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A quantile regression approach to gaining insights for reacquition of defected customers

Changsok Yoo[a], Kyoung Cheon Cha[b], Sang-Hoon Kim[c,*]

[a] Kyung Hee University, Department of Culture & Tourism Contents, Republic of Korea
[b] Dong-A University, Department of Business Administration, Republic of Korea
[c] Seoul National University, Graduate School of Business, Republic of Korea

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ABSTRACT

As customer loyalty keeps declining, the importance of customer relationship management is paramount especially for online-service marketers. Reacquisition of defected customers is better than acquiring new customers in terms of marketing efficiency as well as effectiveness. However, the issue of winning back defected customers has been largely neglected among scholars. In this paper, we present empirical analyses based on real transactional data from 4000 users of one of the most successful online games in Korea to investigate the relationship between demographic, RFM, behavioral, and social network variables and the users' response to reacquisition campaigns. Since the dependent variable is skewed, a quantile regression method was utilized for model estimation. To figure out what kind of characteristics would influence the likelihood of "staying alive" after the campaigns, the results from Period 1(win-back) were compared against those from Period 2(retention). The findings shed many useful insights in targeting and designing win-back campaigns.

1. Introduction

As customer loyalty becomes a key to the profitability of game businesses, companies in game industry have shifted its marketing focus from acquisition to retention of customers. Many scholars who conducted research on online games found that the factors such as flow, customization, social interactions, achievement gratification, social norms, and so on affect the gamers' loyalty (Bae, Koo, & Mattila, 2016; Choi & Kim, 2004; Hsu & Lu, 2004; Kim & Kim, 2013; Kim, Kang, and Taylor, 2018; Teng, 2013; Wu, Wang, & Tsai, 2010; Yee, 2006). Unlike other services, most of online game activities occur in the digital environment, thereby allowing firms to record and analyze the users' past behavior in the hope of keeping them loyal.

Despite the efforts, though, customer loyalty is a depreciating asset. It is impossible to keep all customers. Big or small, some will defect anyway. Leach and Liu (2014) ask marketers to accept the fact that some customers will inevitably switch to alternative suppliers. Various technological updates provide customers with the tools and information that push them to seek value from products in terms of price per performance. Declining trend in customer loyalty is especially visible in the case of online services, thereby having marketers of online games face bigger troubles in keeping their users (Chae, Ko, & Han, 2015; Thaichon & Quach, 2015; Yu, Cho, & Johnson, 2017). In order to maintain or broaden their customer base, marketers should turn to win-back programs for lapsed customers as well as retention programs for current customers.

From a traditional customer management perspective, marketing should focus both on the acquisition and the retention of customers. When the costs of acquiring new customers gets bigger, customer retention programs become more important, thereby making Customer Relationship Management (CRM) very popular among both practitioners and academicians (e.g., Kim & Ko, 2010; Kim, Park, Kim, Aiello, & Donvito, 2012; Rust, Zahori, & Keiningham, 1996; Stauss & Friege, 1999; Zhang, Ko, & Kim, 2010). On the other hand, the issue of winning back defected customers has been largely neglected so far (Dodson, 2000; Tokman, Davis, & Lemon, 2007).

Though not many scholars in the area of CRM have directly investigated the effectiveness of customer reacquisition offers, they have empirically examined the effectiveness of various efforts such as price discounts, rewards, service quality improvements, or apologies to encourage customer reactivation (e.g., Thomas, Blattberg, & Fox, 2004; Tokman et al., 2007; Huang & Xiong, 2010). In addition, there are studies that discuss which customers should be targeted for reacquisition. For instance, target customers for regain should be different from those for retention (Stauss & Friege, 1999). Reasons for defection which explain the extent to which defected customers were satisfied with the

* Corresponding author.
E-mail addresses: csyoo@khu.ac.kr (C. Yoo), kccha@dau.ac.kr (K.C. Cha), profkim@snu.ac.kr (S.-H. Kim).

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service are key variables that presumably correlate with the possibility of return, but they do not provide practical insight to marketing managers looking for solutions to customer win-back. Stauss and Friege (1999) even suggest measuring and using "second lifetime value (SLTV)" for classifying and targeting lost customers. This would provide a means to predict the full future value of the relationship to the customer. However, this method also has limitations since it focuses only on a handful of variables.

The present study is differentiated from the previous ones in terms of the following. First, the targeting is based on the past *behavior* of defected customers, not based on a survey on satisfaction, reasons of defection, etc. In fact, the present study is one of the first attempts to investigate into real transactional data, including customers' past usage behavior, in the context of customer reacquisition.

Second, the authors are interested in not just regaining the lost customers but also keeping them. One of the objectives of the current paper is to figure out who would "stay alive" (i.e. keep using the service) after responding to the reacquisition campaign. In other words, the current study tries to avoid the mistakes the previous researchers made by confusing real reacquisition with temporary responses to reacquisition promotions. Technically, two separate analyses are conducted; one for the four-week period of reacquisition promotion, the other for another four-week period after the promotion. While some studies have examined the effects of customer reactivation campaign, none so far have examined which characteristics explain the behavior of customers who keep using the service after the win-back campaign terminates.

The third differentiation point of the current paper is on methodology. A so-called "quantile regression (QR)" method was used in estimating the coefficients of the model. A big advantage of quantile regression is that its estimates are very robust when the dependent variable is skewed. Since there are very few customers who actively respond to a service provider's reacquisition campaign, the distribution of the response measurement is highly skewed, and therefore, OLS estimates are unreliable. QR estimation also allows the researcher to make interpretations across customers showing diverse level of response, top 10 percent quantile in particular.

Last but not least, the present model includes a broad range of variables that affect the likelihood of customer reactivation. There are four kinds of factors in the model. They are demographic variables, RFM variables, behavioral variables, and social variables. Social variables have never been considered in the customer regain literature, and the estimation results of the current paper proved for the first time that some of them (e.g. in-degree numbers) play significant roles in customer reacquisition.

2. Literature

2.1. Customer management in online game industry

Customer loyalty refers to the intention to purchase and use a specific product or service repeatedly from the same provider (Zeithaml, Berry, & Parasuraman, 1996). Loyal customers tend to have unique characteristics compared to general customers (Winters & Ha, 2012). Reichheld and Schefter (2000) confirmed that loyal customers purchase more and refer more than non-loyal customers do. They further discovered that the value of customer loyalty is greater on the internet since referral effect of loyal customers for the online businesses is greater than that for the offline businesses.

Satisfaction of loyal customers heavily depends upon the frequency of their visit (Bolton & Lemon, 1999). On the other side, frequent usages make loyal customers amplify their expectation on service, and more so as their service frequency increases, which then may cause satisfaction level to decrease (Jonson & Payne, 1985). Interestingly, the negative frequency effect on customer loyalty on the online business is lower than that on the offline business (Shankar, Smith, & Rangaswamy, 2003).

Scholars have seen various studies on customer loyalty that were conducted in the context of game industry. Choi and Kim (2004) suggested a theoretical framework for the relationship between customer loyalty and flow, a unique element in the game experience. They found that personal and social interactions induced by clear goals, and the operation and feedback in the game reinforce the flow and customer loyalty. Hsu and Lu (2004) also revealed that flow and social influence are key factors in the game play using technology acceptance model.

Yee (2006) showed that achievement, social activity, and immersion are three main motivations of game play. Using Yee's motivation theory, Wu et al. (2010) empirically proved that satisfaction on the motivations eventually increases the intention of continuous usage and thus loyalty. Teng (2013) also proved that flow and challenges in the game play work positively on customer loyalty.

Though previous studies provided substantial knowledge about customer loyalty in the domain of game industry, those are limited only in the acquisition and retention. To the best of our knowledge, no study has been conducted so far on win-back programs in the game industry. Despite the deficiency of win-back studies, win-back marketing practices have become extremely important and common in the game industry. The fact that win-back programs have such a meaning is partly due to the nature of entertainment products. That is, games are a hedonic and experience good that the quality of it is uncertain before being experienced, and the values depend upon intangible, symbolic, social and aesthetic attributes of them (Elberse & Eliashberg, 2003; Kahnx, Ratner, & Kahneman, 1997; Lee & Johnson, 2010; Sawhney & Eliashberg, 1996). Furthermore, the typical sales pattern of the games follows that of a fad, which rapidly reaches its peak and then slowly decreases (Clement, Fabel, & Schmidt-Stolting, 2006; Kim, Kim, & Lee, 2016). In order to overcome the problems of the short life cycle and sudden defection of users, game companies are trying their best not only to keep the current users but also to reacquire the users who quit the games for various reasons. Besides, winning back the lost users seem to be the most cost-effective venue of retention management relative to other mechanisms.

2.2. Regain management

Stauss and Friege (1999) attempted one of the first studies that examined the reacquisition of lost customers, and defined regain management as rebuilding the relationship with customers who explicitly quit the business relationship. Moreover, they explained that lost customers show totally different behaviors from new or current customers and thus need to be approached with different analysis methods. They thus proposed to measure SLTV (Second Life Time Value) by extending the concept of LTV (Life Time Value) method used in traditional customer analysis. Griffin and Lowenstein (2001) also rationalized the needs for regain management from a commercial perspective and explained various indices, cases, and detailed strategies to back up their analysis. Thomas et al. (2004) also defined customer reacquisition as "the process of firms' revitalizing relationships with customers who defected“. They were the first to try to answer the question of which customer win-back strategies need to be implemented in terms of price. Their work highlighted the importance of dynamic pricing and linked the customer's prior history with the firm to a profitable win-back strategy.

Thereafter, regain management began drawing attention in the field and numerous studies followed. These can be categorized into two groups. The first group of studies focuses on "how" to regain lost customers, and the other group of studies focuses on "which customers" are more effective. Many studies that explored which factors lead lost customers to come back found factors such as price, service, social capital, perceived importance, defection reason, communication, customer satisfaction, and prior experience as critical to customers' decision to return. Thomas et al. (2004) found that while the price factor turned out to be very important in customer's win-back decision, regained customers who were offered lower discount, in fact, stayed with the services more than those who were offered higher discount. Moreover, they revealed that customers who stayed with service longer or had shorter leave tended to show both higher regain rates and higher retention rates.

Tokman et al. (2007) verified that 'perceived importance' along with price and service benefits are significant determinants in the win-back offer. Perceived importance can be referred to as the service's personal meaning and relevance to the customer. The customers who regarded win-back offer as being important to them had the tendency to evaluate the offer closely and preferred a customized win-back offer. The study also evaluated the role of social capital between the firm and its customers for the win-back offer, but failed to find any direct relationship. However, social capital along with perceived importance had moderating effects in the customers' decision making process. Customers with high social capital tended to become less sensitive to win-back offers with higher service quality but not with price. Moreover, when customers switched to other services, social capital regarding the previous service did not have an impact on the win-back offer, while social capital regarding the new service proved a barrier for the success of the win-back offer.

Homburg, Hoyer, and Stock (2007) discovered that the satisfaction level on communication interaction and the process of the win-back offer had an impact on offer acceptability, and so did customer characteristics such as age, participation rate, and past satisfaction level. On the other hand, the reasons for defection turned out to have no statistically significant influence. This conflicts with the results of other studies such as Leach and Liu (2014)'s in which the success rates of win-back offers increased when customers were provided with improved offers in relation to their reasons of defection. Kumar, Bhagwat, and Zhang (2015) also provided insights on whether firms should chase lost customers by investigating the impact of the reasons for defection on reacquisition and second-lifetime duration and firm's profitability. Pick, Thomas, and Tillmanns (2016) proposed a new variable, i.e., general willingness to return (GWR), and argued that GWR has a positive relationship with the actual return decision. They also found that economic, social, and emotional value perceptions influence GWR. In a review paper, Kumar and Reinartz (2016) summarized findings from the studies on customer churn and win-back.

In fact, there continues a controversy regarding the influence of defection reasons on the success of win-back offers. Theoretically, reasons of defection are not only very important in customers accepting the win-back offer (Stauss & Friege, 1999), but are also critical to customers defining a brand of the company (Bogomolova & Romaniuk, 2010) and to the sales people evaluating reacquisition possibilities of customers (Leach & Liu, 2014). However, many empirical studies proved that the reasons of defection did not have an impact on win-back offers (Tokman et al., 2007; Homburg et al., 2007) although there are some limitations in interpreting their results as these studies are based on experiments or surveys rather than the customers' actual behavior.

It is surely impossible to regain all defected customers, just as it is impossible to maintain a retention rate at 100 percent. Therefore, researchers have made efforts to discover an effective customer segmentation scheme. Stauss and Friege (1999) for example argued that customers' SLTV (Second life time value) and the reasons of defection should play key roles in customer segmentation. Based on the reasons of defection, they classified customers into five groups: (1) the unintentionally pushed away (customers who are mistreated or neglected); (2) the pulled away (customers that left for better value); (3) the bought away (customers that are vulnerable to price competition); (4) the intentionally pushed away (problematic or unprofitable customers); and, (5) the moved away (customers that no longer see value in the supplier's offering). Undoubtedly, the bought away, the intentionally pushed away, and the moved away customers are not a wise target segment for the firm in regain management.

Akerlund (2005) classified four types of lost customers using a relationship-fading process. These are; (1) the crash landing — where a customer leaves abruptly, typically caused by significant negative experiences and emotions; (2) the altitude drop — where the customer reduces their level of sales, often caused by external economic challenges; (3) the fizzle out — where sales volumes continue to shift to competitors; and, (4) the try out process — where the customer leaves relatively early in the relationship because the customer was price sensitive or uncertain about the value proposition from the start. Although this classification is developed for early warning in customer retention strategy, it gives some clues for reasons of defection from customer behavior patterns (Leach & Liu, 2014).

Although customer segmentation based on their values is considered the most desirable method for the segmentation, it has not yet been discussed in detail from the regain management perspective. As mentioned above, Stauss and Friege (1999) proposed the SLTV method and explained the factors that contribute to SLTV in terms of ROI. However, they only provided theoretical explanations for framing customers' value in a financial perspective. Leach and Liu (2014) picked out factors that can evaluate B2B customers' values by interviewing 50 sales people, and they found that factors such as account size, account profitability, market influence of account, and cross-selling opportunities are significant in measuring customer value. Furthermore, Blömeke, Clement, and Bijmolt (2010) studied whether or not low-tier customers, among others, are appropriate targets for reacquisition. They asked 12,000 low-tier customers whether they would continue to stay with the service or not through a 10 Euro voucher attached to a mail, and they also tracked customers' behavior for 30 weeks and re-surveyed at the end. Their results showed that only a small fraction of low-tier customers reactivated with the win-back offer. However, as Hogan, Lemon, and Libai (2003) emphasize, defection and disadoption must be separately considered when customers are segmented in terms of customer values. The rationale behind the argument is that while defection happens when customer switches to the competing services, disadoption occurs when customer leaves the industry, and if defection and disadoption are treated equally, researchers may over-estimate the values of lost customers especially in today's world where disruptive technologies frequently emerge.

There is no debate among scholars that mining and evaluation of a firm's database for defected customers is a key element of effective customer segmentation in the regain management literature. Leach and Liu (2014) said, “When customers defect, they may leave behind a wealth of transaction specific information, including transaction history, preference motives, and evidence of what prompted their defection.” Notwithstanding this opportunity, extant literature in regain management only uses surveys and experiments to find the key factors of win-back offer adoption, and to segment the defected customers. As far as the authors know, there has been no study that segmented customers or analyzed factors that influence the win-back offer adoption based on a real company database, i.e., the customers' real behavior.

2.3. Data

For the analyses of gamers' real behavior, a dataset on one of the most successful online games in Korea, *Sudden Attack*, was utilized. *Sudden Attack*, a First Person Shooting (FPS) game, was developed and launched in 2005 by Nexon GT, a subsidiary of Nexon Group. The main mission of the participants of this game is to annihilate the enemies, as snipers or defense officers, in a given time of 3–5 min (see Fig. 1(b)).

Usually the players join the battle in a team of eight and compete with the enemy team also consisting of eight users. Therefore, cooperation and competition with other users is a key to winning the game. In 2012, seven years after the service was launched, numerous customers defected due to major changes in the service platform. To recoup the loss, the company conducted a 4-week marketing campaign,

(a) Main Marketing Campaign image of Sudden attack in 2012

(b) Game screenshot of Sudden Attack

Fig. 1. Key images of sudden attack.

starting from July 12th, mainly targeting the inactive accounts. It placed advertisements endorsed by celebrities in various media sources, and it also provided free items valued at $100, in order to get the inactive users back (see Fig. 1(a)). The campaign was successful. The number of users that logged in to the game in one month increased 44 percent compared to that in the previous month, and about one million users returned by the campaign.

This current study focused on the customers who were active in the 12-week period of January 26th to April 18th (“Period 0”) and became inactive, i.e., no log-ins, during the next 12-week period of April 19th to July 11th (“Lapse”). Some of them returned when the win-back campaign was conducted beginning July 12th until August 8th (“Period 1”), and others didn’t. And further, some of those who returned stayed active (i.e., logged in) during the 4-week period after the campaign was over (“Period 2”), and others left again. Table 1 summarizes the four different cases. In each of the four cases, a random sample of 1000 users was drawn for the analysis.

Recency, frequency, and monetary value (RFM) are the three key variables that are considered important in the practice of customer relationship management (CRM), and were therefore also included in the model. Recency was measured by the date of the user’s most recent play in Period 0, with number 1 given to the date of January 26th, 2012. Therefore, the value of the recency variable is higher when the customer left the game more recently. Frequency was measured by the number of logged-in days during the Periods 0, 1, and 2 separately. And, monetary value was measured by the purchase amount during Period 0.

In terms of customers' behavior, four variables were examined. First, the gamer’s ‘level’, or the social status of the user within the game can be considered to tell us how passionate the customers are for the game. There are 60 levels, with 60 being the highest. Second, 'kills per death', or how many competitors each user killed in each game-life, was measure to reflect the proficiency of users. It was measured as the number of kills divided by the total of number of kills and the number of deaths. Third, the 'experience score' was measured by the rewards users achieved from the game as an indicator of how hard they played the game. Last, 'number of chats with other players' was also included in the analysis to indicate how much each player enjoyed the game in an interactive mode.

This study also includes social network variables as interrelation among users is an important aspect of online games. Online gaming services allow users to manage their own list of friends using the game and are notified when they log-in using an alarm service. Therefore, the customer database had the list of friends that each user established, and this study included a customers’ number of friends in the analysis. In addition, the number of people who added the player as a friend (i.e., indegree number) and the number of gifts the game player sent to friends were also measured and incorporated in the model as social networking variables.

Two more variables that characterize the player were included in the model, which are age and the players’ playing location (home or PC Café). Operational definitions of all independent variables are summarized in Table 2.

Table 3 provides the descriptive statistics of the variables, both dependent and independent. The average age of the game users included in the sample was 30.5. As one can see, distributions of many

Table 1
Summaries of data samples.

	Period 0	Lapse	Period 1 (Promotion)	Period 2 (Retention)
Length (date)	12 weeks (1/26–4/18)	12 weeks (4/19–7/11)	4 weeks (7/12–8/8)	4 weeks (8/9–9/5)
Case 1 (n = 1000)	Logged-in	Left	Logged-in	Logged-in
Case 2 (n = 1000)	Logged-in	Left	Logged-in	Left
Case 3 (n = 1000)	Logged-in	Left	Left	Logged-in
Case 4 (n = 1000)	Logged-in	Left	Left	Left

Table 2
Operational definitions of independent variables.

Variable		Definition
Demographic	AGE	Game player’s age
	LOCATION	Proportion of Game playing location (home = “0”, PC Café = “1”)
RFM	RECENCY	Date of most recent play in Period 0
	FREQUENCY_#	Number of days the game player logged in to play in Period #
	MONETARY	Cumulative amount of money the game player spent in Period 0
Behavioral	LEVEL	The game player’s level in the game
	KILL_P_DEATH	Number of kills / (Number of kills + Number of deaths)
	EXPERIENCE	Reward scores gained
	CHAT	Number of chat with other players
Social network	NO_FRIEND	Number of Game player’s friends
	INDEGREE	Number of people who added the player as a friend
	NO_GIFT	Number of gifts the game player sent to friends

Table 3
Descriptive statistics of variables (n = 4,000).

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness
FREQUENCY_1	2.81	1	28	1	3.2	2.87
FREQUENCY_2	2.174	0	27	0	3.979	2.92
AGE	30.529	25	88	15	12.113	1.111
LOCATION	0.26	0	1	0	0.392	1.056
RECENCY	46.485	46.5	84	1	24.018	−0.157
FREQUENCY_0	5.609	2	64	1	8.208	3.26
MONETARY	875.25	0	100,000	0	5330.936	11.254
LEVEL	22.322	21	57	0	13.812	0.384
KILL_P_DEATH	0.393	0.437	1	0	0.171	−1.014
EXPERIENCE	34713.9	6924	4,081,860	0	123508.3	19.386
CHAT	0.27	0	65	0	2.013	22.542
NO_FRIEND	16.003	13	50	0	13.551	0.745
INDEGREE	10.031	8	39	0	8.51	0.809
NO_GIFT	0.695	0	45	0	2.595	7.727

variables are skewed to the right. The greatest number of friends was 50, and that of indegree was 39.

2.4. Analysis

Quantile regression is a type of regression analysis often used in statistics and econometrics. Whereas the ordinary least squares (OLS) results in estimates that approximate the conditional mean of the response variable given certain values of the predictor variables, quantile regression allows one to estimate the effects of predictor variables on the various quantiles of the response variable, including the median. Quantile regression analysis has often been used in the field of education and economics. For example, Eide and Showalter (1998) examined the effect of school quality on student performance applying a quantile regression approach.

One advantage of quantile regressions is that its estimates are robust against outliers in the response measurements, while OLS estimates are not. Quantile regressions were initially introduced as an answer for a robust regression technique which allows for estimation where the typical assumption of normality of the error term might not be strictly satisfied (Koenker & Bassett, 1978).

Fig. 2 shows that the distributions of 'frequency' in Period 1 and 2 are skewed to the right and are not normal, with skewness of 2.87 and 2.92. That is, they don't meet the general assumption of normality for OLS. Therefore, a quantile regression method that is more robust to outliers seems more appropriate.

Furthermore, while estimating how 'on average' online gamers' behavior affects frequency after win-back may yield a more straightforward interpretation, this standard OLS methodology may miss what is crucial for marketing managers. Specifically, marketing managers are interested in how online game players' behavior changes differently at different points of the conditional frequency distribution after win-back. We use a quantile regression for our analysis precisely because it can monitor the changes in the effect of online game players' behavior across different 'quantiles' in the distribution of frequency after win-back.

Let $Q_\tau(\omega|z)$ for $\tau \in (0, 1)$ denote the τ^{th} quantile of the distribution of the dependent variable of frequency (ω), given a vector of explanatory variables (z). We model these conditional quantiles by

$$Q_\tau(\omega|z) = z'\beta(\tau) \tag{1}$$

where $\beta(\tau)$ is a vector of the quantile regression coefficients.

For given $\tau \in (0, 1)$, $\beta(\tau)$ can be estimated by minimizing β (Koenker & Bassett, 1978);

$$\min_{\beta \in R^k} n^{-1} \sum_{i=1}^{n} \rho_\tau(\omega_i - z_i'\beta)$$

with

$$\rho_\tau(\varepsilon) = \begin{cases} \tau\varepsilon & \text{if } \varepsilon \geqslant o \\ (\tau - 1)\varepsilon & \text{if } \varepsilon < o \end{cases}$$

The special case of $\tau = 0.5$ is equivalent to median regression. Since the early 1950s it has been recognized that median regression can be formulated as a linear programming problem and solved efficiently with a form of the simplex algorithm. Like median regression, general quantile regression fits into the standard primal-dual formulations of linear programming.

3. Results and discussion

Statistical software packages, such as R, E-views, Stata, gretl, RATS, Vowpal Wabbit, and SAS (through proc quantreg and proc quantselect) are available for estimation of quantile regression. In this paper, E-views version 6.0 was used.

3.1. Period 1 (Win-back)

In this section we present the estimation results regarding the effect of online game users' past behavior on the response to the win-back campaign. We estimated the model both by OLS and QR at quantiles $\tau = 0.5, 0.6, 0.7, 0.8, 0.9$. The results are presented in Table 4. The dependent variable was the frequency in Period 1 (Frequency_1) and the number of observations was 4000.

3.1.1. RFM variables

According to CRM literature, recency, frequency, and monetary value are presumably the most important factors that contribute to the customers' lifetime value (LTV). Therefore, the current study assumed that RFM variables will have significant impacts on the lost customers' SLTV (Second Life Time Value) as well. However, recency turned out to have no significant impact on the win-back behavior. Both OLS and QR analysis indicated that the defection period tends to have no influence on usage frequency after the win-back. This may be due to the fact that our study examined gamers who left the service for at least three months. As for the frequency before the defection (Frequency_0), though, both OLS and Quantile analysis proved a positive impact on the frequency after the win-back. QR results revealed a more dramatic pattern. That is, as τ increased, the effect of frequency became larger (See Fig. 3(a)). Y-axis in Fig. 3 is the value of estimated coefficients.

On the other hand, the result on the monetary value pointed to the other direction. Those with high purchase amounts in the past played less frequently after coming back (OLS). This behavior may be explained as follows. When customers who spent big left the service they must have had more serious reasons for defection. Therefore, once

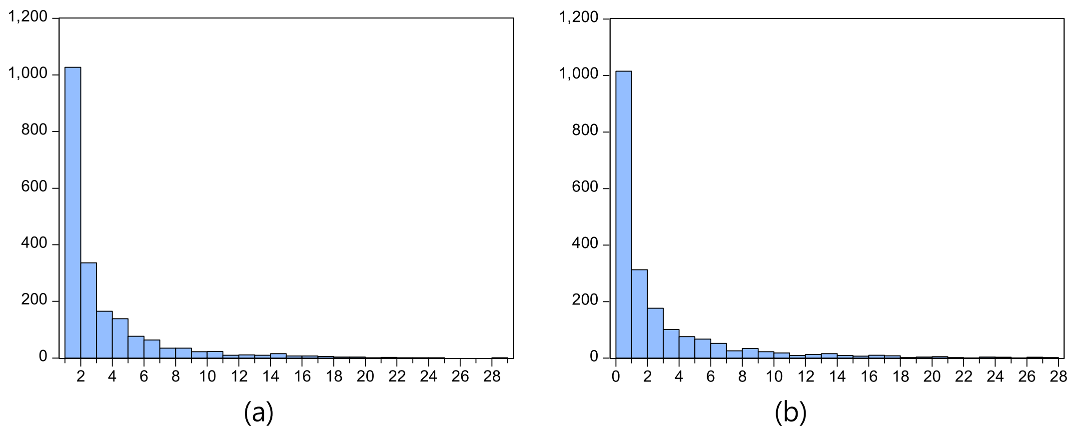

Fig. 2. The distributions of (a) Frequency_1 and (b) Frequency_2.

Table 4
Quantile regression results for period 1 (Dep = Frequency 1, n = 4000).

Variable	OLS	Quantile				
		τ = 0.5	τ = 0.6	τ = 0.7	τ = 0.8	τ = 0.9
AGE	0.011***	−0.002*	−0.005**	$-1.67*10^{-4}$	0.013*	0.048***
LOCATION	0.349***	−0.008	0.047	−0.014	0.428	1.427***
RECENCY	0.002	0.001	0.004***	0.001	0.003	0.004
FREQUENCY_0	0.034***	0.001	0.005	0.034***	0.056***	0.081**
MONETARY	$-1.76*10^{-5}$**	$-0.78*10^{-5}$	$-1.21*10^{-5}$	$-1.59*10^{-6}$	$-1.9*10^{-5}$	$-1.11*10^{-5}$*
LEVEL	0.023***	0.020***	0.022***	0.008***	0.034***	0.061***
KILL_P_DEATH	0.223	−0.093	−0.049	−0.043	−0.177	0.316
EXPERIENCE	$-9.63*10^{-7}$***	$-2.88*10^{-7}$*	$-3.78*10^{-7}$*	$-12.1*10^{-7}$***	$-15.9*10^{-7}$***	$-24.0*10^{-7}$***
CHAT	0.019	0.031	0.046***	0.077	0.164	0.156*
NO_FRIEND	−0.056***	0.047***	0.031**	−0.003	−0.043*	−0.207***
NO_FRIEND^2	0.001*	$-4.87*10^{-4}$***	−0.001**	$-0.185*10^{-4}$	$2.08*10^{-4}$	0.003***
INDEGREE	0.036	−0.05***	−0.016	−0.001	0.039	0.178**
$INDEGREE^2$	−0.001	0.001*	$0.86*10^{-4}$	$1.7*10^{-4}$	$-1.26*10^{-4}$	−0.003
NO_GIFT	0.065***	0.070**	0.085*	0.228**	0.269***	0.272**
Constant	0.472***	0.029	0.206*	0.858***	0.603**	1.040*
Adj R^2	0.038	0.058	0.002	0.011	0.032	0.063

customers with high purchases left the service, it would be much more difficult to turn them around. [1]Further, QR results provide additional explanations (statistically significant only whenτ = 0.9). For 0.9 quantile customers who showed a very high frequency after win-back, high purchases in the past lowered the frequency after the win-back. For most of the others (τ = 0.5–0.8), there was no relationship between past purchases and frequency after the win-back.

3.1.2. Behavioral variables

'Level' implies a social status of a user within the game world, but it also means a big switching cost. Therefore, users at high levels tend to be more loyal to the game. The OLS results illustrate that the users with high levels show higher usage after the win-back, and QR results confirmed that this occurs across all customer groups, although the effect of level was bigger for the users with high frequency after the win-back (τ = 0.8, 0.9).

Game companies assume that people with high K/D ratio will be more loyal to the service. However, it was found that the K/D ratio had no impact on the usage frequency after win-back. It may be due to the unique characteristics of online games where players get to choose the degree of harshness of the game they participate in. Users have tendency to choose competitors with lower skills in order to boost their K/D ratios. This is a good example of a well-known performance index being challenged by the real data.

'Experience scores' indicate how hard a player played the game in a certain period. This index is based on the hours users played the game for, not the frequency or logged-in times. OLS analysis results demonstrated that users with high experience score, in other words, those who played hard in the past, showed lower frequency after the win-back. Moreover, QR results exhibit that this negative effect was higher for those with high frequency after the win-back (See Fig. 3(b)). This result is similar to that for the monetary value variable, and may be due to the business model of the online game, which is free to play, but users are lured into paying small amounts of money for virtual items. Since only 10–30 percent of users pay money, the variable of monetary value doesn't properly reflect on a typical user. On the other hand, the variable 'experience' applies to every user, thereby bringing in the effect of the user's memory about the reasons for quitting the game.

'Number of chats' measures how actively the user communicated with other users in Period 0. OLS analysis results displayed that the number of chats did not have statistically significant impact on the frequency after the win-back. However, quantile analysis results exhibited that the number of chats has positive impact on the frequency, and the impact is stronger for those with high frequency.

3.1.3. Social network variables

A quadratic term was added to the analysis for the social network variables because there might be nonlinear rather than linear relationships between them and frequency. The result of OLS analysis showed that the effect of the number of friends is U-shaped. The results

[1] Customers who did not make purchases in the past may have reacted to the win-back campaigns because of financial incentives. But the possibility is low, considering that the online game users are not very sensitive to the price.

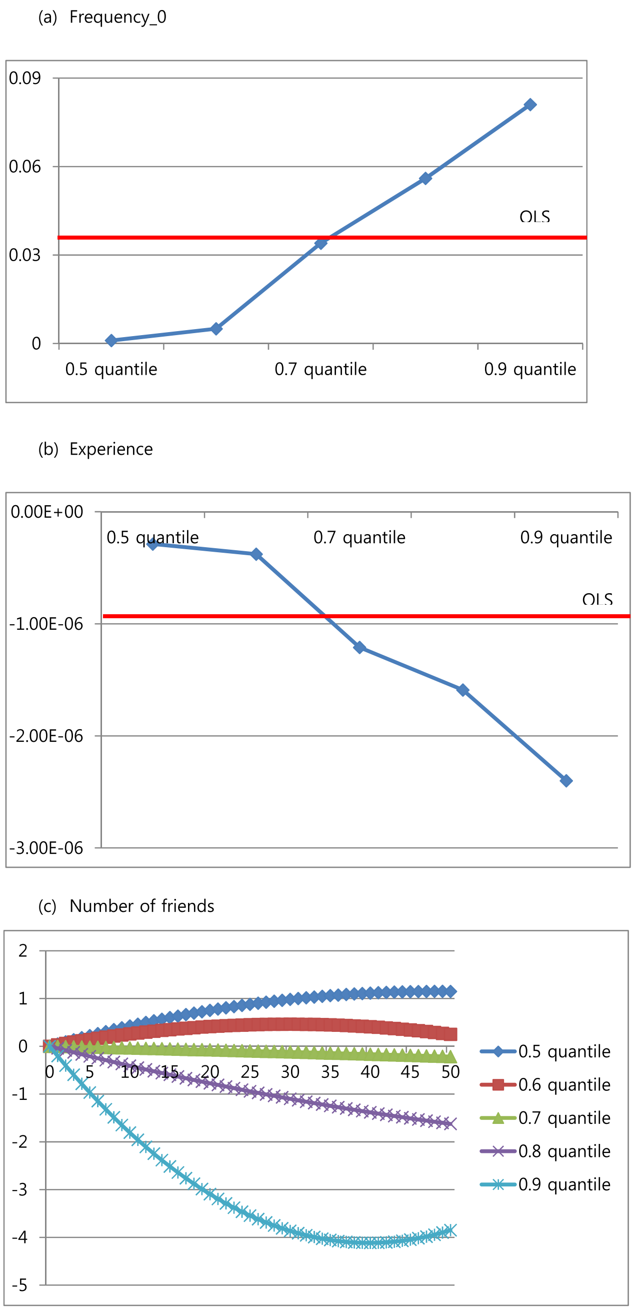

Fig. 3. Period 1 Results.

of QR are shown in Fig. 3(c). According to the figure, QR results were different for each group – for the users with lower frequency ($\tau = 0.5$, 0.6), greater number of friends led to active plays after the win-back, but for the users with high frequency ($\tau = 0.8$, 0.9), greater number of friends led to less activity after their return. The effects of 'indegree' were also predicted to be quadratic, but no statistically significant relationships were found. The OLS analysis results illustrated that even the linear relationship was not statistically significant. In case of QR, it was significant only when $\tau = 0.5$, 0.9. The number of gifts showed a positive influence on the frequency after the win-back, and the effect was more evident for the users with high frequency.

3.1.4. Demographic variables

The current study included two demographic variables: age and location. Both OLS and QR analyses confirmed statistically significant relationships between age and the usage frequency after win-back. In the case of OLS, it was positive. QR results showed a more complicated pattern where the age effect was mixed (sometimes positive and other times negative) according to the frequency after the win-back.

The variable 'location' indicates the proportion of game playing locations, whether at home or at a PC café. According to the results of OLS analysis, the users who played the game at the PC café turned out to show higher frequency after the win-back. These results seem appropriate when we consider the phenomenon from an experiential marketing perspective; that greater experience with the service leads to higher loyalty (Schmitt, 1999; Pine and Gilmore, 1998). PC cafés allow users to communicate more easily with other users and amplifies the users' participations and immersion in the game. In this case as well, QR results provided more sophisticated estimates. For the group of users who showed high frequency for 4 weeks after the return ($\tau = 0.9$), experiences at PC café influenced the frequency after the win-back, but it did not influence for the other groups. Therefore, for win-backs, experiential marketing strategies have better success when they target highly loyal customers rather than all customers.

3.2. Period 2 (Retention after Winback)

In this section we discuss the estimation results about the effects of online game players' behavior on the usage frequency during Period 2 (Frequency_2), i.e. 4 weeks after the win-back campaign. Again, we estimated the model first by OLS and then by QR at quantiles $\tau = 0.5$, 0.6, 0.7, 0.8, 0.9. This section will give valuable insights on who would stay active after a win-back campaign. The estimation results are presented in Table 5. The number of observations was 2000.

3.2.1. RFM variables

Recency again turned out to have no influence on whether users stay with the service after the return, while frequency played an important role. The OLS results of period 2 display that monetary value is not significant while QR results demonstrate that it is not only significant for top quantiles ($\tau = 0.8$, 0.9) but also has a negative impact on the frequency after the return, as explained earlier in this study.

3.2.2. Behavioral variables

'Level' had a very positive impact in period 1. Level refers to the assets that the users gathered through gameplay and is representative of increasing switching costs. Therefore, if the level is high, the player is more likely to respond to the win-back campaign, which is consistent with the findings in previous studies on switching costs (Tokman et al., 2007). However, it is not true of period 2. For those who returned, the level proved to have no impact on the frequency after the return. This is a very interesting result, and QR analysis even provided evidence of a negative impact for low quantile users ($\tau = 0.5$, 0.6). That is, for those with low frequency after the return, low level actually leads to higher frequency after the return. This is due to a unique characteristic of online games. Games lead to a so-called "flow" experience, and the flow is maintained only when the skill of the player and the challenges provided by the game match at the appropriate level (Kim, Kim, Kim, & Ko, 2018; Schell, 2008). Challenge is regarded as the most important index to predict the flow experience (Hoffman & Novak, 2009). However, unfortunately, the games cannot provide challenges to infinite number of customers and has to close the service when there are no more challenges to be provided. Thus levels can play a role as a switching cost, but they also represent the number of challenges taken by the users. As the user plays most of the challenges, the reasons to stay with the game begin diminishing. Therefore, players with high level may show lower frequency after the return.

K/D ratio was not significant in period 1 but it was in period 2. That is, K/D ratio has no influence on whether customers would return, but it does have influence on the frequency after the return. Since K/D ratio represents the skill level, when the K/D ratio is low, users would have a hard time maintaining the flow in most of the challenges. However, the

Table 5
Quantile Regression Results for Period 2 (Dep = Frequency 2, n = 2000).

Variable	OLS	Quantile				
		τ = 0.5	τ = 0.6	τ = 0.7	τ = 0.8	τ = 0.9
AGE	0.057***	0.039***	0.048***	0.062***	0.087***	0.140***
LOCATION	0.754***	0.020	0.063	0.386	1.433***	3.146**
RECENCY	−0.001	$-1.89*10^{-4}$	$-2.08*10^{-4}$	−0.002	0.002	−0.004
FREQUENCY_0	0.066***	0.053***	0.084	0.120***	0.144**	0.127***
MONETARY	$-1.48*10^{-5}$	$-0.54*10^{-5}$	$-1.99*10^{-5}$	$-2.85*10^{-5}$	$-4.96*10^{-5}$***	$-4.46*10^{-5}$***
LEVEL	0.002	−0.009***	−0.009**	−0.007	0.009	0.030
KILL_P_DEATH	0.876*	0.456***	0.368	0.367	0.436	1.192
EXPERIENCE	$-1.66*10^{-6}$*	$-1.68*10^{-6}$	$-1.44*10^{-6}$	$-1.73*10^{-6}$***	$-2.5*10^{-6}$***	$-3.16*10^{-6}$***
CHAT	0.035	0.058***	0.048***	0.042	0.003	−0.045**
NO_FRIEND	−0.243***	−0.090***	−0.119***	−0.199***	−0.293***	−0.554***
NO_FRIEND^2	0.003***	0.001***	0.002***	0.003***	0.004***	0.007***
INDEGREE	0.192***	0.074***	0.092***	0.149***	0.200***	0.465***
$INDEGREE^2$	−0.003*	−0.001***	−0.002***	−0.003***	−0.003**	−0.009***
Constant	0.711*	−0.191	−0.077	0.504	0.886*	1.960
NO_GIFT	0.043	0.032	0.092**	0.100	0.126	0.167*
Adj R^2	0.115	0.098	0.093	0.108	0.127	0.129

players with high K/D ratio will show positive behavior after the return because they can easily maintain the flow.

As in period 1, experience had a negative impact as shown in Fig. 4(a). Same explanation as for the K/D ratio can be applied and OLS analysis results verified that number of chats has no influence. In period 2, QR results showed two conflicting effects; the numbers of chats produced positive impact in lower quantiles (τ = 0.5, 0.6) but also showed a negative impact in the highest quantile (τ = 0.9).

3.2.3. Social variables

Number of friends had mixed effects (positive or negative) in different quantiles in period 1, but it had negative influence on all quantiles in period 2 (See Fig. 4(b)). In high quantiles, the negative impact was stronger, and strongest impact on frequency after win-back when τ = 0.9. In case of τ = 0.9, the number of friends had the most negative impact at around 40.

While indegree had no influence in period 1, it did have a significant impact on the frequency in period 2. QR results confirmed that for higher quantiles, indegree has a greater and more significant impact. According to Fig. 4(c), these effects peaked at around 30, and then decreased thereafter. For users with τ = 0.9, one can see a clear inverted U-shape, which can be explained by 'Dunbar's number'. Dunbar (1993) argued that there is a maximum size for social relationships. Namely, humans and animals are limited in their information-processing capacity, and thus social relationships, based on neocortex neurons. Dunbar's number for social relationships is around 150, but it may vary upon the characteristics of the relationships (Dunbar, 2011; Gladwell, 2000). Based on the results of the current study, one can conclude that social factors are critical in retaining returned customers, and that the Dunbar's number for online games is around 30. The number of gifts was significant in period 1 but not in period 2, though QR results suggested a positive impact in certain groups (τ=0.6, 0.9).

3.2.4. Demographic variables

Age was still significant according to OLS results, and QR results also confirmed that it has a very strong impact. Moreover, age effect becomes greater as the quantile gets higher. Location effect was similar but bigger compared to that in period 1. Again, QR results verified that location effects get stronger as the quantile gets higher. This explains why game companies' promotion strategies tend to put more emphasis on the PC café users than at home gamers.

4. Conclusion

Customers show less and less loyalty and they will continue to do so. It is not only because more choices are offered to the customers but also because new technologies keep facilitating brand switches. That is why retaining current customers is of paramount importance to service marketers. Many scholars as well as practitioners have argued that retention is better than acquisition from the perspective of return on marketing investment. Furthermore, customer reacquisition is even better in terms of marketing efficiency and effectiveness. However, marketing scholars have seen few studies that tackled the issue of winning back the defected customers.

The present study contributes to the literature from previous win-back studies in four areas. First, this study is based on the customers' real past behavior data, not surveys or anecdotes. Second, this study considers not only how customers respond to win-back promotions, but also who stays after the campaign is complete. Third, this study applies a novel analysis method, quantile regression, which is useful when the distribution of dependent variable is skewed. Last but not least, the empirical model comprised comprehensive variables such as demographic, RFM, behavioral, and social network variables.

Some of the findings shed much insight useful to practitioners in the gaming industry. The study for Period 1 verified that frequency and monetary value of before-lapse period influence the customers' second lifetime value. Surprisingly, recency had no influence. Customers who spent big and/or have much experience score proved to have less likelihood to come back, and even if they returned, they play less. Social network variables such as number of friends showed different effects across different quantile groups, and customers who played the game at PC cafés showed higher activities after the win-back.

The results in period 2 were as follows. Recency again was not significant, frequency was positively significant, and experience was negatively significant as predictors for retaining customers after win-back. In period 2, level became insignificant, but the K/D ratio was significant. The effect of number of friends exhibited a U-shape while indegree effect turned out to show an inverted U-shape.

These findings provide marketing managers with useful insights. Our findings imply that behavioral and social characteristics of customers are critical to the success of win-back programs. Besides, targeting average customers (vs. highly experienced customers) in win-back campaigns would be more effective. Our study also confirms the importance of customer retention especially for the high-valued customers. The quantile regression results indicate that upper 10% customers are hard to reacquire after the defection, and hard to maintain after the reacquisition as well. As for the retention of reacquired customers, our study provides interesting implications. That is, good experience after the reacquisition, which is not correlated with RFM, is more crucial than the past behavior. Besides, traditional retention tools like

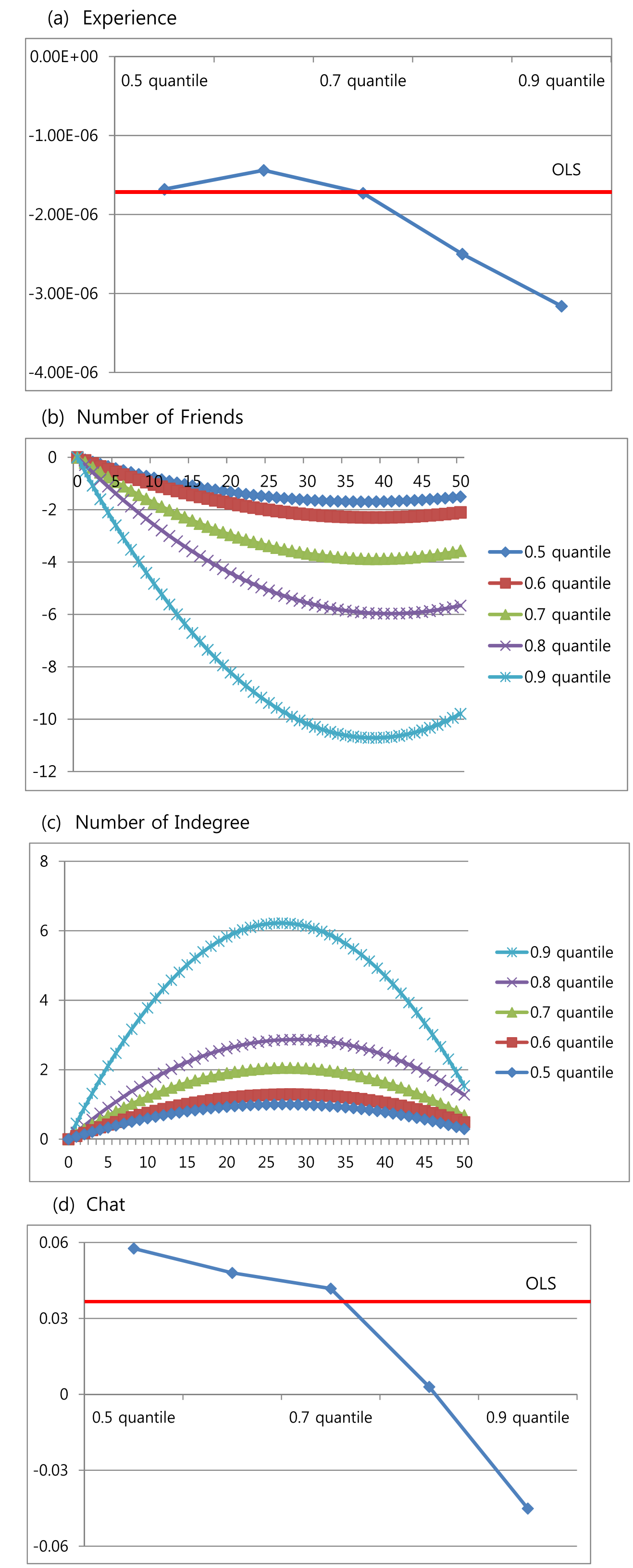

Fig. 4. Period 2 Results.

switching cost do not work properly for the reacquired customers, which means that new measures for good experiences should be developed to increase effectiveness of win-back programs.

This study can be considered as the first study that answered whom to target during the customer win-back program based on the customers' past usage behavior. This study also showed that the quantile regression approach is useful in better evaluating the effectiveness of win-back program. The results of the current study provide online service companies with many implications about how to design customer database for better customer management and to establish marketing strategies for reacquisition of customers.

The empirical analysis was based on a sample of 4000 users of an online gaming company. Therefore, in order to secure external validity, additional studies on various other online services (e.g., online shopping) would be warranted. Methodologically, a dynamic modeling approach that combines the two time periods investigated may also provide another venue for further research.

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