed a unidirectional effect of promotion, our finding of latent groups showing a heterogeneous response to platform promotion coupons demonstrates that the promotion effect is not straightforward but may depend on the consumer state and class. Therefore, systematic errors may exist in a simple regression model that does not consider such heterogeneity in consumer responses. For example, when most consumers belong to Class 1 and are low in transaction intention, the overall promotion effect may be positive and significant. When they are high in transaction intention, however, the same promotion may result in an insignificant increase in sales. Similarly, when most consumers belong to Class 2, we may find a significantly different overall effect of the same promotion. As such, identifying promotion effects should be carried out while considering consumer heterogeneity.

Methodologically, our hidden Markov model provides a more appropriate and flexible way of measuring customers' transaction intentions than prior linear models. Further, the state transition matrix allows for flexible direction transitions among latent states, which better reflects changes in transaction intention. Previous studies relying on their linear model or surveys are limited in accounting for complex transactional states of different consumer classes. Our study closely looks into online consumers' purchase intention changes by adopting a behavior-grounded model.

This study also provides valuable managerial implications for e-market platforms. E-market platforms should be aware of consumers' heterogeneous responses to platform promotions. Further, it is imperative to identify who belongs to Class 1 or Class 2. Class 1 consumers are cherry-pickers who are more likely to purchase products when their platform coupons are available. Class 2 consumers purchase more than Class 1 but are less sensitive to such platform coupons. Classifying consumers concerning their heterogeneous responses to platform promotions would generate valuable business insight for e-market platforms to conduct more effective promotion campaigns. Also, based on the consumer characteristics of each class, e-market platforms may put more effort into cultivating a particular consumer class than others for their profits. For example, e-market platforms may find different effects of their promotions on their selection of consumer panels.

We conclude by articulating the limitations of this study and suggesting future research directions. First, as the archival data analysis, our results do not provide a causal effect of platform promotions but show a mere snapshot of consumer responses to them. One may tease out their causal impact on sales with corresponding consumer responses by conducting a field experiment. Second, we suggest replicating our analysis with a newer data set containing more mobile transactions. Our data set also includes mobile transactions, but their proportion is small (around 6%) as the data window covers the introductory phase of mobile shopping channels. Although our main message of heterogeneous consumer responses to platform promotions is not restricted to the shopping channel, the composition of Class 1 and Class 2 may depend on where their transactions are conducted (e.g., PC vs. Mobile channels). With greater access to e-marketplaces, consumers may make frequent purchases, leading to a heightened proportion of Class 2 (Bang et al., 2013). However, competition dynamics among e-market platforms with multiple channels also affect their promotion strategies, setting an empirical question. Third, although we started with a large random sample, our primary data set contains only 1,081 consumers and their 117,289 transactions. We focused on consumers who made the first sign on the platform during our observation window to identify their initial state. We further chose consumers who purchased items for at least six months. A larger sample needs to be analyzed to ensure the generalizability of our findings.

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