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The Essays on the Economic Analyses of New IT Online Contents Business: Game, Music and Smartphone

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ABSTRACT

The Essays on the Economic Analyses of New IT Online Contents Business: Game, Music and Smartphone

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The study on consumers' actual value for online service consumptions offers new business insights as online contents business and technology are dramatically converging. Ubiquitous Internet penetration is leading to networked gaming and greater online participation. The values driven from engagement in online communities underpin value based pricing. Trans-information mechanism that enables the right choice captures consumers' attention. The slot-design mechanism reflects the value of the attention. The digital contents business promises increasing productivity as smartphone becomes more powerful. Lately, smartphone acts as a key channel to deliver online content services. The consumers' value based pricing and the information delivery mechanism to rivet their attention have been prevalent and rapidly studied in an emerging technology. The research interest is to identify the value creation of online content consumptions and its new delivery channel. This thesis examines the values tide up with online gaming participants, the ranking mechanism reflecting customers' attentions, and impact of smartphone on online content services.

In the first essay, the study reports on the valuation of the time that a user participates in an online community. To estimate the value, I conducted econometric analysis for a large data set from a massive multi-player online role-playing game from Korea. I specified the model based on knowledge of the game players and the activities in which they engage in a field study. The results permit us to estimate hedonic value in monetary terms per minute of participant game play. I discuss how to use this type of information to create incentives through participation fees and subsidies to maximize consumer value, while creating additional network benefits for others. I also extend the empirical work through the development of an analytical model with related numerical simulation to show how a gaming service provider can support differential pricing, including the possibility of early participation subsidized pricing, over a participant's life time of activities in the game. I further discuss the applications of the approach that I present, and why and how it can be used to evaluate other types of mechanisms that involve hedonic and utilitarian value.

In the second essay, I analyze the music charts of an online digital music distributor that displays real time and weekly rankings on its website, and study how ranking policy should be set to maximize the value of its online music ranking service. The existing mechanisms considers only streaming and download volumes, while the new ranking mechanism reflects more accurate preferences for popularity, pricing policy, and the slot effect based on the exponential decay of attention. The new ranking model is designed to verify correlations with two kinds of service volumes for popularity, pricing policy, and the slot effect. Slot mechanism design is analyzed in a heuristic way. My analysis shows that music content sellers maximize benefits by assigning their own music items to the highest-ranking slot, which provides visibility. Also sellers can strategically design the slot size to influence the popularity of music items. Music content buyers

gain indirect benefits by getting segmented ranking slots and reducing search costs. Empirical analysis illustrates the features of the online music industry and validates hypotheses constructed around the new ranking model. The results show that the new ranking mechanism is more effective.

In the last essay, emerging technologies have created disruptions in organizational, business process and industry contexts. They act as shocks to a system. I focus on a retail telecom service provider's offerings of different bundles, including mobile phones, Internet and cable TV services. I conduct empirical regularities analysis for one country in Asia, which was affected by the emergence of smartphones in 2009. I assess the impacts on the service bundle choices of a provider's customers. I analyze customer switching among service bundles involving three services. I compute switching probabilities for each of the service levels offered, as well as between bundles. I use Markov chain transition analysis to describe the patterns. I find evidence for: smartphone effects on the contents of service demand; substitution between different kinds of Internet services; and migration of video consumption from cable TV to mobile services. In addition, I compute the instantaneous transition rate from feature phone services to smartphone services on a monthly basis. In our estimation, I identify the marginal effects of price and remaining contract on the transition rate. The results provide a basis for improved management of retail services bundling and pricing strategies.

Keywords: MMORPG, Hedonic Value, Online Music, Slot Effect, Smartphone, Transition Rate

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Chapter 1

Hedonic Valuation of Online Game Participation

1. Introduction

Social network activities have been studied in diverse disciplines, such as Psychology, Information Systems (IS), Communications and Marketing, to understand and explain the nature of people's interactions within online communities. A social network-related issue of importance in industry today is to find the value of social network participation. Determining customer valuation of a product or service is a key issue. In the past, value from the customer's perspective has been conceptualized in terms of *quality* and *willingness-to-pay*. Recent research views value in a more complex manner though [Bolton and Drew 1991]. For example, a customer's valuation can be viewed in terms of *utilitarian value* and *hedonic value*. These terms represent the idea that consumers spend money to purchase goods or services because they are needed, or because the goods or services make them happy. The latter represents the process of *hedonic gratification* [Batra and Ahtola 1990]. In online social network activities, user behavior can be utilitarian or hedonic also – or both at once – based on different aspects of the interactions that occur or the experiences that are obtained. Users tend to prefer efficiency in utilitarian tasks to achieve the benefits they hope to acquire with less time and effort, such as purchasing a book from Amazon [Payne et al. 1993]. They may be less concerned with their expenditure of time and effort when they engage in hedonic tasks, such as surfing the Internet, participating in a social network or playing games on the Internet [Voss et al. 2003].

The Internet has created the basis for new experiences in online users' lives by supporting new forms of online interactions and enhancing offline relationships. It has extended the meeting spaces for those with common interests in the digital world. Online users are attracted to the Internet because it can save them time [Bellman et al. 1999]. In Internet use, longer site visit times correlate with the quality of a user's experience [Novak et al. 2000]. So utilitarian value and hedonic value appear to co-exist for online network participation. In addition to online user participation, social media are in widespread use in almost every area of business.

Network effects are useful for estimating consumers' willingness-to-pay for information technology (IT) applications. This perspective has been used to evaluate the sales of operating systems, for example [Economides 2000]. Other research has linked hedonic value to network effects, by assessing a hedonic price index for spreadsheet software [Gandal 1994]. Still other research found that hedonic value was a good predictor of people's willingness-to-pay in the market for spreadsheet software [Brynjolfsson and Kemerer 1996]. More recently, I have seen the role of network effects in social networks, in which well-known participants generate interest and encourage greater participation than network effects theory predicts.

Playing a videogame is a hedonic activity similar to music appreciation, as discussed by Stigler and Becker [1977]. People are often willing to spend a lot of money and time to obtain hedonic pleasure through different kinds of consumption. Efficiency gained through their knowledge and skills in a given setting tends to increase their demand for the hedonic experience too [Murray and Bellman 2011]. The nature of efficiency is different for hedonic consumption and utilitarian consumption though. The former allows people to extract enjoyment from participating in online networks, while the latter allows people to make better use of their money and time.

This study leverages hedonic valuation in utility theory in the presence of network effects, as a means to measure the value of user participation in online network activities. An online user's willingness-to-pay is endogenous; it depends on the participant's investment of money and time. It also depends on the number of other participants who create beneficial network effects. Each user's valuation for joining can be derived from her net gains from social network participation and her online activities. The value of online network participation can be assessed in terms of the time and money she invests based on utilitarian value and hedonic value of online participants in the presence of network effects. I also study how utilitarian and hedonic value translate into the participant's willingness-to-pay, as the person experiences increasing difficulty as she progresses through the beginner, intermediate and advanced levels of a game. My analysis suggests an initial stage with subsidized pricing, followed by the implementation of more aggressive charges in pricing once the user's valuation rises with her experience and greater commitment to online game play.

The *hedonic pricing model* regresses the price of one unit of a commodity on a function of its *attributes*. A related theoretical question is related to the microeconomic interpretation of the function of the attributes on the right-hand side of the regression [Diewert 2001]. Many studies have used hedonic price models to measure consumer valuation of product attributes when they are part of a larger purchase bundle [Goodman 1978]. The hedonic price model also has been used widely in estimating the price changes in automobiles [Agarwal and Ratchford 1980]. The model also has been applied to IT to estimate evolving quality as the price for mainframe computers has declined [Chow 1967]. Others have modeled hedonic value in the mainframe computer market based on the product attributes of main memory and secondary storage size [Michaels 1979]. This approach has been used to further estimate the value of computer workstation attributes [Rao and Lynch 1993].

Social networking services, meanwhile, have simplified social interactions among online users. The growth of online network participation has been driven by the entry of these services into mainstream culture, with the result that it has become integrated into many people's daily lives. Traditional approaches for measuring customer value have involved utilitarian value and hedonic value, and social network users obtain their benefits to varying degrees. For example, a user may join a social network because of its utilitarian value of providing a way to visit with friends. In addition, the same person may join because of its hedonic attributes – the sheer pleasure of being in touch with everyone all the time [Wu 2009]. Consumers typically have preferences relative to utilitarian and hedonic value, and these are driven by the different attributes and quality of a product or a service. For most things, there is maximum amount that consumers will spend, their willingness-to-pay.

One network is stable when participants are able to create value that is sustainable over time. A business network needs to have immediate value from its co-production activities, and also have to generate present value of growth opportunities [Kauffman et al 2010]. The participants in the network need incentives and subsidies to invest to support initial investments to start the value flows [Riggins et al 1994]. Previous studies examines network growths where a monopolist manipulates the network subscription price in order to encourage participations some critical points to reach a profit maximizing network size, and followed by setting sustain nonlinear pricing beyond the critical mass point [Oren and Smith 1981]. In this study, subsidy is characterized in order to encourage user participation in the gaming network at early stage, and aggressive pricing is proposed in order to maximize a game vender's profit after early stage.

The present study employs the hedonic pricing model to estimate hedonic and utilitarian value the time a participant plays an online game. The estimation identifies the marginal effects of the characteristics of a game as a *complex hedonic commodity*. I will report empirical results to show the importance and effects of various drivers on game time valuation. They include a player's skills in the game, the level of the game that she has reached the benefits that she reaps from building up experience points in the game environment, and the impact of the network effect associated with the number of other game players involved. The value of online network participation is informative for game vendors, who can use the information to set up appropriate pricing schemes. And, social planners can use it to gauge the impact of the value of online network participation in the entertainment industry.

The main thrust of my investigation, then, is to assess the value of online network participation, and to apply my approach for assessment in the online game setting. Section 2 presents the background of my online gaming setting, and the data that I will analyze. Section 3 tests econometric models to estimate the hedonic value in monetary terms of network participation and for the monetary value per minute of participant game play. Section 4 complements the empirical results by extending them to including the possibility of differential pricing, and why it may be appropriate to change prices over time, as participants' willingness-to-pay for game play changes. Section 5 discusses model appropriateness, methodology issues, and other important considerations for further study. Section 6 concludes with a discussion of the theoretical and managerial contributions. It also offers some thoughts on the limitations of the methods and data that I have used, and where it may be possible to sharpen the results further.

2. Research Setting and Data

2.1 Research Setting

The research setting is a point-and-click *massive multi-player online role-playing game* (MMORPG) developed in Korea, involving movement, combat and other commands that all are mouse-controlled. (See Table 1.) The game has seven different player roles, or personas that players take on which control the kinds of powers they can use, and the style of their interactions with other game players. I refer to them as Roles A through G. After making progress through the game's play levels, a player in any role can change to another role.[1]

Table 1. Overview of Research Context: A Massive Multi-Play Online Role-Playing Game

MMORPG	DESCRIPTION
Mode	MMORPGs are subscription-based virtual worlds that host thousands of players who interact with one another
Method	Point-and-click; movement, combat, etc. controlled by a mouse
Story	Players: learn skills to trade; open or join a guild after completing a quest; open a chat room; create groups to fight monsters more effectively; and hold or collect game items and game money
Process	Players obtain skill or experience points to strengthen their roles, and progress to higher levels of the game
Role	Players choose a game role from among the seven that are available

The players perform different *quests*, which are tasks that involve the development

[1] For example, Role A uses a dagger as a weapon and attacks at close range. Role B uses a hammer and can attack but cannot aim well, while Role C uses a rolled-up newspaper. Role D uses a one-handed sword, and has the highest defensive power among the roles. Role E uses a two-handed sword, and moves up the game levels faster as a result. Role F uses a mace and gets stronger as its magical powers increase. Role G uses a staff for fighting and can attack with fire and ice, but has low defensive capabilities.

of their abilities in the different roles of the game. The game tracks the participants' progress based on their level of play and experience points (*ExperPts*). Participants can buy weapons so they are able to reach a higher level. Each level requires slightly more equipment for players to be successful. Player can earn *money* in the game by solving different tasks, and this permits them to buy additional equipment. After reaching a higher level, a player's money earnings will grow arithmetically, while the cost of the equipment that is relevant for making additional progress will grow exponentially. As a result, devoted players sometimes choose to spend their own real money to make additional purchases.

Travel in the online game is made possible with *warp gates*, located in various towns on different maps. Travel involves movement from one town to another and also one map to another, with different means that are specified in the game environment. Along the way, players learn how to trade, open or join craft guilds after completing qualifying tasks, open a chat room, and other things. They also can open a bank account to hold or collect game items and money. The online game also uses points to reward players who go from one level to the next. These points strengthen their capabilities in the roles they take on.

The emphasis in game design is to make games challenging for players with high interest and skills and attractive for novices who just want to have fun. Players who reach a high level of performance in the game usually get there through increasingly sophisticated use of weapons and better skills (*Skills*), so their demand for them rises as they rise through the game levels. Weapons are sometimes *substitutes* (e.g., a sword for a spear) or complements (e.g., a sword with a shield). The prices of weapons within the digital boundaries of the game are fixed, however, players can invest money to make their weapons more efficient for battle. Players express different levels of willingness-to-pay when they have different needs for various weapons, and when they are in the flow of the gaming experience. When they are having a lot of fun they will be willing to pay more for a given weapon.

2.2. Variables, Data

The field study data are from between July 1 and December 21, 2006. I obtained data on 775 role-playing participants in the seven different roles (*Roles*) described above. I also obtained individual-level data for a number of different game-related variables, as a basis for estimating the value of participant playing time. They include: the actual time the participant played the game (*Time*), the individual's spending in the game (*Money*) and game level (*GameLevel*), as well as the number of game participants *(NetEffect*). *Wage* is the opportunity per unit time for a person to spend time playing the game, based on the applicable minimal wage for work. *Access* is the number of times that a player accesses the online game during the time of the empirical observation. (See Tables 2 and 3 for descriptive statistics and correlations.)

Table 2. Descriptive Statistics for the MMORPG Data Set

FEATURE	MEAN	STD. DEV.	MIN	MAX
Roles	3.18	2.00	1	7
Money	344,861	582,366	440	5,771,700
Wage	757,596	1,065,466	150	6,621,700
NetEffect	65.25	44.32	1	178
Time	15,151.94	21,309.33	3	132,434
Access	854.40	972.83	6	8,739
Skills	4,387.80	6,072.25	2	45,582
ExperPts	1.47e+09	5.14e+09	42	7.01e+10
GameLevel	95	59	2	251
Notes: 775 observations in the data set.				

Table 3. Correlations

	Wage	*NetEffect*	*Time*	*Access*	*Skills*	*ExperPts*	*GameLevel*
Wage	1.00						
NetEffect	0.34	1.00					
Time	1.00	0.34	1.00				
Access	0.72	0.31	0.72	1.00			
Skills	0.35	0.18	0.35	0.57	1.00		
ExperPts	0.47	0.23	0.47	0.56	0.28	1.00	
GameLevel	0.67	0.34	0.67	0.73	0.46	0.52	1.00

2.3. Analysis Process in This Research

The main steps of the analysis process are empirical estimation and parameter-driven numerical simulations. Step 1 develops the analysis of the basic hedonic pricing model. Since I am studying a setting in which the players engage in an online game, I adapt this constructs so that a number of attributes represent it. A key goal is to identify users' prices demand to establish confident estimates of the key variables (hedonic value: experience points and frequency, utilitarian value: skills and game levels) under economic variables (opportunity costs and network effect) stratifications. Another core is to specify the monetary value of game play time by confirming the substitution between prices and time. Step 2 provides the estimation results, together with various model diagnostics that ensure robustness of the results. I use econometrical tests to examine the stability of the coefficient estimations. The checks include heterogeneity, omitted variable and outlier diagnostic.

Step 3 develops simulated-analysis to supplement the empirical estimations. A primary goal is to link the estimation result of game play time to the utility of online participation under the condition of subsidy and network effect at different stages (early, middle, and later). In step 4, I propose subsidy value at early stage, optimal pricing based on willingness to pay, and varying prices over stages, together with numerical simulations that ensure the clarity of the propositions.

Figure 1. The Research Process in This Study

Empirical modeling and estimation		**→**	**Pricing design and simulation**
1. Analysis of the basic hedonic pricing model.	2. Analysis of hedonic pricing model to assess robustness of empirical results	3. Modeling of prices using game participants' utility	4. Simulation of impacts of the use of a subsidy and network size in pricing strategy
1.1. Value estimation for a participant's game playing time	2.1. Heterogeneity, omitted variable and outlier diagnosis	3.1. Modeling analysis of pricing with subsidy and network effect	4.1. Participant subsidy simulation in early stage of game play 4.2. Participant lifecycle differential pricing over time

The goals of each step are:

- **Step 1**: Develop a basic understanding of the hedonic pricing model for game play. Identify the value of the attributes of the game overall through a measurement approach that is based on an estimation model.
- **Step 2**: Check for the robustness of the empirical results by diagnosing heterogeneity, omitted variables, outlier influences.
- **Step 3**: Design a pricing scheme to complement the empirical results, and extend the insights from the results.
- **Step 4**: Analyze performance of pricing design over time and with a pricing subsidy via simulation.

3. Empirical analysis

3.1. Hedonic value of network participation

The empirical model is:

$$\ln(Money)_i = \beta_0 + \beta_1 \ln(Wage)_i + \beta_2 \ln(NetEff)_i + \beta_3 \ln(Time)_i + \beta_4 \ln(Skills)_i$$
$$+ \beta_5 \ln(ExpPts)_i + \beta_6 \ln(GLevel)_i + \varepsilon_i$$

There is a possibility of measurement error in the explanatory variables, specifically the *Time* variable. This is because the observed time includes on-going playtime and other playtime, combined with items that were purchased by the participant:

$$PlayTime_i = OngoingPlayTime_i + PaidItemPlayTime_i$$

Furthermore, *Time* is clearly correlated with *Wage* variable and it will cause collinearity. When the regression error term is correlated with an independent or omitted variable, biased coefficient estimates may result. So it is appropriate to find an instrumental variable, if there is evidence for this endogeneity problem. I assume that *Time* variable is endogenous and *NetEff*, *Skill*, and *ExpPts* are exogenous. Moreover assume that I have two instruments available: *Access* and *GLevel*. However, if I need it, *Access* is an appropriate instrumental variable. From Table 2, I see it is correlated with the *Time* variable (72.2%). I performed a Hansen test for the validity of the instruments and for the exogeneity of all variables as well. The test result shows Durbin chi2 (0.5848) with p-value (0.444) and Wu-Hausman F (0.5815) with p-value (0.4459) which indicates all variables are exogenous. Thus, the specific functional form without time measurement error to address the endogenity problem is:

$$\ln(Money)_i = \beta_0 + \beta_1 \ln(Wage)_i + \beta_2 \ln(NetEff)_i + \beta_3 \ln(Access)_i + \beta_4 \ln(Skills)_i$$
$$+ \beta_5 \ln(ExpPts)_i + \beta_6 \ln(GLevel)_i + \varepsilon_i$$

The maximum likelihood estimates in the model were obtained in two different forms. In the first estimation, *Wage* and *Access* were obtained relative to game playing time. *Wage* is time spent times 50 Korean won (KRW) per minute. This is the minimum wage or opportunity cost per minute in gaming. If I assume that the minimum wage is KRW3,000 per hour for workers in Korea, a game player who spends one hour in gaming would be paid at least KRW3,000 for her hourly work there. *Access* is an instrumental variable to replace the *Time* variable because of measurement error. It defines the number of times that a player accessing the online game in a given period of time.

Table 4. Results: model with instrumental variable *Access*

ROLE	*ALL*	*ROLE A*	*ROLE B*	*ROLE C*	*ROLE D*	*ROLE E*	*ROLE F*	*ROLE G*
Constant	-3.89*** (0.083)	1.68*** (0.348)	3.989*** (0.298)	7.399*** (0.354)	-0.27*** (0.280)	3.114*** (0.285)	0.622** (0.251)	1.811*** (0.202)
Wage	-0.012 (0.011)	-0.044 (0.050)	0.001 (0.038)	-0.010 (0.060)	0.034 (0.032)	-0.008 (0.031)	-0.036 (0.034)	-0.007 (0.027)
NetEff	2.66*** (0.009)	2.528*** (0.043)	2.247*** (0.032)	1.765*** (0.082)	2.744*** (0.028)	2.518*** (0.030)	2.379*** (0.027)	2.632*** (0.022)
Access	0.041** (0.016)	-0.118* (0.070)	-0.055 (0.070)	0.057 (0.088)	0.074 (0.052)	-0.002 (0.058)	0.096** (0.047)	0.055 (0.041)
Skills	-0.026** (0.011)	-0.79 (0.058)	-0.070 (0.058)	-0.25** (0.095)	-0.096** (0.038)	-0.098 (0.059)	-0.06*** (0.026)	-0.030 (0.025)
ExpPts	0.041** (0.018)	0.233** (0.102)	0.142 (0.093)	0.395** (0.156)	0.126* (0.066)	0.189** (0.090)	0.082** (0.040)	0.022 (0.038)
GLevel	-0.17*** (0.064)	-0.758* (0.384)	-0.437 (0.317)	-1.144** (0.510)	-0.589** (0.251)	-0.654** (0.313)	-0.327** (0.160)	-0.150 (0.148)
N	775	109	106	34	178	76	164	104
Note: Dep. Var.: ln(*Money*). All variables are logarithms. * $p < .1$, ** $p < .05$, *** $p < .01$.								

There is collinearity between *Wage* and *Access* though, so I estimated a second model with a hedonic equation omitting ln *Wage*. (See Table 4.)

Table 5. Results: model with *Wage* omitted

ROLE	*ALL*	*ROLE A*	*ROLE B*	*ROLE C*	*ROLE D*	*ROLE E*	*ROLE F*	*ROLE G*
Constant	-3.96*** (0.072)	1.910*** (0.305)	3.997*** (0.231)	7.36*** (0.240)	0.203 (0.255)	3.071*** (0.236)	0.456** (0.208)	1.770*** (0.178)
NetEff	2.664*** (0.008)	2.51*** (0.043)	2.246*** (0.032)	1.767*** (0.078)	2.753*** (0.028)	2.524*** (0.030)	2.377*** (0.027)	2.634*** (0.023)
Access	0.025** (0.012)	0.076 (0.058)	-0.537** (0.038)	0.044 (0.051)	0.112*** (0.039)	-0.010 (0.043)	0.061* (0.036)	0.049** (0.031)
Skills	-0.02*** (0.011)	-0.081** (0.058)	-0.071 (0.057)	-0.251** (0.092)	-0.094** (0.038)	-0.096* (0.056)	-0.60** (0.026)	-0.027 (0.025)
ExpPts	0.041*** (0.018)	0.240** (0.102)	0.142 (0.092)	0.395** (0.152)	0.120* (0.065)	0.191** (0.089)	0.076* (0.040)	0.019 (0.037)
GLevel	-0.17*** (0.064)	-0.76* (0.384)	-0.439 (0.311)	-0.150** (0.497)	-0.548** (0.246)	-0.67** (0.313)	-0.32** (0.161)	-0.147 (.141)
N	775	109	106	34	178	76	164	103
Note: Dep. Var.: ln(*Money*). All variables are logarithms.* $p < .1$, ** $p < .05$, *** $p < .01$.								

Table 3 shows high correlations involving three variables: W*age, Access* and *GLevel*. When I assume than those variables are endogenous, then ordinary least square (OLS) estimates are not consistent, but IV estimates are consistent. The difference in the estimates represents the presence of endogeneity.Thus, I checked for this with the Hausman test and the results indicate no endogeneity.

Table 6. Hausman test (ivreg vs. olsreg)

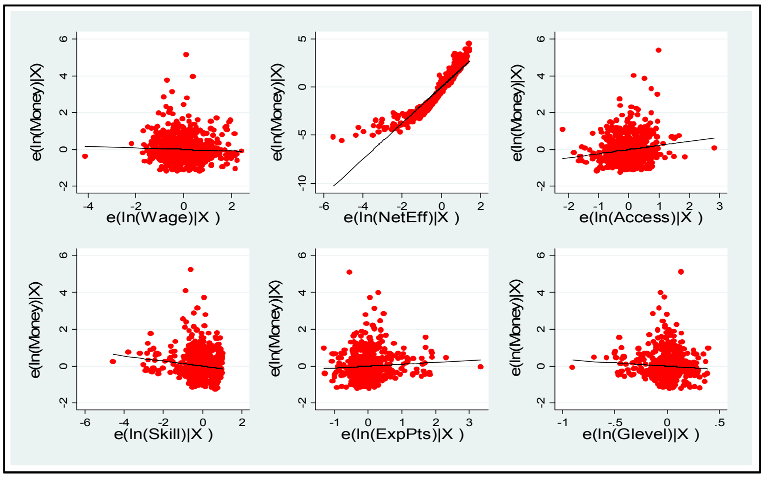
ROLE	*ALL*	*ROLE A*	*ROLE B*	*ROLE C*	*ROLE D*	*ROLE E*	*ROLE F*	*ROLE G*
●	Instrumented: *Access*; Instrument: *Wage, NetEff, Skills, ExpPts, GLevel*							
Prob $>\chi^2$	0.684	0.982	0.999	0.995	0.867	0.984	0.996	1.000
●	Instrumented: *Wage*; Instrument : *NetEff, Acces,s Skills, ExpPts, GLevel*							
Prob $>\chi^2$	0.831	0.995	0.998	1.000	0.863	0.982	1.000	0.998
●	Instrumented: *Skill*; Instrument: *Wage, NetEff, Access, ExpPts, GLevel*							
Prob $>\chi^2$	0.609	0.677	0.987	0.502	0.465	0.991	0.689	0.987
Note: All variables are logarithms. No variables are endogenous.								

Most of the coefficient estimates have the expected signs, implying that willingness to pay to participate in the online game in this study increases as network effects *NetEff* grow and the qualities of the hedonic game commodity change for the better. However, *Wage* is not significant across all different estimations. The efficiency gained based on participant knowledge, *Skill,* and *GLevel* is negative, since the dependent variable, *Money*, generally decreases as gaming skills increase. The coefficients of *NetEff* and experience points *ExpPts* are significant while the opportunity cost of playing time, *Wage*, is not. The effects of the roles are different, which may indicate fixed effects. The empirical results show that the value of online network participation is affected by time, fun, and efficiency of skills in support of game enjoyment.

Figure 2 plots quality versus the log of willingness to pay. The *hedonic line* for *Wage* passes through the center of the data, and forms the *hedonic line* for *Access*, *Skill, ExpPts, and GamerLevel*. The hedonic line for Wage, *Skill, and GamerLevel* slightly decrease, while the line for *NetEff and ExpPts* increases. These movements correspond to the coefficient value of each quality. Furthermore, I show the response surfaces for combinations of variables based on estimated coefficients in Appendix A.

Online users invest time in using online services such as social networks and online entertainment. Due to their intangible benefits, it is hard to calculate the value they receive. By analyzing their efficiency, user value can be calculated by the increase in level of their playtime by calculating the substitutability of items they paid for in cash and their playtime. The results suggest that I can apply my approach to calculate the value of user time in any type of social network services or online games.

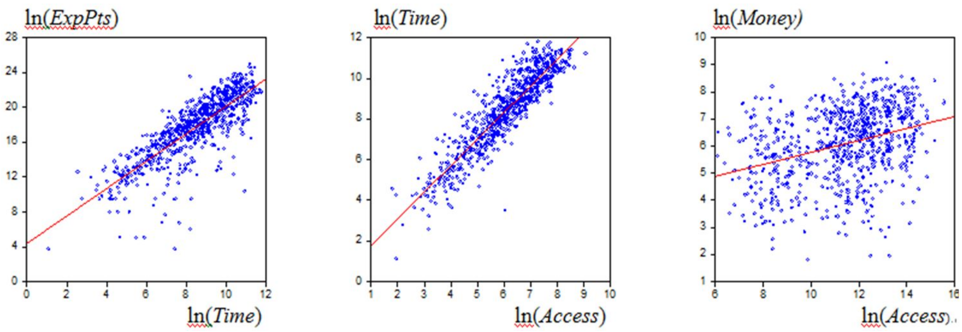
Figure 2. Logarithm of price versus quality



e:Residual, X:*OppCost(wage), NetEff, Access, Skill, ExpPts, GLevel*

The top-left case is e(ln(Money)/X) vs. e(ln(*OppCost*/X)

Figure 3. Scatter plots and regression lines



I value playtime with a *constant elasticity of substitution* (CES) function. The parameters β and $1 - \beta$ are coefficients for the contribution of *Time* and *Money*. The elasticity of substitution σ between these depends on the parameter γ, with $\sigma = 1$ for Cobb-Douglas and very large values of $\sigma > 1$ indicating higher substitutability.

CES: $ExpPts = f(\beta(Time)^r + (1 - \beta)(Money)^r)^{1/r}), \sigma = 1/(1 - r)$

Base: $\ln(ExpPts)_i = \beta_1+\beta_2\ln[\beta_3(Time)\hat{}\beta_{4i}+(1-\beta_3(Money)\hat{}\beta_{4i}]+\varepsilon_i$

IV: $\ln(ExpPts)_i = \beta_1+\beta_2\ln[\beta_3(Access)\hat{}\beta_{4i}+(1-\beta_3(Money)\hat{}\beta_{4i}]+\varepsilon_i$

I conduct estimation to obtain β_4 for all game roles in a pooled data set.The estimate of β_4 suggests a Cobb-Douglas function is appropriate to measure the value of gaming playtime.

When consuming social network or online entertainment services, a user's propensity to spend time or money when faced with some game challenge may be different, depending on their game role and approach to the game, so valuation needs to reflect this. I estimated a fixed-effects cross-sectional model to examine individual users' consumption of time and money. the results show that the intercepts vary across the different game roles, which suggests that the intercept is sufficient to capture the differences. I also employed a one-way *analysis of variance* (ANOVA) to identify group differences for the players across the different game roles. The results suggest that players in different roles consume different amounts of time and money, while the ANOVA results verify this effect.

Finally, I employed OLS and the *two-stage generalized method of moments* (2SGMM) estimation for an instrumental variable to measure the value of user time in consuming online services. The OLS and 2SGMM estimates were significant.

I can identify the value of user time from consuming online gaming services based on the models I proposed, in terms of money spent per unit of online game-playing time. I present the results for *Role* from the data set, as an illustration:

OLS: $\ln(ExpPts)$: $3.17 + 2.03 \ln(Time) + 0.25 \ln(Money)$

2SGMM: $\ln(ExpPts)$: $3.17 + 2.03 \ln(Time) + 0.25 \ln(Money)$

The marginal rate of substitution is:

$$\frac{\beta_2}{\beta_3} \times \frac{AverageMoney}{AverageTime} = \frac{2.03}{0.25} \times \frac{117,549.24}{17,363.86} = 54.97$$

Thus, the value of a gamer's playtime is KRW54.97 per minute. For additional details, see Table 6.

Table 7. Value of participant playtime for each role

Role	*All*	*Role A*	*Role B*	*Role C*	*Role D*	*Role E*	*Role F*	*Role G*
β_2	2.34	2.33	1.97	2.41	2.23	2.26	2.03	2.15
β_3	-0.07	0.13	0.07	-0.83	-0.02	-0.12	0.25	0.03
Money	344,862	369,320	5,221,467	533,629	364,024	4,199,645	117,549	347,119
Time	15,152	9,8780	13,781	5,223	15,738	22156	17,764	15,686
Value	-	669.99	1,066.27	-	-	-	54.97	1,585.89

4. Pricing Scheme Design in Online Gaming

As seen at table 7, for example, the monetary value of one minute in game play is KRW 669.99 for *Role A*. The monetary value is partially dependent on different roles, a game level and experience points which a game player of a different role obtains. To achieve expected utility with more efficiency, gamer players are required to acquire skills. The required skills can be gained by different game plays and game tools. Under the different game stories which each role engages in, a game player is likely to feel the game difficulty in a different way. She decides to substitute the game play time by the money for the purchase of gaming tools. Those tools help users achieve their goals or save user game play times. The game difficulty varies over time which means as game level increases. This game design drives the varying degree of game difficulty which each game player faces over time. Thus, the empirical results of time value at table 7 represent on the average value and do not represent the accurate value of time which each game player concerns as time passed. I need to estimate the time value which varies in process of time and game levels. For example, the time value will become differentiated such as KRW 600 at early game level and KRW 300 at later game level. That is, I need to examine the degree of substitution between time and money which each game player generally performs or prefers because it is informative to put a price on the game players' subscription fee or on the gaming tools as their game levels increase. However, it is very difficult to have a rich data set where the degree can be examined. Thus I study the differential pricing based on the varying time-value and the empirical results of hedonic pricing model through the application of analytical estimation and its parameter-driven simulations.

The empirical results (the negative coefficient values of *Skill, GLevels* and the positive coefficient values of *ExtPts, NetEff*) show that prices of users reduce when their game level increases. However, their prices increase when the experience point and the number of game players increases because the value of playing game increases. The results clearly show that game players are not likely to pay as their required gamming skills increases because they can go through the game without purchasing game tools. However, they are willing to pay as they deeply engage in the game when their achieved utility is greater than their expected utility, so stay in the game. Furthermore, playing game with her friends or other online game players is another pleasure. Network effect is a well-known factor to game participants tied up to online social activities. However, the results do not show which one is stronger over game levels or whether net effect is positive or negative. For example, a game player achieves required gaming skills against game difficulty, but it is not enough. Nevertheless if he wants to get more fun from game play, he is willing to pay more. Thus, in order to complement the empirical results, I analyze and simulate a pricing strategy in online gaming.

Table 8. Mathematical notation and definitions

Notation	Definition	Comments
Hedonic pricing model		
Money	Total amount of real money spent by an individual game player	
Earning (Wage)	User i's opportunity cost of time spent for game play based on the wage per unit time	*Wage* is the maximum monetary value which users are able to gain by using the time on working instead of playing game
Time	Time units of playing game	I consider *Time* as a unit to be able to spend.
Access	The number of times accessing to the game	I use *Access* as an instrument for time variable on the regression because the time variable causes measurement error.
Skills	The degree of achieving required gaming skills e.g., how to defeat monsters or enemy, how to level up quickly and effectively.	
ExperPts	The points which a user gains whenever he levels up or which he obtain when he completes some quests or required tasks.	
GameLevel	The game level which each user engages in when data were collected.	I use game level to distinguish each user. Each user is heterogeneous with respect to his age, gender, income, education. However, the data set do not include demo variables.
Pricing scheme design		
$f(UtilEff_i, NetEff_i; GLvel)$	The utility driven by a game player i per game level	
$f(UtilEff_G, NetEff_G)$	The average utility driven by game players in a given game level	
$UtilEff_i$	The utility parameter which represents the degree of the utility achievement of a gamer i as his game level increase	

$AvgUtilEff_G$	The average utility parameter which represents the degree of the utility achievement of gamers within a certain game level g. e.g., if n game players exists with a certain game level.	$AvgUtilEff_G = \frac{\sum_{i=1}^{N} UtilEff_i}{Nusers}$
$NetEff_i$	The utility parameter which represents the degree of network effect leverage to a user i.	
$AvgNetEff_G$	The average utility parameter which represents the degree of network effect leverage to gamers within a certain game level. N players exist in the given level.	$AvgNetEff_G = \frac{\sum_{i=1}^{N} NetEff_i}{Nusers}$
$G(GameLevel)$	The game levels designed by a game vender	
$Price_G$	A vector of price per game level	
$AvgPrice$	The average price	The average price is the monetary value of game play time at table 7. The value is estimated across every user within all different roles and game levels.
$NewPrice_G$	The new price due to the subsidy	
$Nusers$	The number of online participants in the game server	I only consider N users at early stage. And the number will decrease because of increasing game difficulty after early stage
$Subsidy_G$	The subsidy rate based on the average utility of game players in early stage	

Table 9. Assumptions

Assumptions	Definition
Assumption 1	A game vendor knows the average of utility parameter values $AvgUtilEff_G$ and $AvgNetEff_G$ in given game level.
Assumption 2	The average parameter values $AvgUtilEff_G$ and $AvgNetEff_G$ are always positive.
Assumption 3	The subsidy is dependent on the average utility which gamers achieve over game levels
Assumption 4	The number of game participants decreases as their *game levels* increase due to the increasing game difficulty.

Price for playing game is tied up with a user i's willingness to pay when he is getting through over game levels. Thus, I set a game player i's utility function as following.

$$\max utility_i = f(UtilEff_i, NetEff_i; G) - Price_G \tag{1}$$

The utility function $f(UtilEff_i, NetEff_i; G)$ represents the characteristic of a user i in the given game level. The utility parameter $UtilEff_i$ defines the degree of utility achievement of a user i. The network parameter $NetEff_i$ defines the degree of network effect leverage to a user i. The model assumes full information which is, a game vender is always aware of the average utility parameters' value of game players who engage in the same game level. Thus, the $f(AvgUtilEff_G, AvgNetEff_G)$ is exogenously decided. That is, the average parameter values $AvgUtilEff_G$ and $AvgNetEff_G$ are exogenously determined constant in the given game level. I assume that the parameter value $AvgUtilEff_G$ is always positive. However, it might be controversial. For example, a game provider usually designs varying game difficulties over different game levels. It starts easy-going but gets harder, and then provides much challenging level. When users face the highest difficulty, implying that the average parameter value $AvgUtilEff_G$ might be negative, they can get through the game by purchasing a useful product because it makes them powerful against enemies or difficult quests. Otherwise, they might terminate their participation in the game. Thus, the assumption that the parameter value is positive is a strong assumption. Nevertheless from the perspective of managerial issue, a game provider designs the structure of game difficulty very carefully in order to minimize the churn of game players because the number of game participants is the critical source to make benefits for him. Thus, I suppose the parameter value always positive across game levels. I also assume that the parameter value $AvgNetEff_G$ is always positive. Network effect, the large utility of game participants in the same game server draws an inducement for a user to engage in and stay in the game. And it partially drives the increment of hedonic value of game participants.

In this section, I consider firstly subsidy value to encourage beginners to continue playing the game, secondly optimal pricing by imposing an aggressive price on heavy game participants, and lastly pricing differentiation by changing subsidy from the average price level. At table 7, the empirical results show the monetary value of playing time. It is the estimated average value from beginners and experts across all different levels. The subsidy is closely related to the utility which users achieve over different game levels. In general, the utility which users obtain from gaming is less than the utility which they expect at early stage, while the achieved utility is getting close to the expected utility at later stage. It might be the cause of offering subsidy to beginners at early stage.

I want to estimate the subsidy rate which correlates with the average utility of N users in a given level. Thus, I set $Subsidy_G = Subsidy(\overline{v_G})$ where $\overline{v_G} = f(AvgUtilEff_G, AvgNetEff_G)$. The new price is $NewPrice_G = (1 - Subsidy_G)AvgPrice$. The utility function is

$$\max_{Subsdy_G} utility_G = f(AvgUtilEff_G, AvgNetEff_G) - Nusers(1 - Subsidy_G)AvgPrice \tag{2}$$

In order to derive the demand function, after transforming the user i's level into the aggregated level of users, which means from $UtilEff_i$ to $AvgUtilEff_G$ and $AvgNetEff_i$ to $AvgNetEff_G$, I divide the equation (2)'s both sides by $f(AvgUtilEff_G, AvgNetEff_G)$. And then, I get $\frac{utility_G}{f(AvgUtilEff_G, AvgNetEff_G)} = 1 - \frac{Nusers(1 - Subsidy_G)AvgPrice}{f(AvgUtilEff_G, AvgNetEff_G)}$, which defines the average utility in a given game level. The vender's revenue function is

$$\max_{Subsdy_G} Revenue = [1 - \frac{Nusers(1 - Subsidy_G)AvgPrice}{f(AvgUtilEff_G, AvgNetEff_G)}]Nusers(1 - Subsidy_G)AvgPrice \tag{3}$$

$$\text{s.t.} \quad 0 < Subsidy_G < 1 \tag{4}$$

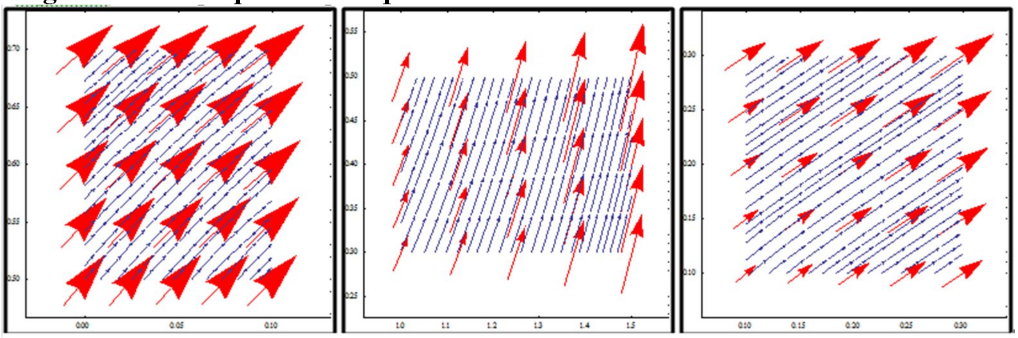
The pricing scheme will be different in three different game stages; early, middle and later stage. I assume the average utility increases slightly in early stage, and increases at an incremental rate in middle stage, and then increase at a diminishing rate in later stage. On the other hand, network effect draws many participants in early stage and makes them stay in middle stage. However, the effect gradually grows weak with the stage passing. The table below shows the growth of average utility over different gaming stages.

Table 10. Assumptions over stages

Early stage
$0 < AvgUtilEff_G + AvgNetEff_G < 1$, $0 < AvgUtilEff_G < AvgNetEff_G < 1$
$\frac{\partial f}{\partial AvgUtilEff_G} > 0$ and $\frac{\partial^2 f}{\partial^2 AvgUtilEff_G} = 0$, $\frac{\partial f}{\partial AvgNetEff_G} > 0$ and $\frac{\partial^2 f}{\partial^2 AvgNetEff_G} < 0$
Middle stage
$1 < AvgUtilEff_G + AvgNetEff_G$, $0 < AvgUtilEff_G < 1 < AvgNetEff_G$
$\frac{\partial f}{\partial AvgUtilEff_G} > 0$ and $\frac{\partial^2 f}{\partial^2 AvgUtilEff_G} > 0$, $\frac{\partial f}{\partial AvgNetEff_G} > 0$ and $\frac{\partial^2 f}{\partial^2 AvgNetEff_G} < 0$
Lager stage
$0 < AvgUtilEff_G + AvgNetEff_G < 1$, $0 < AvgUtilEff_G < 1 < AvgNetEff_G$
$\frac{\partial f}{\partial AvgUtilEff_G} > 0$ and $\frac{\partial^2 f}{\partial^2 AvgUtilEff_G} < 0$, $\frac{\partial f}{\partial AvgNetEff_G} > 0$ and $\frac{\partial^2 f}{\partial^2 AvgNetEff_G} = 0$

The figure 4 shows the stream plot of average utility at different stages. The plot shape is dependent on parameter values $AvgUtilEff_G$ and $AvgNetEff_G$. Early stage expects linear utility plot with low values $AvgUtilEff_G$ but high value $AvgNetEff_G$. Middle stage prospects convex utility with highest values $AvgUtilEff_G$ and low value $AvgNetEff_G$. Later stage is projected with concave with lower values $AvgUtilEff_G$ and lower value $AvgNetEff_G$. These expectations of utility are established on the strong assumptions I set up according to the common structure. The phased utility prospection will be informative for a game provider to form a managerial price or subsidy strategy.

Figure 4. Stream plots under parameters



Y axis: β 0.5~0.7 / X axis: α 0~0.1 Y axis: β 0.3~0.5 / X axis: α 1~1.5 Y axis: β 0.1~0.3 / X axis: α 0~0.3

Early game level: linear Middle game level: convex Later game level: concave

Based on the assumptions, I differentiate equation (3) with respect to subsidy $Subsidy_G$. I get the optimal subsidy level $Subsidy_G^* = \frac{2Nusers \times AvgPrice - f}{2Nusers \times AvgPrice}$ and $AvgPrice = \frac{f}{2Nusers(1 - Subsidy_G^*)}$. The optimal price level $NewPrice_G^* = \frac{f}{2Nusers}$ when considers only subsidy level (endogenous variable) in order to maximize the revenue of a game vender.

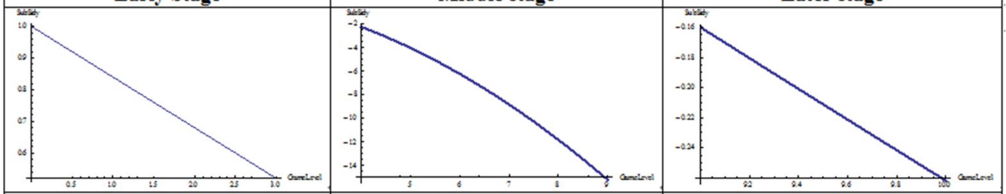
Proposition 1 (subsidy value at early stage). A game vender will subsidize beginners in early stage if new participants experience positive gains from the number of user joining the network. Subsidy is valuable to encourage new online participants staying in game play at early stage. Network effect plays an important role to draw increments of hedonic value from game users.

Proof. In order to identify the marginal effect of the average utility parameters $AvgUtilEff_G$ and $AvgNetEff_G$ on the optimal subsidy $Subsidy_G^*$, I differentiate the optimal subsidy level with respect to the parameters. And I get, $\frac{\text{-}Inverse.f\,(UtilEff_G, NetEff_G)}{2Nusers?\quad vgPrice} < 0$ because utility function f is always greater than zero (Assumption at early stage: $\frac{\partial f}{\partial AvgUtilEff_G} > 0$ and $\frac{\partial f}{\partial AvgNetEff_G} > 0$). The differential value decreases as the number of users decreases over game levels after early stage (Assumption 4) e.g., $\frac{-30}{N=10} > \frac{-30}{N=5}$.

Thus, the subsidy value is greatest when network effect is largest at early stage.

Figure 5. Optimal subsidy level

Early Stage	Middle stage	Later stage



$AvgUtilEff_G = 0.1$ $AvgNetEff_G = 0.7$	$AvgUtilEff_G = 1.5$ $AvgNetEff_G = 0.5$	$AvgUtilEff_G = 0.5$ $AvgNetEff_G = 0.3$

Figure 5 shows subsidy levels over different stages. The optimal subsidy decreases as game level increases at early stage. However, after early stage the subsidy is not effective to encourage game players joining the online network. Negative value of subsidy, which corresponds to aggressive pricing, is effective to maximize a game vender's profit.

Proposition 2 (optimal pricing on users' willingness to pay). The price in the network increases as game players' utility increases when the number of users (N users) decreases after early stage.

Proof. . In this case, I only consider *N users* at early stage. The *N users* decrease as their game levels increase because of game difficulty after early stage. New optimal price $NewPrice_G^* = \frac{f}{2Nusers}$ is dependent on utility in the condition of the varying number of users in the network. I assume the marginal effect of $AvgUtilEff_G$ increase, while the marginal effect of $AvgNetEff_G$ decreases and I assume $AvgUtilEff_G$ is greater than $AvgNetEff_G$ as well. Thus, utility function $f(UtilEff_G, NetEff_G)$ increases at an increasing rate under Assumption 4.

Figure 6. Optimal price level

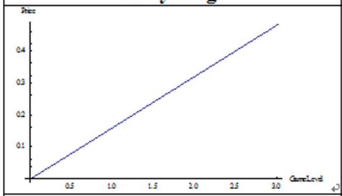
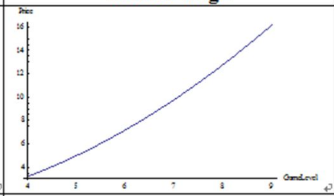
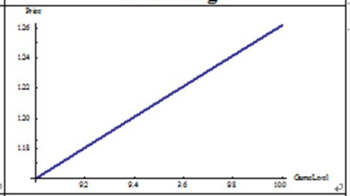
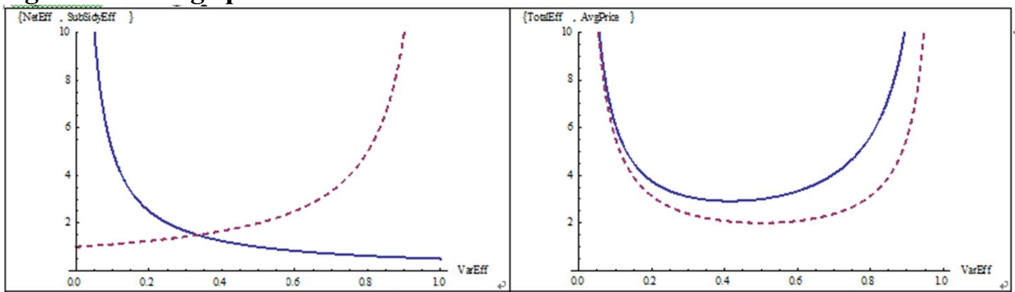
Early Stage	**Middle stage**	**Later stage**
		
$AvgUtilEff_G = 0.1$ $AvgNetEff_G = 0.7$	$AvgUtilEff_G = 1.5$ $AvgNetEff_G = 0.5$	$AvgUtilEff_G = 0.5$ $AvgNetEff_G = 0.3$

Figure 6 shows optimal price levels over different stages. The optimal price increases at a different rate (slightly at early stage, sharply at middle stage, and somewhat monotonically at later stage) as game level increases.

Proposition 3 (average price in the presence of varying subsidy level and network effect). Average price level decreases when optimal subsidy level is reduced for *N* users at early stage. However when network effect from the *N* users is greater than subsidy effect, the average price increases at early stage. In addition, the price level in middle stage is greater than the price level in later stage as network effect decreases.

Proof. The average price level is $\frac{f}{2Nusers(1-Subsidy_G^*)}$. It is proportional to utility, but is inversely proportional to N users and (1-*Subsidy*). In a condition of normalizing the average price, we get $0 \le \frac{f}{2Nusers(1-Subsidy_G^*)} \le 1$. I divide the price in order to identify two different effects $\frac{1}{2Nusers}$ and $\frac{1}{(1-Subsidy_G^*)}$ where f is constant. Now the N users is converted into $VarEff_{Nusers}$, and $Subsidy_G^*$ is converted into $VarEff_{Subsidy}$. The turning point is $VarEff_{Nusers} = \frac{1-VarEff_{Subsidy}}{2}$. For the normalization of two effects, two effects are transformed into one variable effect, $\frac{1}{2VarEff}$ and $\frac{1}{(1-VarEff)}$. I define that $\frac{1}{(1-VarEff)}$ is subsidy effect, and $\frac{1}{2VarEff}$ is network effect where $VarEff$ corresponds to optimal subsidy level at early stage. As the $VarEff$ decreases from 1 to 0, subsidy effect decreases while network effect increases. Thus, two combined effects are formed in a U-shape. The average price is proportionate to the combined effects. The price decreases up to the turning point, but increases after the point because network effect is greater than subsidy effect after the point. The figure 7 shows the results.

Figure 7. Average price level



$NetEff = \frac{1}{2VarEff}$, $SubsidyEff = \frac{1}{(1-VarEff)}$ | $TotalEff = \frac{1}{2VarEff} + \frac{1}{(1-VarEff)}$

At middle stage, assumption $\frac{\partial f}{\partial AvgUtilEff_G} > 0$ indicates that a game vender do not subsidize to users. Average price level is $AvgPrice = \frac{f}{2Nusers(1-Subsidy_G^*)}$. Assumption

$0 < AvgUtilEff_G < 1 < AvgNetEff_G$ in middle stage and assumption

$0 < AvgUtilEff_G < 1 < AvgNetEff_G$ in later stage indicate $AvgPrice_{middle} > AvgPrice_{later} > 0$.

5. Discussion

5.1. Model Issues

The first set of issues that I will discuss related to the modeling and empirical analysis is related to its representation, robustness with respect to the game environment structure, and the significance, depth and frailty of the results. Hedonic value in an online game arises from the player's experience. Players may become aroused and involved, and enjoy the fantasy aspects of their experience, which they will view as being hedonically valuable. People also want to be able to participate in online games in an efficient and effective manner to achieve their goals, much like a skier wants fast and efficient skis, or a tennis player needs a high quality racket. Online gamers seek the benefits of appropriate game functionality when they do specific things in the game.

I think the basic premises of my approach involving hedonic and utilitarian value are appropriate. Game players who get into the flow of the game may become unaware of the passage of time. The tasks that they have to complete are all characterized by some degree of learning, and practice enhances learning efficiency, which simultaneously increases their involvement and game enjoyment. For a beginner, playing an online game will be slow and clumsy, but a skilled player will be proficient and will know the right kinds of moves.

Hedonic models for other applied contexts often use sales information, and information about prices and product attributes. I have included network effects, time, and player characteristics, including flow factors and game skills, to represent her capacity to achieve efficiency, in addition to estimating the hedonic value of online game participation. As a result, I have formulated a reasonable basis for developing appropriate and meaningful insights that will not be frail with respect to the main elements of theory that I have identified as being relevant.

5.2. Empirical Issues

In terms of empirical modeling and estimation issues, I need to consider the quality of the data I have developed for this research, as well as the quality of empirical modeling choices I have made to extract useful information from it. The research design tested a number of variables that I believe would affect hedonic value. I estimated the price of a complex hedonic commodity relative to the characteristics of the game setting and user, and included a time variable. I used a relatively small and exploratory cross-sectional data set. So, clearly, there are limitations to the level of statistical significance that I have been able to achieve.

In this study context, estimation of the effects of the independent variables can be further improved by including more players, and longer time duration of observation. I can also control for game levels that the players reach – something that I have not done to date. For example, it may be the case that distinguishing between the different kinds of value that arise will be different in the beginner phase of a player's participation, as opposed to when she becomes an intermediate or an expert player. At present, this estimation approach cannot distinguish the differences.

Another issue with respect to measurement involves the choice of proxy variables for the various constructs that I am interested in studying. The use of *Wage* for the opportunity cost of a player's time of participation in a game is reasonable, I believe, but nevertheless imperfect. Different game players surely will have different opportunity costs of time spent based on their different personal situations. Another proxy variable-related issue is how I coded for a user's experience. I use the game-captured *ExpPts*, which does not truly discriminate among the different amounts of effort that players put in to achieve their current level.

I also expressed concerns about measurement error, and regressor and error term correlation as possible signs of endogeneity. This led us to estimate coefficients for multiple forms of the base model, and present the results shown in Tables 2, 3 and 4. I employed maximize likelihood (ML) and the two-stage generalized method of moments (2SGMM) with instrumental variables (IV) estimation to measure the value of user time in consuming online game services. These estimations yielded similar results at somewhat different but acceptable levels of significance. ML estimations use distributions for the random variables and the parameters most likely to fit the data. GMM estimation, in contrast, leverages the moments of the random variables and established parameter estimates that are the consistent with them. The former is often a more efficient means of estimation in that information on the entire distribution is used. GMM only uses the specified moments, and may be more robust but less efficient. Other modeling choices are possible, but the present choices seemed like good ones for exploratory analysis.

I further note that hedonic regression models typically include the characteristics of a hedonic commodity and include a dummy variable for time. But since the data are cross-sectional rather than in panel data form, I cannot estimate the full time-wise effects of each variable in my model.

5.3. Measurement Issues

The empirical analysis assesses the hedonic value of online game participation, however, there is some additional complexity in the setting that I didn't attempt to model or estimate so far. This also touches on the issue of omitted variables. If important regressors have been missed out in the model, then the coefficient estimates will be biased. It's appropriate to disclose this, and to comment on the potential direction of the bias. For example, the data set includes information about the different game levels that players achieve, but I have not attempted to establish stratified results for players at different achievement levels. The difficulty with this for us at present is the lack of sufficient observations from the game setting to make this process effective.

The limited observations that I obtained on players' online game activities also do not represent the complete behavioral patterns of the players. For example, I also did not try to represent in the exploratory model the possibility that players can take on more than one game role. This is actually a part of the game environment though, and it suggests that there is likely to be some degree of correlated game-playing behavior across the different interacting roles. Although the empirical analysis did not examine this possibility, I nevertheless can imagine how the bias might work. There are likely to be some instances in which greater hedonic value arises in game play when a player shifts from one role to another role. This might involve re-establishing new flow in participation, as one role reaches a dead end for advancement, or is under-resourced, etc. This also creates the opportunity for *role alliances* created by the same player. Such alliances might permit a player with a given base role to be more effective in achieving a higher level in the game without the additional weapons and resources that usually are required, for example.

Another aspect of the game play that I have not attempted to model yet involves the possibility that players may choose to exercise *outside options* to purchase resources for the game that are not available to them inside the game. This is a common phenomenon in online game-playing: participants develop relationships with one another for exchange outside the game setting boundaries, or they may go to externally-established marketplaces, where it is possible to make game resource-related transactions. There is no way to track this kind of thing, so it suggests that the *Money* variable, as a measure for game resource expenditures, may not be a perfect measure. It probably captures most of the individual differences in game resource purchases though.

There are several other aspects of the game setting that I did not try to model in this research so far, because they are somewhat more complex. Still they deserve comment and full disclosure, so the reader will have an idea of the issues I am dealing with. I have reason to believe that not all equal durations of time in which a player participates in an online game will produce equivalent hedonic value. A simple observation is that the time spent by a beginner to get acquainted with the gaming environment might not be the same in hedonic value terms as the time spent by a much more experienced person. The player's *starting level* may condition the hedonic value they ascribe to the gaming experience. I think of this as a possible *starting level effect.*

I also conjecture that a player's *starting level and ending level* in the game, achieved during a period of play or over several periods of play, may be associated with different amounts of hedonic value. For example, if one player solves tasks that permit her to go up two game levels, as opposed to another who only goes up one level in the same time duration of play, I can guess that hedonic value might be greater for the one who rises faster and farther. This *delta level effect* would be consistent with hedonic value arising from a relatively greater *sense of accomplishment* on the part of the player, all else equal.

5.4. Managerial Issues

A well-known characteristic of online game is the huge amount of time spent playing the games. If the opportunity cost of a player's time is estimated by her wage rate, every game player invests big bucks worth of play time every week or month. The great volume of play time is not always enjoyable because most game players need to practice for the achievements of required skills, experience points, game money by repeating the same action, while some players spend real money to reduce the unenjoyable play time by purchasing game goods in the game world. Thus, the value of the countless hours in the game can be measured by the characteristics of game play and real money spent as well. The measurement of play time in a monetary term will be very informative for a game vender to set the pricing scheme over time or game levels. For example, a particular game player who engages in a given level willingly spends the optimal amount of real money and time in order to achieve her hedonic gratification. Once a game vender analyzes those gamer players' willingness to pay or play over game levels (early, intermediate, and later stage), he will take advantage of their willingness to maximize his profit.

When a game player enjoys the game, each player's propensity to spend time or money may be different across specific game roles such as warrior, knight, wizard, etc. Thus, valuation needs to reflect this. The role balancing between each distinguished players is very important to keep each role' player participate in the game and not to lose their interest. For example, the most famous strategic simulation game, StarCraft, offers the immaculate role balancing of three different tribes (combat avatars). The value measurement of play time across specific roles presents how a game vender analyzes the economic nature of each role's game play wants.

6. Conclusion

This research has focused on the analysis of an online game-playing environment, and the extent to which participants achieve hedonic value and utilitarian value from their network activities. I began with the basic premise that game players both enjoy the flow aspects of the game, by enjoying the gaming experience and losing themselves in the time they spend online, as well as the practical aspects of playing the game well because they are equipped to be efficient and effective players. I drew an analogy between online game playing, and the kinds of hedonic value and utilitarian value that may arise, to other settings involving sports, for example. The same applies to other offline activities, such as music participation activities and playing an instrument, or learning a foreign language. I see similar things online also, for example, playing chess with a machine, or playing poker in a gaming market – or doing a myriad of other things so simple as searching or surfing the web with tools that power a user's experience to extraordinary efficiency while maintaining their high interest and a loss of sensation with respect to the passage of time.

I employed a hedonic valuation model from economics as a means to model the phenomena that we have studied. I used an exploratory data set of modest size as a basis for developing a number of useful insights in this research. (1) the theoretical model provides a basis for estimating the hedonic value and utilitarian value of a user's online game participation. (2) I also offer evidence related to the substitution between time and money spent on gaming, and offered an illustration for a player who participates in the game in a specific game role. (3) I also found that a game player's hedonic value for participation is likely to be role-dependent, and not all of the roles are created equal in terms of how they generate hedonic and utilitarian value. In physical sports, such as football, I can imagine that the level of hedonic value that players obtained will be based on the positions they play, including: linesman for the offense and defense; the quarterback, fullback and halfbacks; the offensive receivers and defensive linebackers; and even the field goal kicker and punter. A variety of team sports (cricket, soccer, baseball, hockey, basketball) are all likely to be similar in this way, and are helpful to translate my findings to readers who aren't online gamers.

Although I have obtained some results to assess hedonic and utilitarian value in online gaming, it's fair to say that this work is still in the exploratory stage. I have discussed a number of limitations, including data and modeling choices, as well as some of the complexities of the game setting, that require more consideration before I can create definitive research to value the game mechanism design that I explored. Nevertheless, I believe that my research is notable for the effort and progress is has made in developing conceptual and theoretical knowledge for the valuation of online gaming mechanisms from the user's standpoint. This is a first step, in my view, toward ascertaining how to conceptualize pricing systems for online gaming that are aimed at understanding the behavioral basis for the willingness to pay of the participants. There are some complications in the real-world setting compared to the more limited setting that I have modeled, but I have been careful to note some of these as a basis for the reader to more effectively gauge the value of this research, and to identify some directions for future research on this topic.

More generally, my research suggests the basis for differential pricing in online gaming that is tied to the experiences and different levels of willingness to pay for heterogeneous users. Similar to other IT-mediated digital intermediation settings (search engines, electronic markets, social networks, and so on), it is useful to point out that early stage game play is likely to deliver less utility and value to online gamers than later stage play, when they become more adept at the required skills, and the innovativeness in design of the game and its challenges are revealed through persistent use. This suggests that optimal pricing based on willingness to pay might involve an initial stage of free access or subsidized pricing, followed by the implementation of more aggressive pricing once the participants' differences become more evident to the gaming vendor as the former's participation grows over time. Although it might be impractical to develop individual prices for the heterogeneous individuals who participate, there probably will be ample evidence to identify when online gamers might need a discounted play incentive, or some kind of monetary reward to encourage them to perceive high value in the gaming environment and to continue their participation.

Chapter 2

Online Music Ranking Mechanism Design

1. Introduction

Sales of recorded music in compact disk (CD) format have declined steadily because consumers have increasingly moved toward digital real-time streaming and downloading. The majority of music is now sold in digital format and played or downloaded to online users' audio devices, such as smart phones and portable music players. Online music providers employ a variety of business models for the distribution of digital music, but single-item downloading and subscription fee services are increasingly common as digital content is delivered by online channels.

The characteristics of competition among digital content distributors, specifically online music distributors, closely resemble those of monopolistic competition. Information on the Internet reduces search costs relative to visiting physical stores [Chevalier and Goolsbee 2003], and the accurate ranking of music reduces search costs relative to visiting physical stores and competitors' websites. Online music distributors, which give some portion of their revenue as commission to music source providers, have ranking mechanisms to list the digital contents on ranking slots. The rankings are generally decided based on parameters that include download volumes and streaming volumes. A key issue for the online music distributor is how its ranking policy should be determined to maximize the value of the ranking service and its revenue [Chen 2009]. In this paper, the ranking policy is regenerated through a new ranking mechanism that reflects a more accurate preference pertinent to popularity (based on the bandwagon effect and ranking effect), pricing policy, and slot effect (based on an exponential decay model) for online users.

When people make rational choices based on the information they receive from others, information cascades can quickly form in which people ignore their personal information signals and follow the behavior of others [Leibenstein 1950]. This is the bandwagon effect. The slot effect occurs when people are less likely to listen to or download a song that is farther down in the rankings, because they need to expend more effort to scroll down to see the song [Chen 2009]. Exponential decay occurs when a quantity grows exponentially if it increases by the same percent in each unit of time, and it decreases exponentially if it decreases by the same percent in each unit of time. Feng et al. (2007) computed the average click-through based on exponential decay of attention. The method is a fair standard to model people's attention when it decreases exponentially by the same percent in each unit of time [Breese et al. 1998]. A related mechanism is used in online sponsored search advertising, where the search engine ranks the advertisement according to expected revenue [Edelman and Ostrovsky 2007]. A music distributor usually employs two pricing policies: a single-item downloading service and a subscription fee.

I apply a new ranking mechanism to reflect online user preferences and the slot effect more accurately than the existing ranking services offered by online music providers. For this purpose, I use empirical work, including a set of generally available statistics, and an analytical method that tracks how online users respond to the offered ranking service with the proposed parameters. The analysis of popularity and the slot effect have important economic and ranking policy implications, as digital content managers must evaluate the value propositions of the ranking service to maximize revenue. The objective is to propose a new ranking mechanism that reflects accurate popularity based on the bandwagon effect and that reflects the ranking effect, pricing policy, and the slot effect.

The paper proceeds as follows. Section 2 provides a literature review of the application of ranking information services and ranking mechanisms for digital content. Section 3 presents a ranking model of the online music distributor, and considers how the provider should design its ranking algorithm to maximize value. Section 4 presents my empirical work, including data collected from the online music provider, and an illustration of the general features of online music charts and music distributors. Section 5 analyzes popularity and ranking, validates my hypothesis, and considers some possible applications. The last section concludes.

2. Theory and literature

Mechanism design originated from the study of the possibility of efficient resource allocation in socialist societies in the 1930s [Hurwicz 1960, 1973]. Hurwicz (1972) defined a mechanism as a communication system amongst principal and agents, where a pre-specified rule assigns an allocation of goods and services. Incentive compatibility that allows for the incentive of self-interested participants is the key notion for mechanism design theory. An online user who visits an online content website looking for digital content typically faces a screen containing the price of the content, the relative sales ranking on the site, and so on [Chevalier and Goolsbee 2003]. Online users as agents' access music chart information through the ranking mechanism without incurring costs, and achieve reduced search costs. That is, an allocation through the ranking mechanism is realized by an online users' voluntary participation. A designer's advanced ranking mechanism can realize more sophisticated allocation with the participation of the principal and the agent. This should result in increased benefits for the principal, who uses strategically ranked charts. This attracts more latent users. Also, increasing utility for the agent is achieved by providing more accurate ranking information with reduced search costs.

From an economic perspective, the demand for digital content is correlated with sales ranking and pricing policy. The sales ranking is likely to stimulate a herd instinct, and the bandwagon effect diminishes the explanatory capacity of the theory of supply and demand as it relates to content pricing and individual preferences [Leibenstein 1950]. However, the bandwagon effect is important in the increase of demand for digital content. As for the ranking effect, Spoerri (2008) investigated whether the rank position of a document, combined with information about the number of systems that retrieved it, can help to produce a better estimate of a document's probability of being relevant. The result showed that a document's probability of being relevant increases as it is placed higher up in a ranked list, but it decreases exponentially as falls down in a ranked list. The ranking effect suggests a link among digital contents with high rankings for popularity. The literature on ranking relevant works can be categorized into research on estimated sales of ranked items and ranking mechanisms.

2.1. Estimated sales of ranked items

Bradford (1985) estimated the exponentially diminishing returns of extending a search for references in science journals. This pattern is called the Pareto distribution in many disciplines. Pareto (1971) found that income can be approximated using a log-linear distribution, which is a power law probability distribution that coincides with social, scientific, geophysical, actuarial, and many other types of observable phenomena. Zipf (1949) suggested that city size follows a log-linear distribution with a slope of -1. Zipf's law is most easily observed by plotting the data on a log–log graph with the axes' of log rank order and log frequency. Brynjolfsson et al. (2003) fitted data on sales and sales rank to a log-linear Pareto distribution. The ordinary least square (OLS) regression of logsales on log-rank was suggested by Madeline Schnapp of O'Reilly Books, who reported excellent success estimating competitors' unit book sales by comparing the competitors' log sales ranks to O'Reilly's. Chevalier and Goolsbee (2003) also fit sales and sales rank data to a slightly different log-linear distribution with good success. Chen (2009) fit downloads and download ranking data for a popular application to a regression of log-popularity (downloads) on rank. Recently, Brynjolfsson et al. (2010) surveyed the long tail and measured it in three different ways: the absolute long tail, measuring the absolute number of products sold [Brynjolfsson et al. 2003], the relative long tail, focusing on the relative share of sales above or below a certain rank with the 80/20 rule [Brynjolfsson et al. 2011], and the ordinal rank to cardinal sales relationship, following a power law distribution, the exponent of which indicates the relative importance of the head versus the tail of the sales distribution. The most frequently used method is the slope of the log-linear relationship between rank and sales [Brynjolfsson et al. 2010].

2.2 Ranking mechanisms

Feng et al. (2007) determined that the positive correlation between top placement and increased traffic creates significant demand among businesses for top placement on search engines, especially for popular and commercially relevant search terms. Edelman and Ostrovsky (2007) also determined that search engines rank advertisements based on expected revenue, which is the product of expected clicks and price. Wu and Huberman (2008) explored three ranking rules for dynamic aggregation websites. They are novelty, popularity, and expected clicks. The last is defined as the product of past popularity and a novel decay factor, a ranking mechanism that maximizes clicks over time. They found that the best click-maximizing ranking rule depends heavily on the decay rate of novelty. Chen (2009) modeled a ranking mechanism based on popularity and revenue, including application price, quality, and ranking, by arranging different revenue-maximizing ranking rules: sponsored search based on revenue, dynamic websites based on popularity and novelty, and app stores based on popularity and revenue. Breese et al. (1998) confirmed that the exponential decay of attention is a relatively standard assumptions, while Feng et al. (2007) computed the expected number of click throughs for an item in a particular position using an exponentially - decaying attention model. For example, actual click-through data obtained from Overtune for the top five positions across all affiliates (i.e. Yahoo!, MSN and AltaVista, etc.) during 2003 fit an exponential decay model well.

The prior studies on estimated sales of ranked items and ranking mechanisms provide a practical framework to develop the new ranking mechanism because we employ power law distribution and exponential decay model in order to build a clear correlation between the demand of ranked music item and popularity, pricing policy and slot effect. I try to apply the prior studies to the new ranking mechanism more appropriate to online music charts.

3. Ranking model

This paper applies and extends existing ranking mechanisms to reflect online users' preference for popularity and the slot effect on music charts available through the online music distribution industry. The total effects that affect demand for streaming and download volumes are defined in Fig. 1, which shows that the exponential decrease of streaming volumes and download volumes appears specifically in a ranking-range of

1st–100th. This decrease corresponds to the exponential decay of attention assumed by Breese et al. (1998). It represents a slot effect pertinent to the exponential decay of attention and popularity based on the bandwagon effect and the ranking effect.

The massive disparity between the amounts in the two services in the same ranking range indicates that a relative value of each service volume should be estimated differently as the ranking range goes farther up or down. Online music providers usually employ a business model that includes a single-item downloading service (pu) and a subscription service (ps) for the distribution of digital music. The pricing (pu) for single downloading and (ps) for limited downloading and unlimited streaming is responsible for the massive disparity in a ranking-range of 1st–100th. The new model follows the ranking rules of online music distributors and the two service volumes in response to popularity, pricing policy, and the slot effect. Thus, this study determines how demand for the two volumes reflects popularity and the slot effect and which ranking mechanism provides the more valuable ranking information service to customers. As it provides a more valuable ranking information service, the service maximizes the benefit for the online music distributers.

3.1 Ranking application

The ranking of each song (r) includes the demand for streaming volumes (s) and downloaded volumes (d). The streaming counts of a song are calculated using the number of streaming plays by online music listeners, while the download counts are calculated using the number of downloads by online music downloaders. A ranking is a pair (s,d) composed of a song's demand for streaming volumes and demand for download volumes. The value of one streaming volume is not usually equal to the value of one download volume, as the value of a download is regarded as much greater than that of a streaming play in a high ranking range. I further note that the value difference decreases as the ranking range falls, since a download is more valuable than a streaming play in terms of revenue. The more download volumes increase, the more revenue increases.

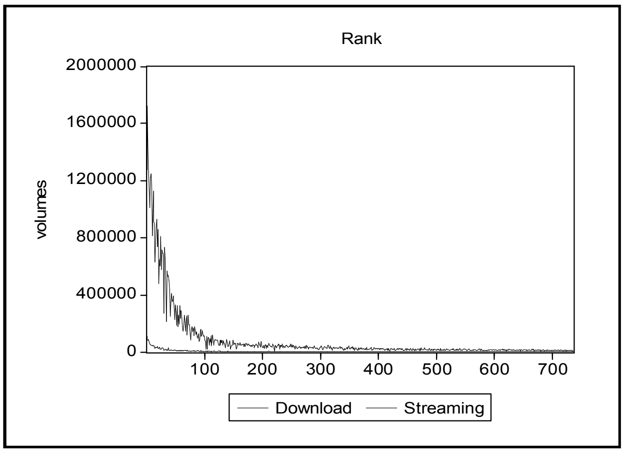


Figure 1. Streaming and download volumes by rank-order of 737 music IDs, July 7- August 13, 2009

In addition, low download volumes are scarcer than low streaming volumes. Therefore, the ranking of each song (r) is composed of adjusted streaming volumes (αs) and adjusted download volumes (βd). The value parameter of a streaming play is $(\alpha \approx 1)$, and the value parameter of a download is $(\beta \approx \sigma \frac{s}{d})$.

The summation of the relative ratios (α, β) is $(\approx 1 + \sigma \frac{s}{d}; \sigma > 1)$, and (σ) is a weight-coefficient for downloads. Online music distributors have a ranking rule that puts most of the weight on downloads. They assign a ranking to each song on the basis of $(\frac{\alpha s}{\alpha s + \beta d} : \frac{\beta d}{\alpha s + \beta d})$. The streaming volumes of a song are easily affected by popularity (θ), resulting in a demand for streaming volumes $s = s(\theta)$. The demand for streaming volumes is convexly increasing in popularity, that is, $\frac{\partial}{\partial\theta}s(\theta) > 0$ and $\frac{\partial^2}{\partial\theta^2}s(\theta) > 0$. Download volumes $d = d(\theta)$ are also easily affected by popularity, and the demand of download volumes is increasing in popularity—that is, $\frac{\partial}{\partial\theta}d(\theta) > 0$—and the marginal demand is positive; that is, $\frac{\partial^2}{\partial\theta^2}d(\theta) > 0$.

From an economic perspective, the bandwagon effect is an observed social behavior in which people tend to go along with what others think without considering their own preferences [Leibenstein1950]. The effect is greatly increased as people adopt an idea or a behavior, so it leads to herd behavior. The bandwagon effect is one among a large group of cognitive biases. Biases are behaviors based on memory and statistical and social attribution errors. Classic examples of the bandwagon effect occur when people decide to join a social networking site or listen to the same musical group. A previous study has indicated that the demand for digital content is correlated with the relative sales ranking and pricing policy and the sales ranking is likely to stimulate the herd instinct [Chevalier and Goolsbee 2003].

In business, the bandwagon effect can be dangerous because it disturbs the theory of supply and demand pertinent to content pricing and individual preference [Leibenstein 1950]. However, it can be an important phenomenon for the demand for digital content based on intensive popularity in my study. For example, as Fig. 1 shows, the exponential decrease of streaming volumes and download volumes appears specifically in a ranking-range of 1st–100th, suggesting that people's preference for high-ranked music increases as the number of people streaming and downloading the music increases. This consideration leads to following hypothesis:

Hypothesis 1 (The Bandwagon Effect Hypothesis). Ranking is positively correlated with popularity in the highest-ranking range.

Subscription fees and single-item pricing is assumed to be identical across all songs. In the case of streaming, each song bears a subscription fee (p_s) but the streaming volumes of a song are not easily affected by the fee. With a subscription fee, each song is played an unlimited number of times in real time for a set period, $s = s(p_s)$ resulting in an increase of streaming volumes, $\frac{\partial}{\partial p_s} s(p_s) > 0$. The download volume of a song is not easily affected by a subscription fee (p_s) but is easily affected by a single-unit price (p_u). Each song can be downloaded up to an allocated volume with a subscription fee, but it tends to be downloaded less often than the allocated volumes for a set period, $d = d(p_s, p_u)$ so the download volumes decrease as the single-unit price increases, resulting in increase in download volumes under a subscription fee $\frac{\partial}{\partial p_s} d(p_s) > 0$ but a decrease in the single-unit price $\frac{\partial}{\partial p_u} d(p_u) < 0$.

Once a subscription fee is paid, it is a sunk cost so digital music listeners are not concerned about additional charges for listening to music for a set period. Users can download their preferences up to the allocated volumes during a given period while other users have to pay a single-unit price per download.

A music contributor usually manages two business models: a subscription-fee model and a single-download model. The subscription- fee model provides unlimited streaming services to customers during a contract period, and this model may be beneficial for music content customers if the business model forces the music distributor to improve its music distributing service. Based on this idea, if customers are not satisfied with the service, they can simply leave the subscription and find another music service when they renew their subscription. Generally, the effective use of a single download or streaming increases with the most preferred music. However, unlimited streaming service in a contract period cannot be used as effectively as a single download or streaming when considering the most preferred music. This consideration leads to the following hypothesis:

Hypothesis 2 (The Pricing Policy Hypothesis). The ranking of streamed songs is positively correlated with a subscription fee model in the highest-ranking range. However, the ranking of downloaded songs is even more positively correlated with a single unit price model in the highest-ranking range.

3.2 Ranking function

Digital music distributors assign a ranking to each song based on the demand for two different services. Each service value is weight-adjusted based on the number of streams and downloads. There may be other parameters, such as the age the music and the artist's reputation. In reality, demand for low-ranked songs is likely to be affected by the other parameters. However, this model concentrates on a mixture of stream and downloaded volumes as two key factors that affect a ranking score. In particular, the online music distributors assign a ranking score to each song and then display its rank on online music charts every day and every week.

The demand $D_i = D_i(s_i, d_i)$ for a given song (i) is a function of its streaming volume (s_i) and download volume (d_i). The demand (D_i) is the expected volumes that song (i) would receive if it were in particular ranking places, such as $1^{st} \sim 5^{th}$, $6^{th} \sim 20^{th}$, $21^{st} \sim 50^{th}$, and $51^{st} \sim 100^{th}$[2]. The expected volumes are scaled down by the slot effect. The

[2] The slot size is dependent on the ranked lists displayed on a laptop screen. The detailed

demand (D_i) increases as popularity (θ_i) increases, that is, $\frac{\partial}{\partial \theta_i} D_i(s_i(\theta_i, p_s), d_i(\theta_i, p_s, p_u)) > 0$, and (D_i) increases as the subscription fee (p_s) increases, that is, $\frac{\partial}{\partial p_s} D_i(s_i(\theta_i, p_s), d_i(\theta_i, p_s, p_u)) > 0$, but (D_i) decreases as the single-unit price (p_u) increases, that is, $\frac{\partial}{\partial p_u} D_i(s_i(\theta_i, p_s), d_i(\theta_i, p_s, p_u)) < 0$. There are no substitutive or complementary relationships between songs, so the demand function is $D_i(s_i(\theta_i, p_s), d_i(\theta_i, p_s, p_u))$.

The ranking of a song based on the demand for streaming volumes and downloads is as follows. The ranking function is $r_i(s_i, d_i) = D_i(\alpha s_i, \beta d_i) = D_i(\alpha s_i(\theta_i, p_s), \beta d_i(\theta_i, p_s, p_u))$. Let (r_i) be a song (i)'s rank, which is based on its score relative to other scores. The parameters (α, β) are assumed to be identical across all songs in a sectionalized ranking range, such as, 1st ~ 5th, 6th ~ 20th, 21st ~ 50th, and 51st ~ 100th. The parameters allow digital music distributors to adjust the total scores based on rank scores of streaming volumes and rank scores of download volumes. That is, (α) is a parameter that represents the relative value of streaming volumes compared with the value of download volumes. (β) is a parameter that represents the relative value of download volumes compared with the value of streaming volumes. For a simple example, if a song has 390 streaming plays and 30 downloads for a ranking estimation period, and the value (α) is 1 and the value (β) is 17 $(\approx 1.3 \times \frac{390}{30}; \sigma = 1.3)$, the total score of the song is $(900 = 1 * 390 + 17 * 30)$. The value of download volumes (510) is adjusted compared with the value of streaming volumes (390) in this case. I will explore the conditions under which online music distributors would prefer certain value of (σ) in future work.

description is given in section 3.3.

3.3 The slot effect

Most songs receive a ranking that is displayed in a ranking slot, which is a limited space on the screen. The ranking of a song can be affected by the slot effect, particularly in high-ranking slots. The slot effect is a phenomenon in which users are less likely to listen or download a song that is farther down in the ranking since they need to expend more effort to scroll down to see the song [Chen 2009]. To amplify ranking slots, the online music distributor has the ranking chart of 1st ~ 5th on the main page, and user can expand the chart to 1st ~ 20th by clicking an expansion icon. The online music chart displays every fifty popular songs on a sectionalized web page. Users capture roughly twenty songs at a time by scrolling down on a wide screen. Therefore, the slots for the 1st ~ 50th songs are approximately categorized into 1st ~ 5th, 6th ~ 20th, and 21st ~ 50th. The slot effect is largely downsized as the ranking category goes down farther after 50th rank. In the literature, the slot effect (ρ) has often been modeled using the exponential decay model, where the click-through rate of slot (j) is decreased by a factor of $\rho(j) = \frac{1}{\varphi^{j-1}}$ for $\varphi > 1$ [Feng et al. 2007]. In this paper, the slot effect (ρ) multiplicatively scales down the demand (D), so the demand for a song (i) in slots ($\phi^{j=1}$: 1st ~ 5th), ($\phi^{j=2}$:6th ~ 20th), ($\phi^{j=3}$:21st ~ 50th), ($\phi^{j=4}$:51st ~ 100th), ($\phi^{j=\infty}$:101th~), is $D_i(\alpha s_i(\theta_i, p_s), \beta d_i(\theta_i, p_s, p_u))\rho(\phi_i^j)$.

3.3.1 Slot mechanism design

I next propose a heuristic method for slot mechanism design. I use the principles of effort reduction and simplification. This is because heuristics allow decision-makers to process information using less effort than one would expect from an optimal decision rule [Shah and Oppenheimer 2008].

The relative share of downloaded music items above or below a certain rank is explained in the Gini coefficient. This is an example of the classic Pareto principle that 20% of the products often generate 80% of the sales [Brynjolfsson et al. 2010]. In general, the Pareto distribution is a standard distribution assumption for the type of ranking data that we use [Chevalier and Goolsbee 2003]. In this study, the probability distribution of downloaded volumes according to ranking fits the Pareto distribution well.

The graphs in Fig. 2 illustrate download volumes against rank from Week 1 to Week 4. The vertical axis is download volumes of ranked music, and the horizontal axis is the rank number from 1 to a certain number, implying a long tail distribution. The graphs show that a Pareto distribution clearly appears.

Table 1 indicates the Pareto principle, the 80/20 rule, which says that the top 20% control 80% of total download volumes. Fig. 2 and Table 1 illustrate that the upper 20% of ranked music items generates the most download sales.

Fig. 3 shows slot mechanism design in a heuristic way. The mechanism follows the 80/20 rule of the Pareto distribution because the distribution fits well for music download volumes against ranking. The key idea for identifying slot ranges is to compare the marginal slope of a unit rank with the average slope of the upper 20% ranking slots. The optimal range and number of slot can be found as follows.

1. Find an average slope between rank 1 and the marginal rank $r_{0.2N}$ of the upper 20 percent.
2. Find the rank r_i^* that has a marginal increase of download volumes that is the same as the average slope.
3. Find an average slope between rank 1 and the rank r_i^*, and find r_i^{**}

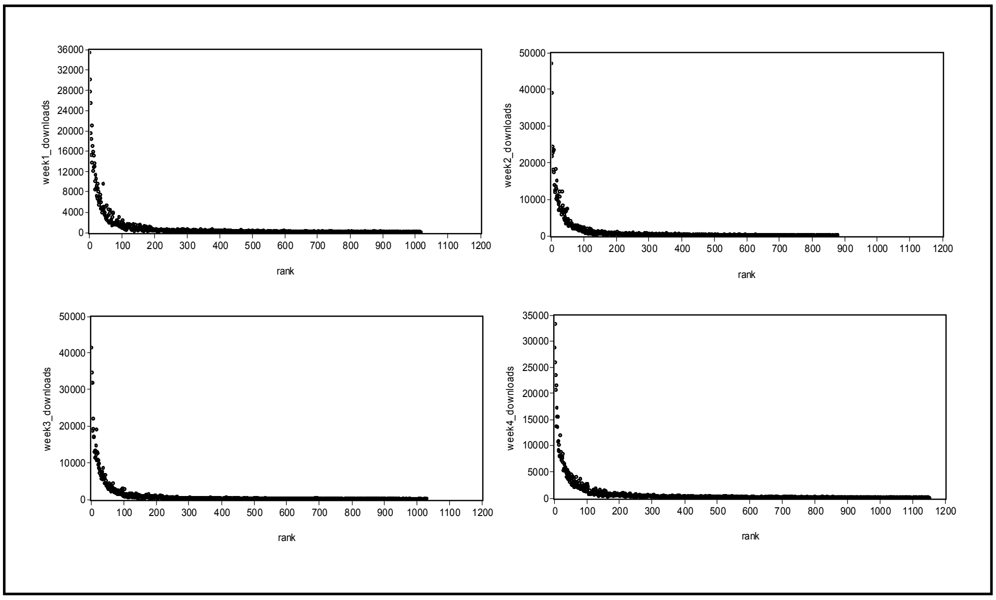


Figure 2: Points demonstrating download volumes against rank, July 15 - August 13, 2009

Table 1: Weekly download volumes and ranking range, July 15 – August 8, 2009

Weekly downloads	Week1	Week2	Week3	Week4
Upper 20% of downloads	737,522(79%)	778,942(79%)	791,448(79%)	711,572(78%)
Lower 80% of downloads	197,023(21%)	203,054(21%)	209,233(21%)	201,068(22%)
Total downloads	934,545	981,996	100,0681	912,640
Ranking range	$1^{st} \sim 1018^{th}$	$1^{st} \sim 885^{th}$	$1^{st} \sim 1029^{th}$	$1^{st} \sim 1153^{th}$

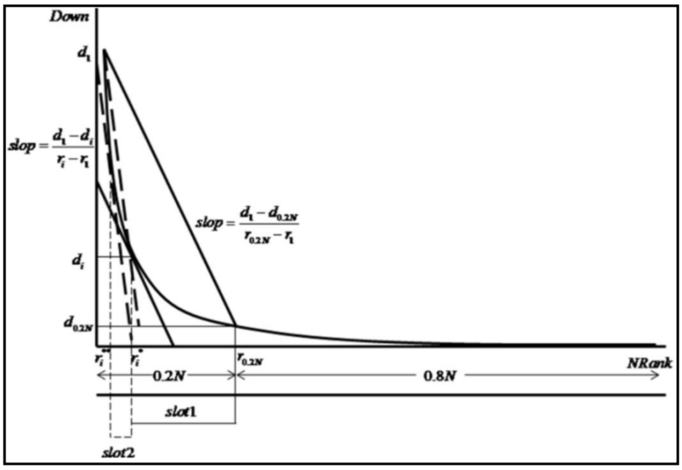


Figure 3: Pareto distribution and geometric slot range

According to its mathematical definition, the Pareto's density function has two primary parameters, shape and location. Therefore, if r_i is the Pareto distribution, the probability density function [Asath 2004] is $p(r_i) = \frac{shape}{location}(\frac{location}{r_i})^{(shape+1)}$, $p(r_i) = \frac{shape.location^{shape}}{r_i^{(shape+1)}}$, $p(r_i) = \frac{\alpha.\beta^{\alpha}}{r_i^{(\alpha+1)}}$ when the shape is (α) and the location is (β).

The location parameter sets the position of the left edge of the probability density, and the shape parameter determines the steepness of the slope. The average slope of the upper 20 percent of download volumes against rank is

is $$\left|\frac{p(r_1) - p(r_{0.2N})}{\frac{r_{0.2N}}{N} - \frac{r_1}{N}}\right| = \left|\frac{\alpha\beta^{\alpha}\left(\frac{1}{(\frac{1}{N})^{\alpha+1}} - \frac{1}{(0.2N)^{\alpha+1}}\right)}{0.2 - \frac{1}{N}}\right|$$

The marginal increase of download volumes of a certain rank r_i^* is

$$\left|\frac{\partial p(r_i^*)}{\partial r_i^*}\right| = \left|-\frac{\alpha\beta^{\alpha}(\alpha+1)}{(\frac{r_i^*}{N})^{\alpha+2}}\right|,$$

resulting in

$$r_i^* = N[(\frac{(0.2N)^{\alpha+1}(\alpha+1)}{(0.2N^2)^{\alpha+1}-1})^{\frac{1}{\alpha+2}}]$$

`in the range of $1 < r_i^* < 0.2N$. Thus, the first slot is $r_i^* \sim 0.2N$. In the same pattern, the average slope of between r_1 and r_i^* is

$$\left|\frac{p(r_1)-p(r_i^*)}{\frac{r_i^*}{N}-\frac{r_1}{N}}\right| = \left|\frac{\alpha\beta^{\alpha}(\frac{1}{(\frac{1}{N})^{\alpha+1}}-\frac{1}{(r_i^*)^{\alpha+1}})}{\frac{r_i^*}{N}-\frac{1}{N}}\right|.$$

The marginal increase of a certain rank r_i^{**} is

$$\left|\frac{\partial p(r_i^{**})}{\partial r_i^{**}}\right| = \left|-\frac{\alpha\beta^{\alpha}(\alpha+1)}{(\frac{r_i^{**}}{N})^{\alpha+2}}\right|,$$

resulting in

$$r_i^{**} = N[(\frac{(r_i^*)^{\alpha+1}(\alpha+1)}{(r_i^{*2})^{\alpha+1}-1)})^{\frac{1}{\alpha+2}}]$$

in the range of $1 < r_i^{**} < r_i^*$. Thus, the second slot is $r_i^{**} \sim r_i^*$.

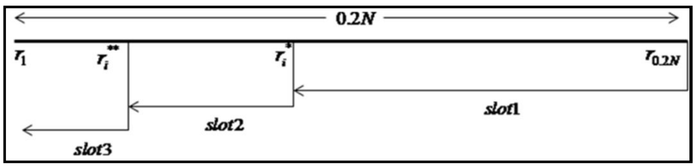
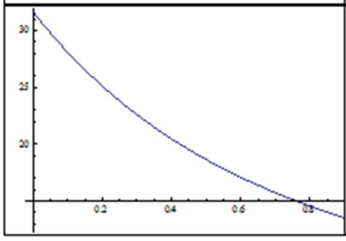
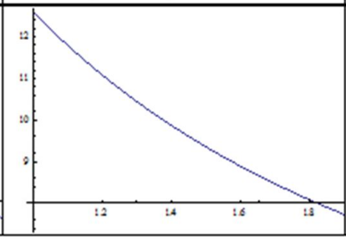
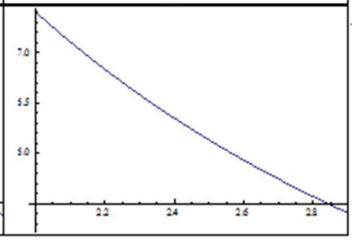


Figure 4. Slot schematization procedure

The slot can be represented as in Fig. 4. The slot range decreases as the rank approaches the highest rank.

Table 2. The rank r_i^* depending on the shape parameter (α)

Shape range (α: 0 ~ 1)	Shape range (α: 1 ~ 2)	Shape range (α: 2 ~ 3)
		

In table 2, X-axis represents a certain ranking number r_i, specifically r_i^* identifying slot1 in figure 4 and Y-axis shows a shape of Pareto probability density function. Each graph illustrates that r_i^* varies depending on the value of shape parameter. For example, r_i^* is about 31 when the shape parameter gets close to 0, while r_i^* is around 12 when the shape parameter approaches to 1 in a ranking range of 1st ~ 1,000th. The results show that increasing steepness of the slope decreases the first slot range. The slot range and certain ranking numbers vary depending on the shape (α) and ranking range (N).

In this slot mechanism design, I represent the concept of slot design and introduce some math to represent it. From a practical point of view, slots displaying ranking information can be represented based on screen size (e.g., notebooks, smartphone, tablet PC, PDP, etc.).

Anderson (2004) showed that attention is the cognitive process of selectively concentrating on one aspect of the environment while ignoring other factors. In cognitive psychology, visual attention is a two-stage process. In the first stage, attention is distributed uniformly over the external visual scene, and processing of information is performed in parallel, where it is concentrated on a specific area of the visual scene and processing of information is performed in a serial fashion. In the second stage, Castiello and Umilta (1990) introduced the size-change mechanism, which discusses how any change in size can be described by a trade-off in the efficiency of processing. It follows that the larger the focus, the slower the processing of that region of the visual scene will be.

The size-change mechanism can be applied to the exponential decay of attention on the region of the visual ranking chart. In a broad interpretation of the size-change mechanism, a characteristic of the music-ranking chart can be the existence of a slot effect that captures the phenomenon in which users are less likely to download an application that is farther down in the rankings because they need to expand more effort to scroll down to see this application [Chen 2009]. For example, the effect is amplified on a music-ranking chart that is approximately categorized into 1st– 5th, 6th–20th, and 21st–50th. This consideration leads to the following hypothesis.

Hypothesis 3 (The Slot Effect Hypothesis). High rankings are positively correlated with the slot effect, while low rankings are not positively correlated with the slot effect.

4. The empirical study

4.1. Overview of findings about online music distributors

The Korean music market exhibits monopolistic competition. Several music service providers distribute only slightly differentiated music content. In economic theory, monopolistic competitive music channels experience a downward-sloping demand curve because market power is driven by distributing differentiated music goods over a short period. Generally, the price elasticity in monopolistic competition is greater than that in monopolistic or oligopolistic competition because several substitutes exist [Varian 1992]. Ranking charts in monopolistic competition music markets are important to differentiate music distribution services. A ranking chart uses a mechanism that reflects information about customer's preferences and a mechanism that delivers information about the company's preference.

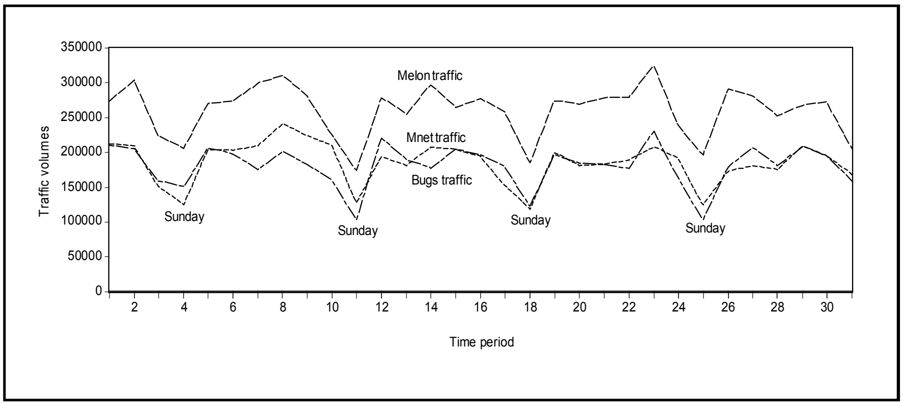


Figure 5. Daily traffic volume[3] of Melon, Bugs, and Mnet, July 7 – August 8, 2009

Fig. 5 shows one-month traffic volumes from the three most popular music distributors in Korea: Melon, Bugs, and Mnet. The Sunday effect clearly appears, traffic volume increases from Monday to Friday and significantly decreases on Saturday and Sunday, suggesting that most people enjoy music service through music devices at their workplaces or at home during weekdays but through business-to-business (B2B) music channels, such as cafeterias and public music places, during weekends. As Fig. 5 illustrates, the three traffic volumes move together in a similar pattern over time. Specifically, Melon's traffic pattern is clearly analogous to Mnet's and Bugs's pattern, suggesting that there must be a relationship among three music distributors' patterns.

The usual properties of the least squares estimator in a regression using time-series data depend on the assumption that the time series variable involves a stationary stochastic process. Therefore, I exercise a unit root test to measure the stationarity of the

[3] http// www.rankey.com

three time series' traffic volumes. Using E-views software, I apply the augmented Dickey–Fuller test.

Online music distributor	Melon	Bugs	Mnet
Stationarity	Non-stationary	Stationary	Stationary

The test result shows that Melon's traffic volume is not stationary, while the other two traffic volumes are stationary. In general, non-stationary data are unpredictable and cannot be modeled or forecasted because means, variances and co-variances change over time. The results obtained by using non-stationary time series may be spurious in that they may indicate a relationship between two variables where one does not exist. Thus, I did the analysis with Bugs and Mnet data, which are stationary and similar to Melon's traffic pattern.

Autoregressive (AR) models are often well-suited for modeling time-series data. The traffic volumes of Bugs and Mnet today also should be affected by their traffic volumes yesterday. A moving average (MA) model can also be a good model for time-series data for the same reason. The mixed ARMA is usually applied to model time series data. I set up four models and chose the best model based on the smallest values of the Akaike information criterion and the Schwarz criterion. The best model for Bugs and Mnet are ARMA, Model 4.

Log(Bugs)	AR(1)	MA(1)	ARMA(1)	ARMA(1)
Constant coefficient				12.07^{***}
AR(1) coefficient	0.99^{***}		0.99^{***}	0.41^{***}
MA(1) coefficient		0.95^{***}	-0.96^{***}	-1.51^{***}
Akaike info criterion	0.28	6.55	-0.32	-1.24
Schwarz criterion	0.33	6.59	-0.23	-1.10
$^{***}p<.01$, $^{**}p<.05$, $^{*}p<.1$				

Log(Mnet)	AR(1)	MA(1)	ARMA(1)	ARMA(1)
Constant coefficient				12.10^{***}
AR(1) coefficient	0.99^{***}		0.99^{***}	-0.68^{***}
MA(1) coefficient		0.95^{***}	-0.99^{***}	0.96^{***}
Akaike info criterion	-0.01	6.55	-0.44	-0.54
Schwarz criterion	0.03	6.60	-0.35	-0.39
$^{***}p<.01$, $^{**}p<.05$, $^{*}p<.1$				

The results indicate that Bugs' previous traffic volumes positively influence its current traffic volumes while Mnet's previous traffic volumes negatively influence its current traffic volumes. However, Bugs' average traffic volumes decrease slightly as time passes, while Mnet's average traffic volumes increase slightly. Melon and Mnet are music service distributors that are based on mobile carriers, while Bugs is a music distributor based on point of contact (POC). The results suggest that there is slightly a substitutive relationship between mobile-carrier-based music distributors and POC-based music distributors, and that the mobile carrier base has advantages compared with the POC base. This result reflects the social trend that emphasizes the mobility of Internet music. Generally, a one-variable ARMA model cannot measure the differences in impulse response between different time-series variables, so I use the vector-autoregressive (VAR) test. I used the E-views software, and applied the unrestricted VAR test (see Fig. 6).

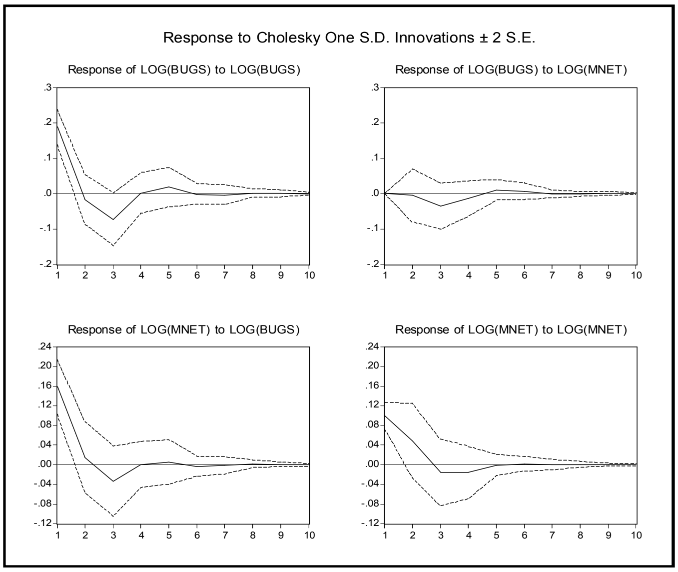


Figure 6. Impulse response between log(Bugs) and log(Mnet)

The result shows that Bugs' traffic volumes significantly influence Mnet's traffic volumes for one day, while the Mnet does not influence Bugs. This result indicates that ranking information in a differentiated music service is important in a monopolistic music

4.2. Data

This paper introduces a new ranking model to reflect the degree to which popularity is associated with the bandwagon effect [Leibenstein 1950], the ranking effect [Spoerri 2008], and the slot effect [Chen 2009]. The bandwagon effect is clearly observed at high ranked slots even though the herd instinct disturbs the theory of supply and demand based on price and personal preference. The slot effect is also observed in high ranked slots.

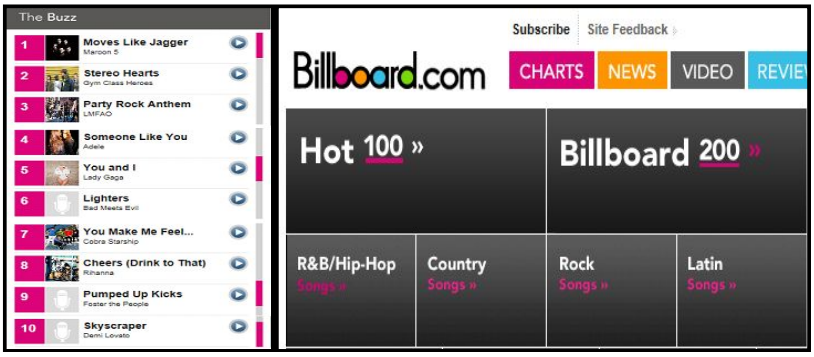


Figure 7. Home page of a music website with ranking information

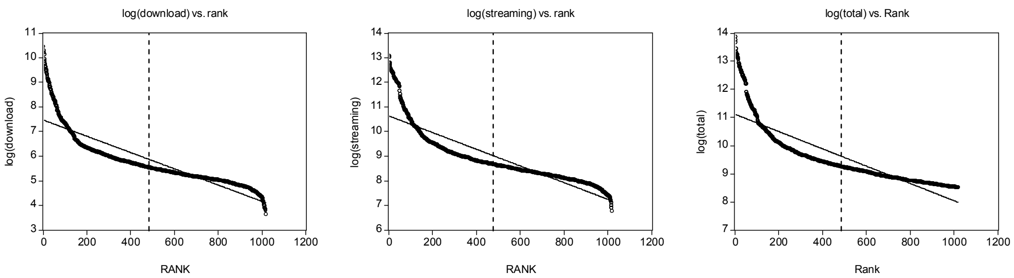
When a user opens the home page of an online music website, she can see a chart of the 1st–10th ranking in the middle of the screen, as shown in Fig. 7. She can then link to other charts by category, such as the ‘‘Hot 100’’ and ‘‘Billboard 200’’ rankings, by clicking an icon on the music chart.

The raw data for my analysis were obtained from one of major music distributors in Korea. The ranking chart data were gathered from July 15, 2009 to August 13, 2009. The gathered data were classified into streaming log files, download history files, and weekly ranking charts. Available data, including login identification (ID), streaming-length, track-id, and track-length were extracted by using structured query language (SQL) from streaming log files. Data such as login-id, subscription-base purchasing, and single unit price-base purchasing were extracted from download history files. Data like music-id, streaming volumes, and download volumes were acquired from weekly ranking charts. The streaming log files provide useful information concerning what song was played, how many times it was played, and by whom it was played in a day. The download history files show who downloaded songs using a subscription fee and who downloaded them using a single unit price. A weekly chart shows that song rankings and how many streaming and downloads volumes each song received in a week. The raw data illustrates how the existing ranking mechanism reflects value measurements for streaming and downloading in relevant ranking services. The following section describes the general features of online music charts and estimates a tight correlation among log (popularity), ranking, and the slot effect to propose a new ranking model.

5. Data analysis and results

5.1. The general analysis of ranking and popularity

This section presents summary statistics for overall volumes of downloads and streaming by an online music provider. Fig. 8 provides graphs of regression lines and scatter plots of the natural logarithm of popularity (download volumes, streaming volumes, and adjusted total volumes) against rank.



(a) log (download) vs. Rank (b) log (streaming) vs. Rank (c) log (total) vs. Rank

Figure 8. Points demonstrating the relationship between log (popularity) and rank

Table 3: Download & streaming volumes and ranking for music-id, and a weekly music chart, July 23, 2009

Rank	Download	Adjusted Rank	Rank	Stream	Adjusted Rank	Total Rank	Adjusted Total
1	**35,408**	1	1	479,763	2	**1**	**106,2278**
2	30,140	3	**2**	**460,342**	1	2	950,782
5	21,046	8	5	357,014	5	5	690,554
6	19,620	5	6	335,015	9	6	621,541
10	15,301	6	10	266,773	4	10	555,243
11	15,161	13	11	266,090	18	11	523,490
1017	45	708	1017	1,013	805	1017	5,011
1018	38	1016	1018	878	875	1018	5,011

$$AdjustedTotal = c + \alpha(\text{Streaming}) + \beta(Download) + \varepsilon$$

Table 4. OLS test results of Adjusted Total against Streaming and Download

Variable	adjusted total
C	455.4281^{***} (36.87642)
Streaming	$\mathbf{0.995890}^{***}$ **(0.001702)**
Download	$\mathbf{17.04846}^{***}$ **(0.031360)**
R^2	0.999872
N	1018 (1^{st}~1018^{th})
$^{***}p<.001$, Standard errors are in parentheses	

Tables 3 and 4 indicate that, in a weekly music chart, the ranking of a song is assigned according to the adjusted total. The adjusted total is calculated by the weight-adjusted volumes of two services, that is, (Download value: 35408 ⁄ 17: 57%) + (Streaming value: 460342 ⁄ 1: 43%) = (Total value: 1062278: 100%). As a result, the rank of download and streaming is changed into the adjusted rank of download and streaming. The data, gathered for 1018 music-ids during the fourth week of July 2009, provide a robust basis for correlating log (popularity) and rank. The variation rates range from 10.5 to 3.6 for log (download), from 13 to 7 for log (streaming), and from 14 to 8.5 for log (mixed volumes). Rank ranges from 1 to 1018. Summary statistics are shown in Table 5.

Table 5. Summary statistics for log (popularity) and rank data

	Rank	log (down-popularity)	log (str-popularity)	log (total-popularity)
Mean	509.5000	5.785148	8.907927	9.547935
Median	509.5000	5.497168	8.617762	9.221972
Maximum	1018.000	**10.47469**	**13.08105**	**13.87593**
Minimum	1.000000	**3.637586**	**6.777647**	**8.519391**
Std. Dev.	294.0156	1.097527	1.118532	1.047553
Observations	1018	1018	1018	1018

Table 6 shows the regression of log (popularity) on rank.

$$\log(popularity) = \varphi_1 + \varphi_2 Rank + \varepsilon$$

Table 6. Ordinary least square test results of log (popularity) against rank

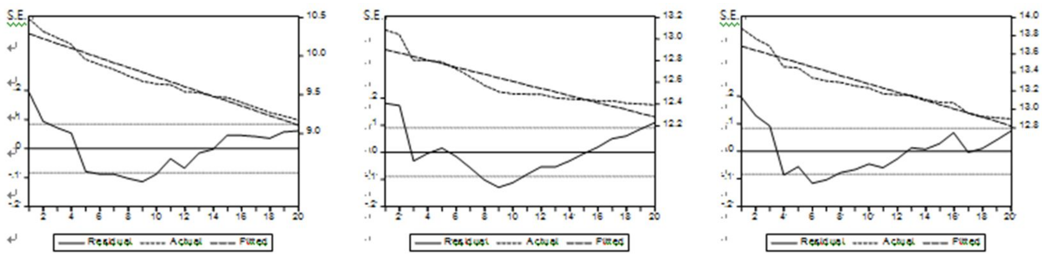
Variable	log(down-popularity)	log(str-popularity)	log(total-popularity)
Rank	-0.003303^{***} (5.45E-05)	-0.003391^{***} (5.41E-05)	-0.003077^{***} (5.64E-05)
C	7.468270^{***} (0.032075)	10.63541^{***} (0.031839)	11.11563^{***} (0.033148)
R^2	0.783164	0.794300	0.745801
N	1018 (1^{st}~1018^{th})	1018 (1^{st}~1018^{th})	1018 (1^{st}~1018^{th})
$^{***}p<.001$, Standard errors are in parentheses			

The dependent variables are log (down-popularity), log (str-popularity), and log (total-popularity). The coefficient -0.3% on each rank is the percentage change in popularity for a unit increase in ranking (i.e., from rank 1 to rank 2). That is, if the ranking of one song drops by 1, its expected popularity will decrease by 0.3%. Every coefficient is significant at the 99% level. Ranking is an important facet of predicting popularity. The R2 value of log (down-popularity) and log (str-popularity) shows that rank alone explains around 78% of the variation in the log (popularity), while the R2 value of log (total-popularity) shows that rank alone explains around 74.5% of the variation.

The power of effect size was reduced slightly after the two services were combined. Fig. 8 shows a large variance between regression lines and scatter plots in a ranking-range of 1st–100th, suggesting that there must be a factor that affects the large variance. The large variance shows the bandwagon effect and the slot effect.

5.2. Analysis of Hypotheses 1 and 2

I sorted the ranking range into several slots in order to analyze the popularity and slot effect. The main page has a ranking slot of 1st–5th and can be extended to 1st–20th by clicking an expansion icon. In general, users can capture roughly twenty songs on a widescreen of laptop by scrolling down at a time. The slot effect is largely reduced as the ranking goes down in the proposed ranking segmentations, as Fig. 8 illustrates. Fig. 9 shows graphs of the residual plots of the natural logarithm of popularity (download volumes, streaming volume, and adjusted total volumes) against rank of 1st–20th.



(a) log (download: 1st~20th) (b) log (streaming: 1st~20th) (c) log (total: 1st~20th)

Figure 9. Residual points between log (popularity) and rank

Table 7. OLS test results of log (popularity) against rank in sectionalized slots (not adjusted)

Variable	log(downpopularity)	log(strpopularity)	log(totalpopularity)
Rank (1^{st}~5^{th}) (R^2)	-0.120497^{***} (97%)	**-0.083295^{**}** **(81%)**	-0.116552^{***} (95%)
Rank (6^{th}~20^{th}) (R^2)	-0.048182^{***} (99%)	**-0.019011^{***}** **(81%)**	-0.033186^{***} (98%)
Rank (21^{st}~50^{th}) (R^2)	-0.030709^{***} (98%)	-0.015610^{***} (93%)	-0.020096^{***} (98%)
Rank (51^{st}~100^{th}) (R^2)	-0.019881^{***} (95%)	-0.019131^{***} (98%)	-0.017783^{***} (95%)
Rank (101^{st}~150^{th}) (R^2)	-0.013399^{***} (98%)	-0.010879^{***} (97%)	-0.008719^{***} (93%)
$^{***}p<.01$, $^{**}p<.05$, $^{*}p<.1$, R-squared are in parentheses			

Table 7 illustrates log (popularity) on rank in sectionalized slots. The R^2 value of log (str-popularity) on rank is 81% in a ranking range of 1st–20th, and the coefficient of rank (1st–5th) is significant at the 5% level. A subscription fee model suggests the low R^2 value of log (str-popularity) because the streaming service is used unlimitedly with a subscription fee. On the other hand, the R2 value of log (down-popularity) maintains a high value of more than 96%, which comes from limited downloading service. This result validates Hypothesis 2. The coefficient values represent the intensive popularity in high-ranking slots, that is, the coefficient -12% of log (down-popularity), which indicates that a demand for download volumes is in a ranking range of 1st–5th, will increase up to 12% as the ranking of a song rises by 1. The R^2 value of log (str-popularity) and log (down-popularity) sustains at 95–99% in most ranking slots. Thus, Hypothesis 1 is supported. It is clear that ranking is the most important factor in predicting popularity. At the same time, a demand for streaming volumes in a high-ranking range is affected by a subscription fee.

Table 8. OLS test results of log (popularity) against rank in sectionalized slots (adjusted)

Variable	log(downpopularity)	log(strpopularity)	log(totalpopularity)
Rank (1^{st}~5^{th}) (R^2)	-0.126112** (83%)	-0.109528 (54%)	-0.116552*** (95%)
Rank (6^{th}~20^{th}) (R^2)	-0.049284*** (71%)	-0.018974** (37%)	-0.033186*** (98%)
Rank (21^{st}~50^{th}) (R^2)	-0.029325*** (63%)	-0.015580*** (41%)	-0.020096*** (98%)
Rank (51^{st}~100^{th}) (R^2)	-0.016564*** (43%)	-0.017858*** (47%)	-0.017783*** (95%)
Rank (101^{st}~150^{th}) (R^2)	-0.008947** (10%)	-0.010118*** (17%)	-0.008719*** (93%)
***p<.01, **p<.05, *p<.1, R-squared are in parentheses			

The R^2 value of log (total-popularity) maintains a high average of around 95% because of the ranking policy that assigns a ranking to each song on an adjusted value basis by artificial means without considering popularity, slot effect, or other factors. Under the ranking policy, Table 8 shows that the R^2 value of the adjusted log (str-popularity). It indicates that that rank alone explains 40–50% of the variation in the 1st–100th ranking slots. The R^2 value of the adjusted log (down-popularity) shows that rank alone explains 43– 83% of the variation in the 1st–100th ranking slots, but the R^2 value decreases sharply as rank drops. The above two tables illustrate that the ranking slot coefficient values are slightly different while the R^2 values are vastly different. This empirical result indicates that popularity predict the rankings or the rankings predicts the popularity in Table 7, while popularity might not predict ranking, but ranking might predict popularity in Table 8.

5.3. Analysis of Hypothesis 3 (Slot effect)

An important characteristic of online music charts is the slot effect due to the exponential decay of attention.

Table 9. Slot effects in sectionalized slots

Slot	ρ = 0.497	Download (average)	ρ = 0.7	Streaming (average)	ρ = 0.588	Total (average)
Slot 1 (1st~5th)	**$\rho^0 = 1$**	**27,688.600**	**$\rho^0 = 1$**	**385,437.4**	$\rho^0 = 1$	856,143.6
Slot 2 (6th~20th)	**ρ^1=0.497**	**13,778.467**	**ρ^1=0.700**	**269,808.5**	ρ^1=0.588	504,042.5
Slot 3 (21st~50th)	**ρ^2=0.222**	**6,161.367**	**ρ^2=0.449**	**173,361.0**	ρ^2=0.324	278,104.2
Slot 4 (51st~100th)	ρ^3=0.084	2,347.380	ρ^3=0.147	56,871.8	ρ^3=0.113	973,41.9
Slot 5 (101st~150th)	ρ^4=0.037	1,040.820	ρ^4=0.066	25,700.2	ρ^4=0.051	44,000.0

Table 9 shows that the slot effect is around $(\rho = 0.7)$ for streaming volumes, so the demand for streaming volumes in slot 1 is roughly $D = D(s(\theta, p_s), d(\theta, p_s, p_u))\rho(\phi^1_{1st\sim 5th})$; that is, $D * 0.7^0$. Demand in slot 2 is $D * 0.7^1$, and demand in slot 3 is $D * 0.7^2$. The slot effect is around ($\rho = 0.4976$) for demand for download volumes. The demand in slot 1 is roughly $D * 0.4976^0$, $D * 0.4976^1$ in slot 2, and $D * 0.4976^2$ in slot 3. The average demand for streaming and download volumes decreases exponentially as the ranking slot falls, so Hypothesis 3 is supported. This result corresponds to the exponential decay of attention assumed by Breese et al. (1998).

5.4. Possible applications of the new ranking mechanism

Digital content sales are directly proportional to their sales rank, top ranking slots are correlated with exponential decay of attention, and a subscription fee creates significant issues for online content business models with reference to the ranking mechanism. As I propose, the new ranking mechanism can be applied to other ranking services in a variety of online content categories and service environments. For example, online music distributors currently design and provide a one-stop service in which users can enjoy streaming service with smart phones on the wireless Internet. Smart phones' small screens display the top ten ranks, so the highest-ranked item has a considerable impact on streaming volumes with subscription fees. Thus, when determining the rank of each music item for real time, a daily chart, and a weekly chart, music content providers can assign their own music items to the limited ranking slots or can design the slot size in order to maximize their own benefit. That is, popularity and the slot effect in the ranking chart of smart phones can be maximized because each slot is clearly segmented when the user scrolls down.

The new mechanism can be applied to a real-time sudden rise in search words. For example, NAVER, the top portal site in Korea, provides a small slot displaying the ten most popular search words in real time. Each listed search word gains intensive visibility because of the bandwagon effect, not only is the word very popular, but the slot effect gives it significant concentration. Thus, a portal that uses a small slot to advertise or announce something commercial can be enormously beneficial. The slots should be regarded as a scarce resource that has to be carefully allocated.

A Korean online auction website, Auction.co.kr, lists the top hundred items in each content category based on rank scores by sales volume. However, the website initially shows only the five best items and fewer than ten recommendations in a price section. Thus, the ranking of each item in the same price section can be assigned by the proposed ranking mechanism, reflecting the bandwagon effect and the slot effect in the high-ranking range.

6. Conclusion

I examined the ranking mechanism in online music distribution and presented a new ranking mechanism in which online music distributors set pricing policy and respond to demand for download volumes and streaming volume with popularity. This is based on the bandwagon, ranking and slot effects. The key issue is to design a ranking mechanism as a communication system between online music providers and online users. Ranking information derived from the new mechanism provides benefits from assigning music items to the highest-ranking slot, providing visibility to online content sellers. In addition, the sellers can design the slot size to influence the popularity of music items. Meanwhile, music content buyers will gain indirect benefits through segmented ranking slots and reduced search costs. As more valuable information is provided, the service provides benefits to both sides.

I developed the new ranking model to reflect popularity and the slot effect occurring in high-ranking slots. The model comprises a song's demand for streaming and download volumes. The streaming demand is increasing in popularity and results in the increase of streaming volumes by subscription fee users. The demand for downloads is also increasing in popularity and results in a decrease in streaming volumes by users of a single-unit price. The model concentrates on the mixture of streaming volume and download volumes as two key factors that affect the ranking score. There are other parameters, such as the age of the online music and the artist's reputation, that also affect it. Ranking slots are segmented in a reasonable way to reflect the changes in demand for streamed and downloaded volumes as the ranking falls.

This empirical work illustrates some of features of online music distribution in Korea. Ranking is an important factor in predicting popularity, as reflected in the demand for downloaded and streamed volumes. The large variance between the estimated values of rank and standard errors in the high- ranking slots suggests the presence of the bandwagon and slot effects. In addition, the empirical result shows that the existing ranking mechanism does not reflect the real popularity of downloaded and streamed music.

From the analysis, it is expected that the new ranking model will be more effective than the existing mechanism, so the new ranking mechanism is recommended when online music charts are designed. However, wider applications in a variety of online content categories or in different service environments should be tested with the proposed mechanism. Thus, this study can be extended by future research. An analytical model for the proposed mechanism will be built to verify correlations between, on one hand, two service volumes and, on the other hand, popularity, pricing policy, and slot effect, and a preferred certain value will be explored. While the empirical result shows a positive bandwagon effect and slot effect for high-ranking slots, it may be possible to apply the new ranking model to other service environments, including smart phone-based rankings and Internet search-based rankings. It is also possible to extend the methodology to analyze ranking mechanisms on other online items available through Internet websites, such as the online sales of movies, electronic books, software like game applications, and goods available on online auction sites.

Chapter 3

Smartphones' Impact on Triple-play Service of Digital Contents

More than a quarter of the world's TV households will subscribe to triple-play services by 2016. The penetration doesn't sound too impressive until you realize that this represents 387 million homes, up from 96 million at end-2010
Triple-play forecast, from Research and Markets [Research and Markets 2011]

1. Introduction

During the decade leading up to 2010 and beyond, I have seen a dramatic rise in individual and organizational interest in mobile systems and technologies, digital entertainment via the Internet, and enhanced cable TV services, including pay-per-view programming. The interest has been so strong that telecoms services providers have also seen an increasing portion of their revenues coming from the offering of triple-play telecom services, which involve the offering of three different kinds of telecom services [Search Telecom 2012]. Two of the services require a lot of bandwidth: cable TV and high-speed Internet. The third is less bandwidth-intensive: voice and telephone services. More recently, the term quadruple-play services has entered the lexicon of the retail telecom business, to mean the inclusion and integration of mobility for the Internet, TV and phone support on the current generation of high-powered mobile phones and tablet PCs.

As a disruptive emerging technology, smartphones have recently been shaking up the technological capabilities behind retail telecom services. This is true for consumer demand for mobile telephony especially, as well as related demand for mobile Internet, TV, and movie services. A smart-phone is a “cellular telephone with built-in applications and Internet access. Smart-phones provide digital voice service as well as text messaging, e-mail, Web browsing, still and video cameras, MP3 players, video viewing and … video calling. In addition to their built-in functions, smartphones can run myriad applications, turning the once single-minded cellphone into a mobile computer" [PC magazine 2012].

Research and Markets, a global digital economy consultancy, has reported that “triple-play revenues will reach US$170 billion by 2016, nearly US$100 billion more than the 2010 total. The U.S. will supply US$39 billion of the additional revenues, with Japan up by US$9 billion and China increasing by US$8 billion” [Research and Markets 2011]. In other words, technological innovations with mobile telephony and the Internet are coming together to create a new technological revolution that will be nothing short of extraordinary for traditional telecom services providers. In addition, new firms will figure out how to harness the power of the different telecom services – and the digital convergence that will occur beyond it, while others provide the digital devices to support the transformation (e.g., Apple’s iPhone and iPad, Samsung's Galaxy phones, and so on).

Growth in single-service plans has shown a decline during the past five years since 2007 in Singapore, the home base for the present research. In contrast, multi-service subscriptions have grown by more than 7%, during a period of total service growth no more than 5% overall. From these numbers, it is clear that, for Singapore at least, smartphone-based telecommunications services are now powering the everyday lives of a large percentage of the population of five million.

The bundling of multiple services is a marketing strategy that is intended to increase revenue for the service provider by encouraging consumers to purchase multiple services at a relative discount. It offers the added benefit of creating relationship stickiness with the customer, who will be forced to endure relatively higher transaction costs, if she wishes to pull out of any of the components of the service bundle. Such services in retail telecoms are not a by-product of “true” integration. Instead, the operators create service bundle on the basis of separate business sectors, so the cost of customer servicing is not easily determined, and profitability is beyond most cost accountants’ grasp.

Prices do matter, but a greater impact was created by the entry of smartphones in 2009 in Singapore. Customers – existing and new – were willing to pay a lot for new smart devices. Smartphones acted as shock to the telecom services system. Consumers reacted in a positive way by switching to new smartphone-centric services bundles. This improved their telecom services experience. The corporate sponsor was delighted about this since, prior to that time, price was the dominant concern related to feature phone services.

In this research, I will investigate the impact of smartphones on retail telecom services subscriptions, including broadband Internet, mobile phones and cable TV. Since the research is still in an early stage, and is intended to capture the empirical regularities that occurred around the emergence of smartphones in the marketplace, I will not model such issues as the marginal value that different services offer in the mix. Nor will I investigate the effects of different prices for each service or bundle discounts.

Instead, to explore the impacts of technological disruption on telecom services bundling, I will answer the following research questions:

1. What evidence is there that consumers who used the provider’s bundled services made decisions to switch to new bundles with smartphone services

2. Do I observe differential substitution between different kinds of retail telecoms services?
3. Did the introduction of smartphones result in bundle downgrade and upgrade effects occur for Internet and cable TV services?
4. What are the key drivers of timing of mobile subscription switches?
5. How do I properly do an estimation and assessment that will yield meaningful information?

To answer these research questions, the remainder of the article is organized as follows. Section 2 provides some theoretical perspectives to guide the exploration of the bundling issues. Section 3 offers information on the research site and the large data set that I will analyze. For this, I will use a Markov chain transition model, as described in Section 4. Sections 5 and 6 present the results on service bundle switching, and an extension for cross-platform effects. Section 7 delineates the estimation results for mobile subscription switches and the related managerial issues. A discussion and conclusions follow.

2. Literature

I offer background on disruptive technologies, and telecom services bundling, switching and churn.

2.1. Disruptive technologies

Disruptive technologies introduce a different level of performance or change the nature of consumer demand, by introducing new functionality and performance. They have the potential to change business processes in organizations and markets. They also cause consumers to shift their purchases to products based on the new technology

[Anders 2002, Christensen 1995]. Technological disruption occurs when a new technology displaces the mainstream technology in the market [Christensen 1995].

Technological innovation in the telecom industry has been especially disruptive. New Internet applications require high bandwidth and stable networks [Frischmann 2007]. The recent proliferation of smartphones and tablet PCs has dramatically boosted demand for mobile Internet use and the related services market [Stobbe 2011]. Smartphones are changing the way people use their phones, with Internet and email, as a camera, map-routing and direction finding GPS device, and as new payment channel. They improve consumers' experience with phones [Wagner 2011].

This disruption has created much higher demand for mobile and entertainment-related applications that need more bandwidth and less response latency than ever before. A delay of a couple of seconds with email is never a problem, but for real-time streaming music and movies, even a tiny delay renders them unusable. A couple of seconds delay can have negative effects for the service provider, causing service churn [Wu 2003].

2.2. Retail telecom services

With the ongoing technological changes in telecom services, new approaches beyond the traditional wired services are developing rapidly. I have seen increasing convergence and competition involving telephony, cable TV and Internet services, as well as their combination with mobile services [Maarten 2008]. When consumers decide whether to adopt broadband Internet, they also consider other services that are complementary to it. For example, the Internet provides consumers with information about TV programs, and the Internet has created ways to substitute for traditional phone services, with email and chat tools on the Internet [Liu et al 2010].

2.3. Bundling

Bundling occurs as: (1) price bundling, involving the sale of two or more separate products as a package at a discount; (2) product bundling, which includes the sale of two or more separate products at any price; (3) pure bundling, in which a firm sells only the bundle, and not the individual items; and (4) mixed bundling, which involves selling the bundle and all of the products separately [Strenmersch 2002]. Bundling is a customary feature of contemporary product markets, even markets in which consumers exhibit considerable discretion in choice [Grawford 2008]. Customers prefer bundled products based on ease of use and convenience [Mikkonen 2008].

Bundled services offer different benefits to consumers. For example, providers offer price discounts when consumers subscribe to more than one service. The providers benefit because bundle customers tend to stay longer [Wall Street Journal 2004]. Other research [Carlton 1997] has shown that retail telecom service discounts alone lead to increased customer turnover, which is undesirable. But discounted bundles including long-distance services have proven to be an effective deterrent of churn, in a competitive environment where companies offer price promotions to steal their competitors' customers [Liu et al 2010].

An early bundling study showed how a monopolist could extra additional customer surplus [Stigler 1968]. I know too that it is better to sell individual products and a bundle, not just the bundle alone [Adams 1976]. Bundling enables a firm to leverage its monopoly power in one product market to deter entry of competitors in a second product market [Tirole 1988, Whinston 1990]. New competitive strategies, such as large-scale bundling [Bakos 2000], emerged in the early days of e-commerce. More recently, telephony companies and cable TV operators have bundled entertainment goods with mobile, Internet, and TV services [Stobbe 2011].

2.4. Customer turnover and account churn

Customer turnover – or account churn – has been a key concern of marketing researchers and telecom industry managers. Their interest is to understand how service quality, different business developments, and events in the marketplace cause customers to switch service providers [Keaveney 1995]. Pricing, failure of core services, ineffective responses to service failures, competition, and other inconveniences have been critical. Others have suggested that customers churn due to changes in their economic circumstances [Bogomolova 2009]. Economists have suggested that price discrimination and bundling can be leveraged to charge customers different prices based on their past behavior [Taylor 2003]. Also, information on past customer behaviors can be used to reduce churn [Shaffer 2002].

3. Research Setting and Data

3.1. Research Setting

The research setting involves a telecom operator that provides three typical services in bundles: mobile phone, Internet and cable TV services. There exist several types of service subscription bundles. See Table 1.

Table 1. Service subscription bundle types

Service Bundles	Bundle Composition
Single	Mobile alone; Internet; Cable TV
Double	(Mobile + Internet); (Mobile + Cable TV); (Internet + Cable TV)
Triple	Mobile + Internet + Cable TV

Mobile services emphasize data upload and down-load capacity, and feature phones and smartphones. The firm launched new mobile voice and data services that focused on high-functionality support for smartphone users in December 2009. With access to an advanced mobile network, smartphone users were able to enjoy diverse functionality, such as Facebook and Twitter, free access to a range of quality TV programs, instant messaging, and so on.

3.2. Data

The data were obtained from multiple data sources and interviews at the research site over a period of several months during 2012 under the conditions of anonymous customers and non-disclosure of their details. They cover the period from June 1, 2007 to May 31, 2012, and describe customer switching among different service bundles, where my interest is centered. Smartphones were introduced in December 2009, around the middle of this period. The data cover a sample of hundreds of thousands of customers and their subscriptions for mobile phone, Internet and cable TV services. They include records collected for any subscription-related events. They represent the start and end dates for new subscriptions, contract renewals, and contract terminations. New subscriptions typically involve two-year contracts, a standard in the industry.

I cleaned the raw data set by excluding duplicate and inconsistent data. For the analysis, I identified tens of thousands of customers who subscribed to bundles with the three services offered by the telecom service provider at various times. I use this group of subscribers to examine service subscription transition patterns following the market entry of smartphones.

The service bundles are organized based on the three different service areas. Within each of the service areas, there are multiple plan options that are available to customers. I will focus on a number of popular plans, as shown in Table 2.

Table 2. Service plans used

Services Plans (#)	Plans Evaluated
Mobile (8)	4 feature phone plans: F1, F2, F3, F4 4 smartphone plans: S1, S2, S3, S4
Internet (7)	FB1, FB2, FB2(M), FB3, FB3(M), FB4, FB4(M)
Cable TV (5)	TV1, TV2, TV3, TV4, TV5

To represent the mobile phone service included in the available plans, I selected four feature phone plans (F) and their matching smartphone plans (S). The index numbers (1, 2, 3, 4) reflect the plans' available of free voice minutes in increasing order. There are seven fixed broadband (FB) services that offer Internet connectivity in the home. The index for these (1, 2, 3, 4) reflects the services in the order of increasing down-load speed. Some mobile plans, indicated by (M), offer a USB-type device (e.g., a dongle) for mobile Internet connectivity outside the home. This permits the customer to use a laptop outdoors, for example, and is in addition to the capabilities of a typical home Internet subscription. The cable TV service (TV) includes five plans reflecting different numbers of channel bundles that customers can select among.

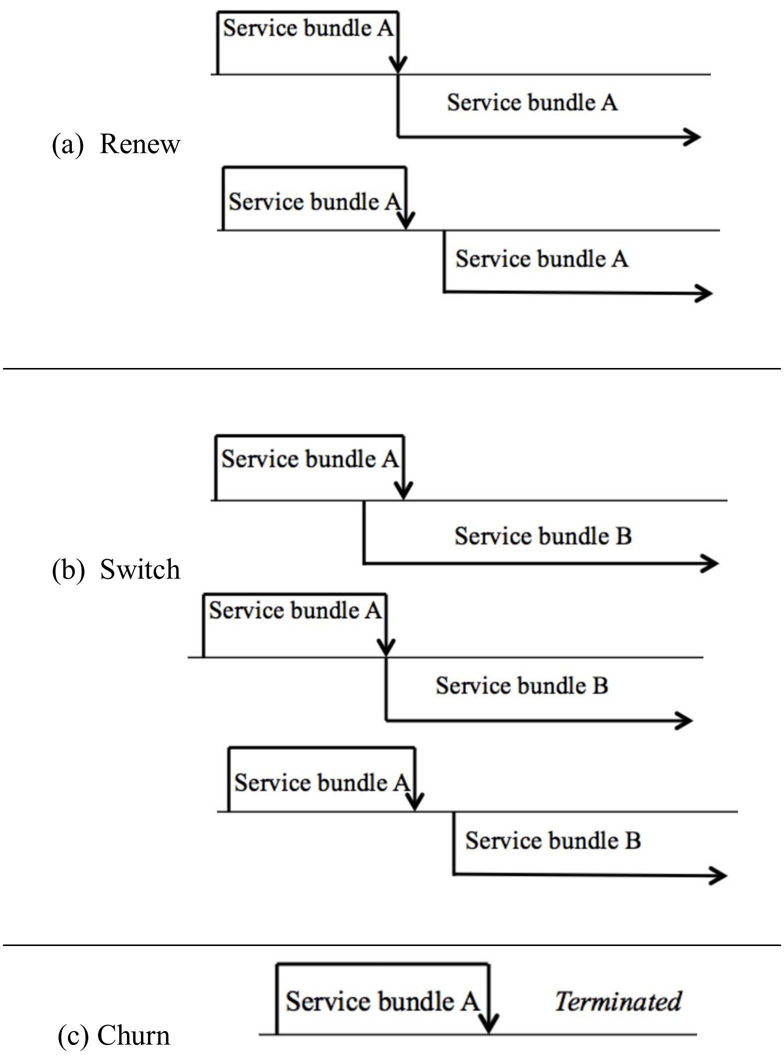
The data contain information about consumer bundle subscriptions, and when those changed. The details of the data include: service bundle names and identifiers; customer service contract start, termination and end dates; and the current status for contracts that are right-censored. Based on Table 2, including the possibility of deciding to discontinue any of the three services at some time.

4. Markov Chain Transition Model

The goal is to characterize and analyze the behavior of customers who switched one or more times from one service or bundle of services to another during the study period, for the Internet, cable TV and mobile services. We use a Markov chain transition matrix to model the switching patterns from any of the 280 different bundles with three services as states. The Markov process represents a customer who starts with, say, a service bundle for mobile, Internet and cable TV services representing a state, and then may switch to an-other service bundle representing a different state. This occurs with some probability that can be estimated.

The transition probability for each service combination is measured based on three different events: a new contract for a new subscription; a contract renewal for the same subscription; and a contract termination. This leads to three cases for each service bundle type, as shown in Figure 1:

Figure 1. Service bundle transitions



The customer renews the service bundle. The customer can do this right after her contract ends, or somewhat later. If the customer renews, this is al-so the equivalent of a decision to keep the service bundle. (See Figure 1a.)

The customer switches to a different service bundle. The customer can do this before or when the currently-chosen service contract expires, or with some lag after expiry. (See Figure 1b.)

The customer no longer uses the company's services, resulting in churn. This can happen in a contract period or at its end. (See Figure 1c.)

5. Baseline Bundle Switching Results

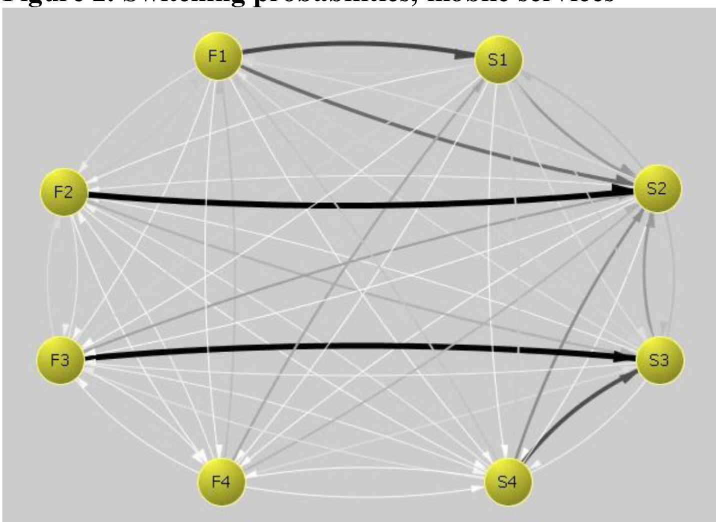
We next present my empirical regularities results for bundle switching that occurred in the aftermath of the December 2009 rollout of smartphone services by the telecom service provider. We use the Markov chain transition matrix approach to identify switching probabilities for the different service bundles. For an effective illustration of the matrices, the analysis utilizes state transition network diagrams, in which the nodes represent the states and the arcs indicate the transitions. Network diagrams are appropriate vehicles with which to present the results of my research, and illustrate the answers to my research questions. They also help to extract relevant business insights from the overall service migration patterns present in the data. For simplicity of presentation, the actual probability values are not included in the diagrams; instead, we include textual legends below the diagram to indicate the probability ranges that are included. Generally speaking, the darker and thicker the arcs are, the higher transition probabilities they represent.

5.1. Single-service switching analysis

To show the switching patterns for individual services, we applied the approach for each of the three services separately first. The results establish some empirical regularity of the data, based on the observations during the two and a half years period following the introduction of smartphone services in December 2009. The provider's services are grouped into two categories: feature phone plans and smartphone plans. Figure 2 shows the state transitions that characterize customer actions for the eight service plans during the observation period.

When smartphone services (S) were launched, there was significant switching behavior that occurred from the different feature phone plans (F1-F4) to other smartphone plans (S1-S4). The transitions were more likely to occur between services that had the same number of voice minutes, such as F1 to S1, F2 to S2, and so on. The figure shows that the most popular plan was S2: it even attracted other smartphone plan users. See the gray arcs from S1, S3 and S4 to S2. We note that there were a small number of smartphone plan adopters who returned to feature phone plans.

Figure 2. Switching probabilities, mobile services

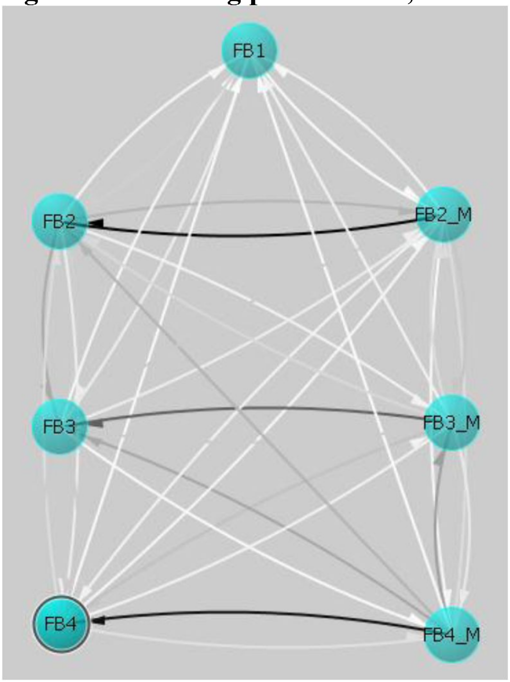


Legend. The figure includes arcs of different tones that represent a range of transition probabilities. (1) White: < 1%; (2) gray: 1% to 5%; (3) black: > 5%. I denote different service plans with F for feature phones, and S for smartphones. The index numbers, 1 to 4, specify increasing voice minutes, with 4 at the high-end number of minutes. The full complexity of the transition paths is not presented in the figure (e.g., We omitted loops to indicate cases where no switches are observed for each state).

We also observed other subscription changes between different smartphone services. For example, some observed switching behavior involved actions to downgrade the customers' services. This includes downgrades of smartphone services; apparently the services did not satisfy customer expectations. Other service upgrades appear to have been occurring in the same timeframe though. Another interesting observation involves customer choices of feature phone services. Though the service was not for smartphone users, there still was some likelihood that customers would switch to it, despite other data and feature phone services that were available.

We also computed the transition probabilities between the plans involving fixed broadband home Inter-net services. There are two main segments here: Inter-net services and Internet services bundled with mobile Internet connectivity. Figure 3 depicts the transition probabilities among these Internet service plans.

Figure 3. Switching probabilities, Internet services



Legend. The figure includes arcs of different tones that each represents a range of transition probabilities: (1) white is < 1%: (2) gray is 1% to 3%: (3) black is > 3%. We denote different fixed broadband service plans with (FB), and (M), which means add-on mobile data services. The index numbers, such as FB1 to FB4, specify increasing download speeds. The full complexity of the transition paths is not included in the figure

Even though the values of the probabilities are slightly smaller than those for the mobile service transitions, a large number of transitions are observed from Internet services with mobility plans to simple Internet services. The arcs from FB2_M to FB2, FB3_M to FB3, and FB4_M to FB4 illustrate this. We also can see a larger number of slightly thicker downgrade arcs than upgrade arcs. These include the arcs from FB4_M to FB2 and FB3 versus the arcs that go in the opposite directions. The switching patterns that we observe may have arisen due to the launch of smartphone services an issue that we will discuss later. Summary statistics for this group of services show that the average probability of no service subscription changes was higher for Internet services bundled with mobile broadband connectivity than for ordinary Internet services without such add-on services.

We further assessed the switching probabilities be-tween the various choices within the cable TV services category. Although we have not included another figure to represent the details of this, suffice to say that there is evidence of downgrades in cable TV services also. We speculate that there might be substitution occurring between the services that customers were able to consume via their smartphones relative to traditional cable TV services available in their homes.

5.2. Triple-service switching analysis

We also investigated switching behavior between different combinations of the three main services: mobile phone, Internet and cable TV services. We can describe each triple-service combination, representing a Markov chain state, with a three-dimensional vector: (mobile phone plan, Internet plan, cable TV plan). The number of possible combinations is 280 (= 8 × 7 × 5). This makes the number of possible transitions to be 280 × 280.

Since it would be visually complicated to render and view the transitions between the hundreds of three-dimensional vectors, we will depict just a part of the entire state transition network diagram, while holding fixed one of the three services in given service plan. See the switching patterns shown in Figure 4.

Figure 4. Switching patterns: triple-service bundles (a)

Between the states: (mobile, Internet, TV1)

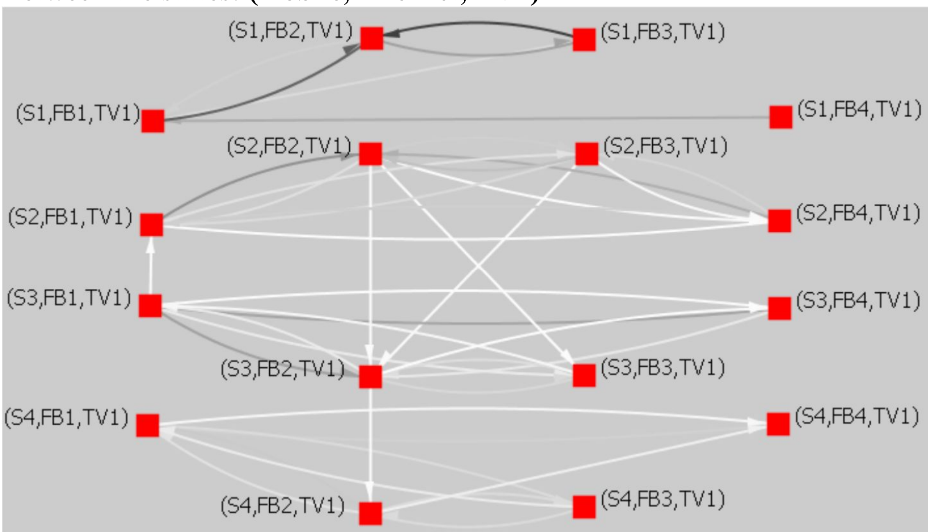
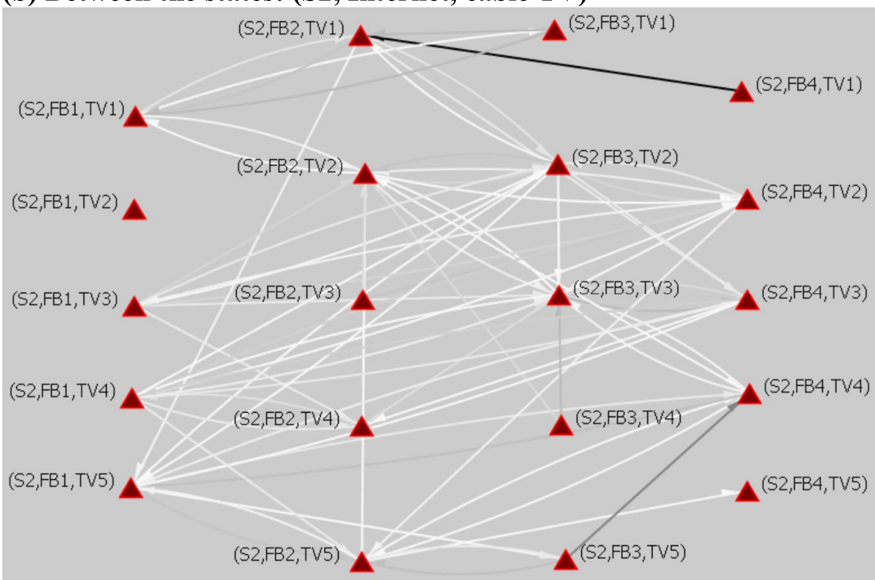


Figure 4a represents service transition probabilities that we have obtained for the smartphone and Internet plans with the cable TV plan fixed to TV1. Figure 4b shows the transitions between the states with different Internet and cable TV plans, while the mobile phone plan is fixed to S2. The states are arrayed in the in-creasing order of service grade from left to right and from top to bottom. Note that the horizontal and vertical arcs indicate changes in single services, while the diagonal arcs show changes in both services.

These figures contribute to the general and specific understanding of the structure of the transitions across the three service areas. In Figure 4a, the majority of transitions occur in the horizontal rather than vertical direction. This may indicate that customers will be less likely to change their mobile phone service plans com-pared to their Internet service plans. This tendency increases if the smartphone plan is of a lower grade, as we observe from the thicker arcs in the upper part of the figure. This may imply that customers who adopted services of lower value will be more likely to optimize their service bundles. Vertical transitions are more likely to be observed for the FB2 Internet plan users, who show some propensity to upgrade their smart-phone plans. In the group of similar fixed broadband services, the FB2 plan acts as terminal node in the net-work; there are many arcs that point to it. This transition network diagram only applies to customers who chose the cable TV1 service. For other customers who choose more TV channels beyond the basic cable TV1 service, it is also possible for us to conduct other similar analyses.

(b) Between the states: (S2, Internet, cable TV)



Legend. The figure includes arcs of different tones that each represents a range of transition probabilities: (1) White: < 1%; (2) gray: 1% to 5%; (3) black: > 5%. In Figure 4a, the cable TV plan is fixed to TV1; in Figure 4b, the mobile phone plan is fixed to S2.

Figure 4b depicts the state transitions for Internet and cable TV services for customers who chose smartphone plan S2. Overall, the transition probabilities appear to be very low, except for a few cases, such as the fixed broadband Internet downgrade from FB4 to FB2, when the customer is subscribed to cable TV1 and smartphone service S2. Unlike Figure 4a, which covers changes between mobile and Internet services, in Figure 4b, we observe more diagonal arcs, which indicate that customers are more likely to subscribe to and change their fixed broadband Internet and cable TV services. This also indicates that Internet and cable

TV services are more likely to be tied to household-level preferences, while mobile phone services are more likely to be tied to individual preferences. Interestingly, the many diagonal arcs indicate that, when service transitions are seen to occur, customers tend to upgrade or downgrade two services together, at the same time. In addition, most of the upgrades and downgrades in cable TV services that were observed occurred in the mid-range fixed broadband Internet services FB2 and FB3.

6. Extension: Cross-Platform Effects

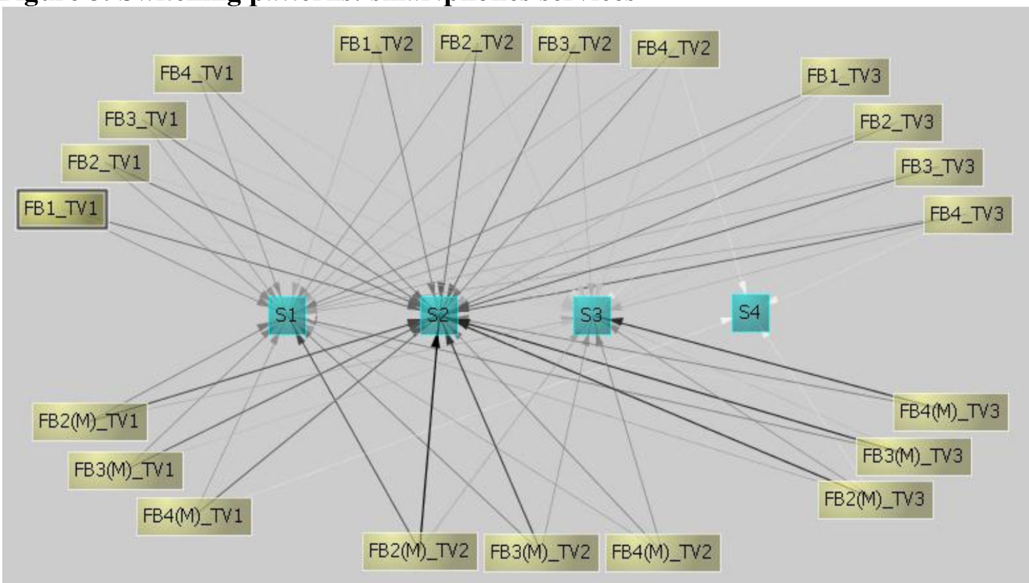
The empirical exploration also makes it appropriate to understand the cross-platform effects on the probabilities of the observation of switching between different services. In this section, we present results from somewhat more constrained analyses to extract relevant knowledge and insights related to the launch of smartphones in the Singapore market.

6.1. New smartphone subscription plans

A key interest in this research is to investigate how the launch of smartphones may have influenced telecom services customers. More specifically, we are interested to assess the nature of customer service transitions from feature phone to smartphone plans relative to their subscriptions in fixed broadband Internet and cable TV services. Figure 5 is the associated service transition diagram that ties in with this purpose. We only considered customers who were once feature phone plan users, and, thereafter, adopted smartphone plans. The four states in the middle of the figure – S1, S2, S3 and S4 – represent the four smartphone plans. The surrounding states represent other Internet and cable TV plans, when customers chose to transition from feature phone to smartphone plans.

The results suggest that higher switching probabilities for bundle composites including fixed broadband Internet paired with additional mobile services (e.g., FB2(M)) to smartphone services (in the lower part of the figure), compared to non-mobile service users (in the upper part of the diagram). In terms of cable TV subscriptions, customers with many channel bundles seem to exhibit a higher propensity to adopt smartphones. This may be due to socioeconomic factors that the Markov chain analysis approach cannot consider. This figure offers preliminary evidence that is suggestive of the effects of the introduction of smartphone services on changes in Internet broadband service subscriptions. Additionally, the leading bundle that includes the most demanded smartphone services (S2) suggests that other factors (e.g., discounts, supplementary services) had an impact on customer choices about their service bundle subscriptions.

Figure 5. Switching patterns: smartphones services

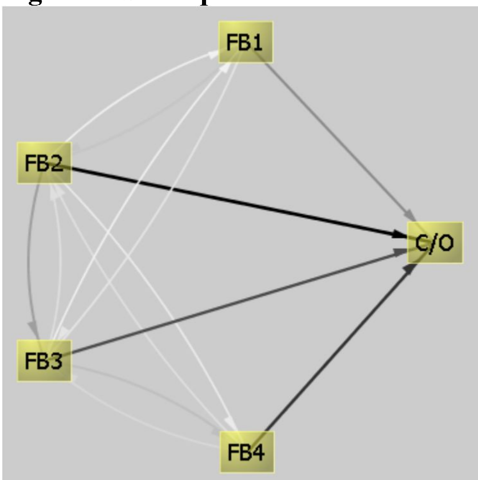


Legend. The figure includes arcs of different tones that each represents a range of transition probabilities. (1) White: < 3%: (2) thin gray: 8% to 15%: (3) thick gray: 15% to 22%; and black: > 22%. It also includes codes for fixed broadband (FB), mobile data download (M) and cable TV services (TV); and for smartphone services (S). The index numbers, such as S1 or S4, specify increasing voice minutes, with '4' representing the high-end number of minutes for smartphones. The full complexity of the transition paths is not shown in the figure.

6.2. Substitution Involving Smartphones

Smartphones have capabilities to provide broad-band services in the fixed broadband Internet and mobile Internet environments. To identify evidence of a substitution effect away from fixed broadband Internet services after the introduction of smartphones, I focused on new smartphone plans adopters. We did this to see if could observe the extent to which they changed their Internet service plans to smartphone plans. See Figure 6.

Figure 6. Smartphone effects on fixed broadband



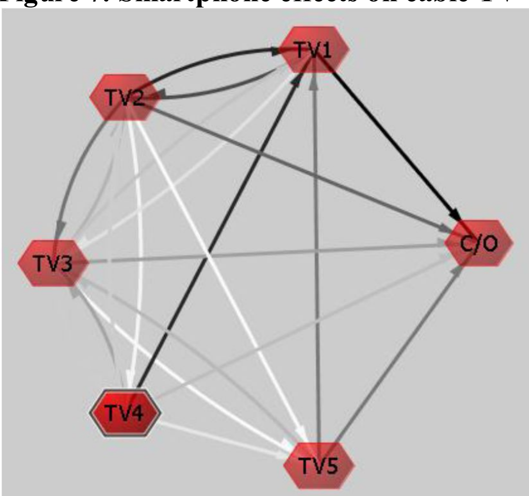
Legend. The transition probabilities are as follows. (1) White: < 1%; (2) gray: 1% to 3%; (3) black: > 3%. The index numbers, such as FB1 or FB4, specify increasing voice minutes, with '4' representing the high-end number of minutes for mobile phones. FB means fixed broadband. C/O stands for churn.

The figure shows the results of fixed broadband Internet service plan changes conditioned on the transition from feature phone services to smartphone services. The results suggest that there is some likelihood that demand for Internet services is diminished due to customer adoption of new smartphone services. The latter services are able to provide Internet connectivity, and substitute for the existing home Internet services. The results represent the increasing penetration of mobile services as a basis for people to gain access to the Internet.

6.3. Changes in cable TV subscriptions

Smartphone users and those with wi-fi-based Inter-net connectivity via their PCs are able to access a range of TV content, albeit with somewhat slower connectivity than through fixed broadband Internet services. The accessibility that mobile devices creates with the Inter-net makes it possible for consumers to upgrade or downgrade their cable TV services and still view their favorite shows and movies via other mobile and Inter-net services.

Figure 7. Smartphone effects on cable TV



Legend. Transition probabilities are represented by the arcs. (1) White: < 0.5%; (2) gray: 0.5% to 2%; (3) black: > 2%. The index numbers, such as TV1 or TV4, specify increasing the number of channels, with '4' representing the high-end number of channels. TV means cable TV. C/O stands for churn.

Figure 7 relates to the change of the cable TV service subscription in which the transition from feature phone service to smartphone services occurred. The results show that switching plainly occurred from TV 5 and TV 4 services to TV 1 which means downgraded cable TV services. The potentially strong effect of the rollout of smartphone services on cable TV subscription downgrades is apparent.

7. Empirical analysis

Since the study is still in an early stage, and is intended to capture the empirical regularities that occurred around the emergence of smartphone in the marketplace. I will not model such issues as the marginal value that different services offer in the mix. However, I investigate the instantaneous transition rate of feature phone services into smartphones services and marginal effects of key variables for the transition.

7.1 Empirical model

Based on the front study, I consider the application of transition rate model. The basic idea is that a baseline rate, which given by period specific constants, varies across time periods. For example, if I split the whole observation time into n-piecewise time periods, the constant transition rate is defined by n time-parameters. As aforementioned, the firm released new mobile services that focused on high functionality support for smartphones users in December 2009. Thus I split the whole time from December 2009 to April 2012 on a monthly basis in order to investigate the monthly transition rate. I only consider the straight change form feature phone services to smartphone services. That is, the cases of the interruption between two different services user and just new smartphone subscriptions are excluded for this study. In the estimation, first I include time-constant covariates in order to identify the important heterogeneity between customers. The covariates can have the same effects in each time period. Second, I generalize the effects of the time-constant covariates to vary across n-piecewise time periods. The covariates can have the period-specific effects in each time period.

The model: Duration = f (Prices, Contracts, Controls)

Duration is the length of time intervals between start time and end time for using feature phone service. In the data set, each customer terminates the service and transits into the smartphone services. Contract is an agreement between the service vender and customers about the service life. In this study, any mobile service is tied up with two-year contracts. Price is the each service's monthly fastened charge (there are four different prices). And controls represent other factors known to influence the transition rate of the mobile services.

Table 3. variables in transition rate model

Type	Variable	Definition
Dependent	Duration	The length of time intervals of using feature phone services
Main effects	Contract 1	Contract 1 dummy stands for experience using the service for 2 years, one whole contract period
	Contract 2	Contract 2 dummy represents experience using the service for 4 years, two consecutive contract periods
	Contract	Remaining contract, how many months left
	Price	Fixed monthly charge tied up with each different feature phone service
Controls	Age	Each customer's age
	Gender	Each customer's gender
	Dwelling type	Each customer's residence type

7.2 Results

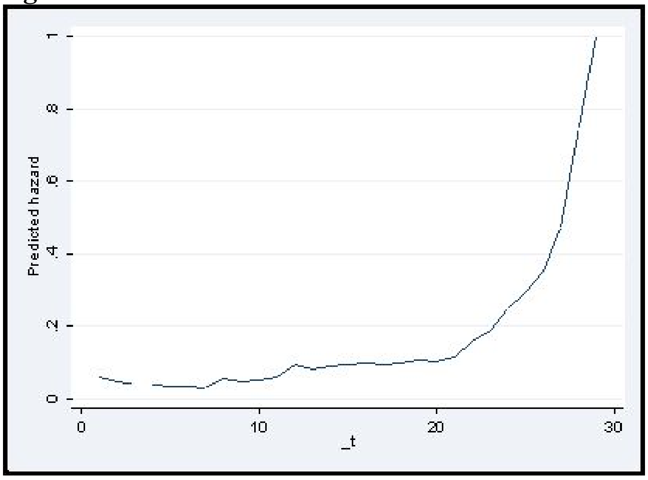
First, I perform the model estimation without the covariates and the estimates allow that the instantaneous transition rate varies across time periods.

Table 4. Transition coefficient value (December. 2009 ~ April. 2012)

Variable	Coef.	Std.	P-val	Variable	Coef.	Std.	P-val	Variable	Coef.	Std.	P-val
Dec.2009	**-2.823**	**0.040**	**0**	Oct.2010	-2.822	0.050	0	Aug.2011	-2.148	0.057	0
Jan.2010	**-3.092**	**0.047**	**0**	Nov.2010	-2.376	0.041	0	Sep.2011	-1.846	0.053	0
Feb.2010	-3.274	0.053	0	Dec.2010	-2.511	0.046	0	**Oct.2011**	**-1.677**	**0.053**	**0**
Mar.2010	-3.264	0.054	0	Jan.2011	-2.403	0.046	0	Nov.2011	-1.384	0.050	0
Apr.2010	-3.415	0.059	0	Feb.2011	-2.381	0.047	0	Dec.2011	-1.222	0.054	0
May.2010	-3.411	0.060	0	Mar.2011	-2.302	0.048	0	Jan.2012	-1.049	0.059	0
Jun.2010	-3.601	0.067	0	Apr.2011	-2.374	0.052	0	Feb.2012	-0.745	0.062	0
July.2010	**-2.892**	**0.048**	**0**	May.2011	-2.328	0.053	0	Mar.2012	-0.284	0.069	0
Aug.2010	-3.051	0.053	0	Jun.2011	-2.243	0.054	0	Apr.2012	5.42E-08	0.120	1
Sep.2010	**-2.949**	**0.052**	**0**	July.2011	-2.298	0.059	0				

In order to obtain the sensitive estimates, each n-piecewise time period needs to include at least one ending event. Otherwise the estimates are not meaningful. The data set, the first 7 months periods do not have episode with ending event times except just one event in January 2010 and February 2010. Thus, the coefficient values from December 2009 to June 2010 do not have meaningful estimates even if they are statistically significant. At July 2010, the estimated parameters for the baseline transition rate at first decrease from -2.892 to -3.051, and increases from -3.051 to -2.949, and then increase continuously. In substantive terms, this convex-shaped rate pattern will be interpreted as the time-lapsed and weighted impact of new service technology on mobile service transition rate patterns. Particularly immediately after a new service launch in October 2011, there is an intensive transition process from -1.677 to -0.284. The following figure 9 shows the increasing transition rate at an increasing rate from July 2010 in each month.

Figure 8. Instantaneous transition rate over time



Firstly without considering the instantaneous transition rate, I perform estimations by assuring a Weibull distribution for the episode durations in order to identify a specific shape of time dependence for the transition rate. For the purpose, I split the whole observed time into four different lengths of time to examine the marginal effects of price and contracts under controls in each different time slot. The period baseline is December 2009. For example, the first column estimation is based on the observed period form December 2009 to July 2010 and so forth. However as aforementioned there are almost never ending events in the first observed period. Thus, the coefficient values in the first column are not sensitive estimates. However, most estimates for second column are significant at 1% significant level. The coefficient value of the covariate price has a positive sign. Thus, each higher price increases the transition rate by 0.9%, 0.22% and 0.1%. This means that customer who has subscribed higher price feature phone services is more willing to transit to smartphone services. Meanwhile old customers are slightly less willing to change the services than young customers. The effects of the contract 1 and contract on transition rate are most significant. When customers have already subscribed the services for 2 years before, they are less mobile than those who are not. However, when remaining contract is large, they are more mobile, the table 5 shows the estimation results.

Table 5. Marginal effects of the covariates (December. 2009 ~ April. 2012)

Marginal effects	July. 2010	Sep. 2010	Oct. 2011	Apr. 2012
Price	1.00%***	0.9%***	0.22%***	0.1%***
Age	-1.53%***	-1.58%***	-0.00%	0.09%***
Gender	-16.38%**	-11.01%**	2.05%**	2.17%***
Dwelling type	0.49%	-2.89%	-1.92%***	-1.61%***
Contract 1	-54.03%***	-56.95%***	-59.28%***	-59.33%***
Contract 2	-99.99%	-99.99%	-99.99%	-81.52%***
Contract	6.69%***	9.33%**	7.09%***	6.2%***
Model: Weibull parametric method. Significance: *p<0.1, **p<0.05, ***p<0.01				

Now I estimate the marginal values of time-constant covariates with considering the instantaneous transition rate. I found the same transition rate pattern along with the consequence of the preceding estimation at table 4. However, I have different estimates of the covariates for tables 5 and 6 because I assume different distribution of episodes.

Table 6. Transition coefficient value with time-constant covariates

Variable	Coef.	Std.	P-vl	Variable	Coef.	Std.	P-vl	Variable	Coef.	Std.	P-vl
Dec.2009	**-5.196**	**0.074**	**0**	Dec.2010	-3.147	0.069	0	Dec.2011	-0.794	0.077	0
Jan.2010	**-5.233**	**0.077**	**0**	Jan.2011	-2.881	0.069	0	Jan.2012	-0.454	0.080	0
Feb.2010	-5.225	0.079	0	Feb.2011	-2.718	0.070	0	Feb.2012	-0.067	0.083	0.42
Mar.2010	-5.051	0.079	0	Mar.2011	-2.517	0.070	0	Mar.2012	0.461	0.087	0
Apr.2010	-5.032	0.082	0	Apr.2011	-2.480	0.073	0	Apr.2012	0.575	0.131	0
May.2010	-4.879	0.082	0	May.2011	-2.355	0.074	0	Price	0.45%***	0.0006	0
Jun.2010	-4.924	0.086	0	Jun.2011	-2.202	0.075	0	Age	0.16%**	0.0008	0.06
July.2010	**-4.098**	**0.072**	**0**	July.2011	-2.205	0.078	0	Gender	6.88%***	0.018	0
Aug.2010	-4.141	0.075	0	Aug.2011	-1.999	0.077	0	Dwelling	-3.33%***	0.013	0.01
Sep.2010	**-3.930**	**0.074**	**0**	Sep.2011	-1.624	0.074	0	Contract1	-92%***	0.031	0
Oct.2010	-3.711	0.072	0	**Oct.2011**	**-1.390**	**0.075**	**0**	Contract2	-99%***	0.104	0
Nov.2010	-3.185	0.066	0	Nov.2011	-1.025	0.074	0	Contract	15.98%***	0.002	0
Model: Exponential parametric method. Significance: *p<0.1, **p<0.05, ***p<0.01											

7.3 Managerial issues

In the previous subsection, I estimated the instantaneous transition rate of straight changes from feature phone services to smartphone services. I found that in the first 7 months, there are almost never episodes with ending event times since the launch of smartphone services. Based on the parameter estimates, I can draw one possible conclusion. The new technology service paired with new technology products is not readily diffused throughout social life, specifically to people who have acclimatized to the previous services. At table 6, the negative marginal values of contract 1 strongly show the customer's decision to the mobile service transition. Those who used the former mobile services are not swept away by the new technology diffusion. That is, the technology acceptance or infrastructure has to be preceded before the new services are boosted. With the course of time, mobile service switching is projected to increase. At figure 9, the incremental transition rate at an increasing rate after July 2010, September 2010 and October 2011 shows that the existing service users have begun to realize the new technology services fastened tight to the new technology products, and put their transition into practice. At table 5, the diminishing marginal values of price, contract 1and contract underpin the transition rate pattern. I can conclude that when new technology services is introduced in the market, customer behavior is kept affected by service internal factors such as price and contract. However, once new technology infrastructure or recognition is established throughout the market, external factors such as new services are getting influential.

8. Discussion

This research has investigated switching patterns between different retail telecom service bundles. I assessed the empirical regularities of transition probabilities for different services to understand the extent to which the introduction of smartphones has affected the service choices that customers make. The assessments are based on the application of Markov chain transition matrix analysis. More specifically, evaluated the potential for smartphones to impact broadband Internet and cable TV subscription changes.

The empirical results show that the impact of smartphones on bundle switching has been strong. Smartphones have acted like a shock-creating disruptive technology in the retail telecom services system. This is because new mobile services designed for smartphone users seem to have influenced consumers to shift the mix of services they are using to a new mix involving mobile services. There was less evidence to suggest that there is substitution between mobile services involving data uploads and downloads and Internet services in the home though. I drew a similar conclusion related to the limited impact of Internet services available in the home and via mobile phones on changes in customer's cable TV subscriptions. I also explore the assessment of the marginal effects of each service's price and remaining contract as a further basis for explaining and predicting mobile switching.

As it has become increasingly convenient for customers to access digital content through smartphones and tablet PCs, the result is that they also have become more and more interested to consume entertainment goods through them. The analysis has yielded practical evidence about the impact of a disruptive technology on the switching patterns among three different retail telecom services. The method helped to identify the primary changes in customer subscriptions. I also assessed the extent to which data services to support mobility have been important.

This study demonstrates the kinds of issues that I can look into with a data set of such a large scale. Although I did not undertake causal modeling at this stage of the present project work, nevertheless I expect that customers who consume higher-priced service subscriptions will keep a watchful eye for the availability of less expensive options. They will be more likely to churn or find less expensive bundles. In addition, managers may be interested to focus more on influencing the trajectories of customers who are likely to move from lower to high revenue-generating service subscriptions.

I expect my future research to take a number of different directions. First, I will explore the development of an explanatory event history model that will be useful for developing explanatory and predictive likelihoods for different kinds of bundle switching activities, based on observable heterogeneity among customers. Second, it may also be useful to evaluate the effect of the attractiveness of the discounts of the various bundles that are possible service switching out-comes for customers who already are consuming a given service bundle. Finally, I hope to look into the range of actions that the provider can take to influence how its customers migrate from one service bundle to another to achieve maximum profit. This may require, for example, the use of customer-specific pricing and bundle content offers.

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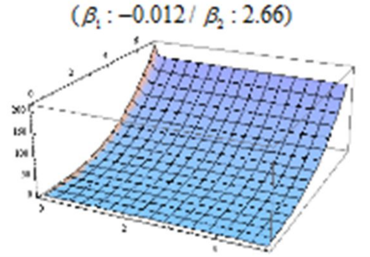
APPENDIX -A

Response Surfaces for Combinations of Variables Based on Estimated Coefficients

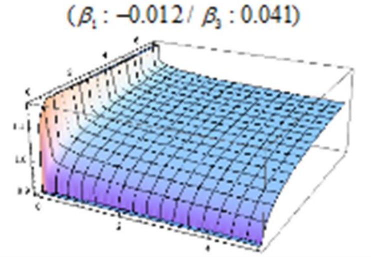
A1. Money = f(Wage, NetEff);

$(\beta_1 : -0.012 \;/\; \beta_2 : 2.66)$



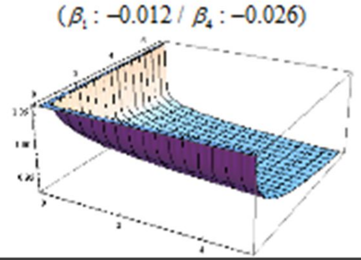
A2. Money = f(*Wage, Access*);

$(\beta_1 : -0.012 \;/\; \beta_3 : 0.041)$



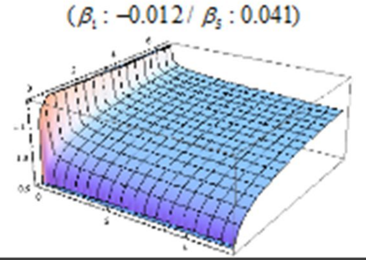
A3. Money = f(Wage, Skills);

$(\beta_1 : -0.012 \;/\; \beta_4 : -0.026)$



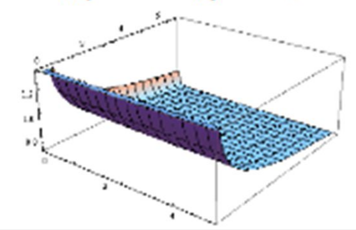
A4. *Money = f(Wage, ExpPts*);

$(\beta_1 : -0.012 \;/\; \beta_3 : 0.041)$



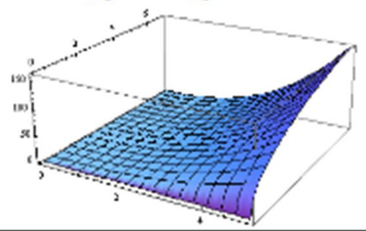
A5. Money = f(Wage,GLevl);

$(\beta_1 : -0.012 \;/\; \beta_6 : -0.17)$



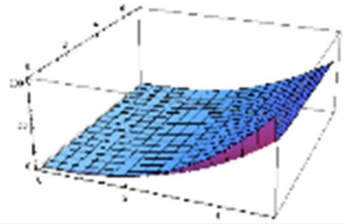
A6. *Money = f(NetEff, Access*);

$(\beta_2 : 2.66 \;/\; \beta_3 : 0.041)$



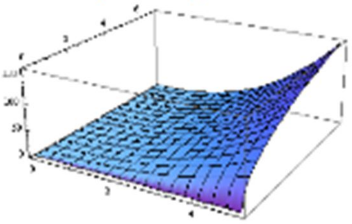
A7. Money = f(NetEff, Skills);

$(\beta_2 : 2.66 \,/\, \beta_4 : -0.026)$



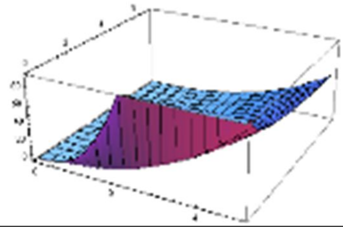
A8. *Money = f(NetEff, ExpPts);*

$(\beta_2 : 2.66 \,/\, \beta_5 : 0.041)$



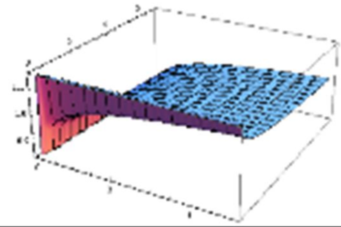
A9. Money = f(NetEff, GLevel);

$(\beta_2 : 2.66 \,/\, \beta_6 : -0.17)$



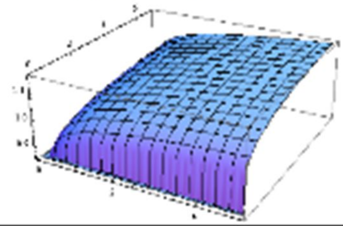
A10. *Money = f(Access, Skills);*

$(\beta_3 : 0.041 \,/\, \beta_4 : -0.026)$



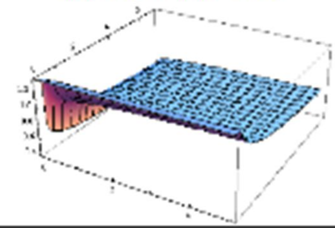
A11. Money = f (Access, ExpPts);

$(\beta_3 : 0.041 \,/\, \beta_5 : 0.041)$



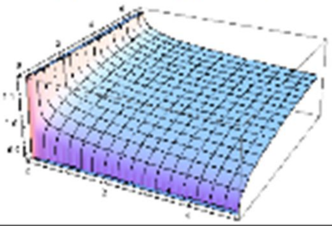
A12. *Money = f(Access, GLevel);*

$(\beta_3 : 0.041 \,/\, \beta_6 : -0.17)$



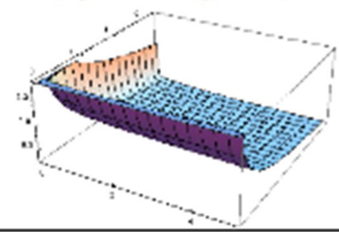
A13. Money = f(Skills, ExpPts);

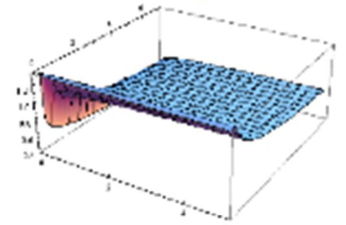
$(\beta_4 : -0.026 \,/\, \beta_5 : 0.041)$



A14. *Money = f(Skills, GLevel);*

$(\beta_4 : -0.026 \,/\, \beta_6 : -0.17)$



<table>
<tr>
<td>A15. Money = f(ExpPts, GLevel);
(β_5 : 0.041 / β_6 : −0.17)
</td>
<td></td>
</tr>
<tr>
<td colspan="2">Note: The figures are based on the Cobb-Douglas function p = asNf(g), and are plotted using the estimated coefficient of empirical model. Money is the dependent variable representing hedonic price or player willingness to pay A1, A6, A7, A8 and A9 show increasing values of the dependent variable due to the coefficient of NetEff, which is much stronger than the others. A3, A5 and A14, in contrast, show a clear decrease because of the negative values of the coefficients. For the rest, an increase is present, but at a diminishing rate because two different coefficient values offset each other, depending on each coefficient value's strength. The 3D plots show the relationships between ln(Money) for hedonic value and all the different explanatory variables in the model. The coefficient values represent the constant elasticity of each explanatory variable, and show the percentage variation of ln(Money) with respect to changes in all variables. For example, a coefficient of 0.24 for the value of ln(Access) is a good illustration. It shows that when game players spend more time, because Access is an instrumental variable (IV) related to time (due to my treatment for endogenity), the hedonic value of online game participation increases by 0.24%. I have sharped up the writing in the paper by making sure this explanation has been improved.</td>
</tr>
</table>

초 록

新 情報技術 컨텐츠 社業의 經濟學적 分析에 대한 論文: 게임, 음악, 그리고 스마트폰

金 官 秀

서울大學校 大學院

經營學科 經營學 專攻

온라인 컨텐츠 사업과 기술이 빠른 속도로 융합됨에 따라 온라인 서비스 소비에 대한 소비자 가치 연구는 새로운 사업 통찰력을 제공한다. 무소부재 인터넷 접속은 네트워크 게임 및 대규모 온라인 참여를 이끌고 있다. 온라인 커뮤니티 참여를 통한 가치연구는 가치 기반 적정가격을 제시한다. 올바른 선택에 영향을 주는 정보전달 방법은 소비자의 관심을 사로잡는다. 슬롯 구조 디자인은 관심의 가치를 반영한다. 스마트폰이 점점 인기화 됨에 따라 디지털 컨텐츠 사업은 계속 성장하고 있다. 최근, 스마트폰은 온라인 컨텐츠 서비스 전달 경로화 되어 가고 있다. 소비자 가치 중심 적정가격 및 고객의 관심을 사로잡는 정보전달 방법은 새로운 기술 환경 속에서 널리 그리고 급속히 연구되고 있다. 본 연구 관심은 온라인 컨텐츠 소비의 가치 창조 및 새로운 정보전달 경로를 알아보는 것이다. 따라서, 온라인 게임 참여자 관련 가치 평가, 소비자 관심을 반영하는 순위 설계 방법 및 온라인 컨텐츠 서비스에 대한 스마트폰의 영향을 살펴본다.

첫번째 논문은 온라인 커뮤니티 참여자가 소비한 시간의 가치를 평가한다. 그 가치를 산정하기 위해, 한국의 한 온라인 게임 데이터를 경제통계학적 방법으로 분석한다. 분석 모델은 게임 참여자의 게임 지식 및 게임 내 활동을 구체화한다. 분석결과는 게임 참여의 단위 시간(분)당 금전적 헤도닉 가치 보여준다. 이 연구는 게임 참여자들의 네트워크 효과 속에서 소비자의 가치를 증가시키는 방법을 실증분석을 통해 논의한다. 본 연구는 경제통계학적 분석 외에 수리 분석적 방법을 발전시킴으로써, 초보 게임 참여자에게 일종의 인센티브(보조금)을 제공할 근거가 되는 가격 설계를 논의한다. 또한, 본 연구는 앞서 제시한 방법론 적용 그리고 헤도닉 및 효용적 가치를 평가하는 방법 및 이유를 논의한다.

두번째 논문은 음원 순위 차트를 분석하고, 음원 순위 서비스 가치를 극대화하기 위해 차트가 어떻게 설계되어야 하는지 연구한다. 기존 음원 차트는 단지 스트리밍과 다운로드만 고려한다. 반면, 새로 제시되는 음원 순위 모델은 인기도, 가격, 그리고 고객 관심의 급격한 감소를 반영하는 슬롯효과를 반영한다. 슬롯 효과는 음원 데이타의 통계학적 분석의 발견적 방법으로 설계된다. 슬롯 분석으로, 음원 판매자는 고객의 관심을 이끄는 슬롯에 전략 음원을 배치하거나 슬롯 크기를 결정해 이익을 극대화 할 수 있다. 음원 구매자는 정확한 정보 및 탐색비용을 줄임으로써 간접이익을 취할 수 있다. 실증 분석은 새로운 음원 모델이 기존보다 효과적임을 보여준다.

마지막 논문은 통신 묶음 서비스(모바일, 인테넷, 그리고 케이블 텔레비젼)에 대한 스마트폰 영향을 분석하다. 이 연구는 세가지 개별 서비스를 포함하는 묶음 서비스간의 이동을 분석한다. 이를 위해 개별

서비스내의 서비스간의 변환 률 및 묶음 서비스간의 변환 률을 마코브 체인 변환 분석을 통해 서술한다. 본 연구는 또한 모바일 서비스내(기존 폰 서비스, 스마트 폰 서비스) 매달 변환 률을 분석하고, 주요 변수로서 서비스 가격과 2년약정 계약기간중 남은기간의 한계효과를 분석한다.

주요어: 온라인 게임, 헤도닉 가치, 온라인 뮤직, 슬롯 효과, 스마트 폰, 변환 률

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