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Valuation of Participation in Social Gaming

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ABSTRACT: This study examines the value of the time that a user spends to participate in a social game. We focus on how a massive multiplayer online role-playing game (MMORPG) vendor can establish prices to encourage participation and retain its players. We estimate value through an application of the hedonic pricing model and analyze a data set for an MMORPG in Korea. The results permit us to estimate the value of game-playing time in monetary terms. Based on our empirical results, we propose an economic model and conduct numerical simulation to show how a game vendor can apply differential pricing in this context. This enables us to design a pricing scheme to maximize a game vendor's profit. Our study affirms the long-standing finding that building network effects associated with other game players' participation is a critical source of benefits for the vendor. Going beyond this, we also find it is appropriate to use differential pricing, by subsidizing a participant's game play initially and then charging more aggressively to extract the available consumer surplus over the player's life cycle in the game, in order to reinforce a vendor's ability to maintain a healthy number of game participants.

KEY WORDS AND PHRASES: Customer valuation, econometrics, field study, hedonic pricing, hedonic value, MMORPGs, online games, role-playing games, social gaming.

Participation in massive multiplayer online role-playing games (MMORPGs) has grown rapidly on the Internet around the world [18]. Their popularity matches the substantial base of paying subscribers that game vendors have developed, and this gaming genre contributes significant revenues to the online gaming industry [24, 34]. The distinguishing features of MMORPGs are that players simultaneously share the game-playing experience, collaborate and compete with other players in the game to accomplish different tasks and earn virtual currency in the game environment [37]. MMORPG players are able to customize and alter the roles they take on, and they also can switch and modify the avatars they adopt with the help of software functionality made available by game vendors [47]. The success of MMORPGs enabled by information technology (IT) critically depends on their usability, similar to traditional Web sites and all kinds of software [33].[1]

The benefits and value of playing MMORPGs are varied and interesting, including social interactions, group interactions, game goods trading, and so on. For example, players can earn game money and trade game goods with other players, which can be downloaded for a small purchase fee in the game market. The game goods can be produced at a very low cost. In the virtual world of online gaming, game vendors provide support for game players to achieve their goals. They also aim to help game players be satisfied with their gaming experience as the players search, navigate, and experience the gaming environment and game goods and interact with other players in different game-play contexts [30]. The value of social game participation and game goods varies widely across individual players, however. Some players put a high value on the goods and participation, but other players put a low value on the same goods and game play. In this sense, pricing for game products and game play should be based on the value that players perceive [39].

This study aims to establish a value-based pricing scheme for MMORPG participation [39]. It focuses on MMORPGs as an instance of social gaming. For this work of applied economics for the information systems (IS) and e-commerce literature, we combine an empirical application of the hedonic pricing model involving real-world data from a field study setting with an analytical model and numerical simulation. We use this approach to develop policies for pricing that are designed to consider the development of game players' skills and experience in the MMORPG over time. The hedonic pricing model has been employed by many researchers to model and predict the prices of products and services, but we have not yet seen its application in social games. Our method of analysis is to blend an empirical model and its results with an analytical model and its findings to determine a willingness-to-pay-based pricing scheme that will support a game vendor that wishes to charge game players differential prices. This study further provides a game vendor with a value-based pricing mechanism for the early, middle, and later stages of game players' participation to maximize its profitability.

Value from the customer's perspective has been conceptualized in terms of *quality* and *willingness to pay.* Value includes multiple factors that involve complex considerations and relationships [5]. For example, a customer's valuation can be viewed in terms of *utilitarian value* or *hedonic value.* These terms represent the idea that consumers are spending money to purchase goods or services because they are needed or because the goods or services make them happy [12, 13]. The latter represents *hedonic gratification* [2]. User behavior can be utilitarian or hedonic 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 [43], such as purchasing a book online from Amazon. They may be less concerned about time and effort when they engage in hedonic tasks, such as surfing the Internet or playing games [54].

The Internet has created the basis for new experiences in online users' lives by supporting new forms of online interactions and enhancing offline relationships. The growth and penetration of Internet access have extended the meeting spaces for those with common interests in the digital world, particularly in the domain of online gaming, where real-time interaction is required [10]. Some online users are attracted to the Internet because it can save them time [3]. In Internet use, the duration of site visits is correlated with the quality of a user's experience [40]. So utilitarian value and hedonic value appear to coexist for online network participation. In addition to online user participation, social media have come into widespread use in almost every area of business.

Network effects associated with other game players' participation play an important role in consumer willingness to pay for information technology (IT) applications. This perspective has been used to evaluate the sales of operating systems, for example [15]. Other researchers have linked hedonic value to network effects by assessing a hedonic payment index for spreadsheet software [16]. Still others have found that hedonic value is a good predictor of willingness to pay in the market for spreadsheet software [7]. More recently, we have seen network effects in social network settings, in which well-known participants generate more interest and participation than network effects theory alone predicts. The frequent interactions among game players promote new kinds of social experiences in the virtual community context [18, 53].

The relationships that underlie such interactions may be complex though. In social games, a player can play the game alone or as a member of a group in the game. The player can also play the game by joining a group that will only be short-lived. Players in a group can send text messages to one another to take actions together against another group or other strong entities in the game. Thus, a player in a group will get involved in more social network activities than a player who does not connect in these ways with others. When game players organize or are members of a group, game vendors have a vested interest to encourage them to develop social relationships to support higher profitability [25]. A player's social ties to others in the game space will have an effect on the player's game enjoyment [20, 21, 22, 23]. Encouraging the acquisition and use of game goods also affects interpersonal interactions, since activities involving buying, selling, and trading such goods are possible, including game role and avatar identities and tools to enhance play [19, 48]. Thus, game vendors also will benefit if they have the capability to support and manage a player's ownership of game goods [50].

Playing a video game is a hedonic activity similar in some ways to music appreciation [52]. 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 in a given setting tends to increase their demand for the hedonic experience [38]. Conceptually, hedonic pleasure allows people to extract enjoyment from participation; efficiency allows people to use money and time better. It is not obvious how to differentiate utilitarian value from hedonic value in social game participation, however. On the whole, hedonic value is a key driver for lasting engagement in the game [6]. Players achieve enjoyment through social interactions and making various accomplishments, such as moving to higher levels in the game and developing more skills. Social interaction is a key issue in MMORPGs because players benefit from cooperation with other players as a team. MMORPGs also have multiple tasks that require different characters with different skills in order to complete a challenge to one another, which reinforces their relationships, providing a good understanding of teamwork [11]. The value of game-based social interactions can be interpreted as hedonic value for social network activities, whereas the value of improvement in a user's accomplishments in terms of game level, for example, can be viewed as utilitarian value.

Our study assesses gaming-level competency as a means of measuring the value of a user's participation, which changes over time in social gaming. A social gamer'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 the user's net gains from social gaming play. The value of participation can be assessed in terms of the time and money the player invests. We also study how the value of social interactions and improvements in gaming skills translates into a participant's willingness to pay as the participant experiences more difficulty while progressing through the beginning, intermediate, and advanced levels of the game. Our analysis suggests an initial stage with subsidized pricing, followed by the implementation of more aggressive charges in pricing once a user's valuation rises with experience and the user makes a greater commitment to social gaming participation through loyalty [22, 50].

The *hedonic pricing model* regresses the price of one unit of a *commodity* on a function of its *attributes* [14]. A related issue is the microeconomic interpretation of the function of the attributes on the right-hand side of the regression. Many studies have used hedonic pricing models to measure consumer valuation of product attributes when they are part of a larger purchase bundle [17]. This model also has been used widely in estimating price changes in automobiles [1] and in evolving quality as the price of mainframe computers has declined [9]. Others have modeled the price of mainframe computers with memory and secondary storage size [36] and in estimating the value of computer workstation attributes [45].

Traditional approaches for measuring customer worth have involved hedonic value assessment, and social network users also obtain this kind of benefit to varying degrees. For example, a user may join a social network because of its utilitarian value in providing a way to connect 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 [56]. Consumers typically have preferences relative to utilitarian and hedonic value, and these are driven by the different attributes and quality of a product or service. For most things, there is a maximum amount that consumers will spend, that is, their willingness to pay or reservation price.

A business network, like an online game platform, performs value co-creation activities and benefits from the present value of future growth opportunities as well [26, 58]. Participants in the network benefit from substantial incentives and appropriate subsidies to encourage them to make initial investments to jump-start the growth of network value [46]. Previous studies have examined network growth for a monopolist that manipulates the price of network subscriptions to encourage participation, with the idea that reaching critical mass in participation will help the network to eventually achieve a profit-maximizing size. Nonlinear pricing has been proposed for participation beyond some critical mass point [41]. In this study, we argue in favor of a participation subsidy for players who are in the early part of their life cycle of game participation, and more aggressive pricing later to maximize the game vendor's profit, while maintaining positive utility for the player in spite of making the player pay a higher price. This helps the vendor to sustain a healthy population of game-play participants.

A common way to develop new product designs in marketing is to identify which product attributes influence consumer purchase decisions. Product category attributes may include size, shape, performance, and style, among others [28]. Identifying attributes and features of game goods that influence players' interest in purchasing them can be readily translated into practice because they describe concrete product attributes [32, 48]. Wang et al. [55] pointed out, in a study of the 24 most popular MMORPGs around the world, that games with more intensive social networking and flatter social hierarchies are associated with lower monetary value for MMORPG goods. Having more active users, however, leads to higher demand for the game and higher value for the game goods. A steeper social hierarchy in the game further reinforces value.

Not all players' motivation and behavior, however, can be explained in terms of individual preferences for game attributes [4, 31]. Our study employs the hedonic pricing model to estimate the value of social interaction, the extent to which a player's advancement in the game matters, and the amount of time a participant plays the social game. Our estimation identifies the marginal effects of the characteristics of a game as a *complex hedonic commodity.* We report empirical results to show the importance and effects of various drivers on the user's valuation of time spent playing the game. The drivers include a player's skills in the game, the level of the game the player has reached, and the impact of the network effects associated with the number of other game players involved. The value of social game participation is informative for game vendors, which can use such knowledge to set up appropriate pricing schemes. Other analysts can use it to gauge value of social game participation in the entertainment industry in a broader sense.[2]

Our main objective is to assess the value of participation in social gaming and to apply our approach in a field study of a specific MMORPG. The following section presents the background of our social gaming setting and the data that we analyze. The empirical analysis section lays out the basis and specification of our empirical model and identifies the reason for estimating multiple econometric models to establish the value of social game participation in monetary terms. The pricing scheme design section builds on our empirical results by extending our exploration to include the possibility of differential pricing. The main connection between the empirical regularities analysis and the analytic model is that coefficient estimates from the empirical model can be leveraged to create a basis for establishing an optimal pricing strategy across the life cycle of gamers' participation in the social gaming platform. We justify why it is appropriate to adjust prices over time, as a participant's willingness to pay for playing the game changes. We discuss the value and management of social games from the different perspectives of vendors, gamers, and researchers in the penultimate section, and then we offer some final remarks.

Research Context, Data, and Process

This section describes our research context, MMORPG variables and data, and research process.

Research Context

We conducted a field study of a point-and-click MMORPG developed in Korea (see Table 1). The game has seven different player roles or personas that can be taken on. These control the types of powers the player can use,

Table 1. Overview of the Research Context: A Massive Multiplayer Online Role-Playing Game.

MMORPG	Description
Model	MMORPGs are subscription-based virtual worlds that host thousands of players who interact with one another
Method	Point-and-click; movement, combat, and so on controlled by a mouse
Story	Players learn skills to trade, open, or join a guild after completing a task, open a chat room, create groups to fight better, hold or collect game items and currency
Process	Players obtain skills to strengthen their roles and progress to higher levels
Role	Players choose a game role from among those that are available.*

* For example, in the MMORPG that we are exploring, 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, and 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. This is the nature of the game.

such as physical power, martial arts, or magic, and the style of the player's interactions with other game players. We refer to them with different role identifiers. After making progress through the game levels, a player in any role can change to another role.

Game players perform different tasks that involve the development of their role abilities. The game tracks a player's progress by level of play and by experience points (*ExperPts*). (See Appendix A for the details of our modeling notation.) After enough experience points are accumulated at each level, a player will move to the next level. Players typically use *game currency* to buy gaming goods, such as weapons, to reach a higher level more easily. As their game levels increase, most players need more equipment to succeed. They can earn game currency by completing tasks, which permits them, in turn, to buy new equipment. After reaching a higher level, a player's earnings will grow arithmetically, and the cost of equipment relevant for making additional progress will grow exponentially. Devoted players sometimes choose to spend *real money*—not game currency—to make purchases to enjoy the game more and move to a higher game level [18, 19, 42, 49]. Experience points are used to reward players who move to a higher level. These points strengthen their capabilities.

The emphasis in design is to make a game challenging for players with high 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* (a sword for a spear) or *complements* (a sword with a shield). The prices of weapons within the digital boundaries of the game are fixed. Players can invest to make their weapons more efficient for battle though. 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 social gaming

Table 2. Descriptive Statistics for the MMORPG Data Set.

Feature	Mean	Standard deviation	Min.	Max.
Spending	344,861	582,366	440	5,771,700
OppCost	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 sample observations are in the data set, reflecting seven different roles that each player can engage in. The average number of players during the observation period who selected each different role is 65.25. This represents the network effect levels for each observation. When we collected the MMORPG data, 775 players participated and established recorded game levels. The data include information on new gamers who just attained Level 2, as well as experts who attained Level 251. Although there may be higher levels that can be achieved, many players will drop out due to loss of interest or the pursuit of other activities. So the reader should not think that the game levels are infinite. The average game level of the 775 players was 95. The applicable exchange rate is 1,100 won : US$1.

experience [8]. When they are having a lot of fun, they will be willing to pay more for a given weapon.

Variables and Data

Our field study data are from between July 1 and December 21, 2006. We obtained data on 775 role-playing participants in seven different roles (*Roles*). We also have 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 real money each individual spent (*Spending*), inclusive of the fee to participate in the game and the cost to buy some types of powers as the game progresses; the game level (*GameLevel*); and the number of game players, which is a proxy variable (*NetEffect*) representing the extent of relevant network effects.[3] *OppCost* is the opportunity cost per unit time for a person to spend time playing the game, based on the applicable minimal wage for work per unit time. Game access is the number of times a player accessed the game (*Access*) (for details, see Tables 2 and 3).

Research Process

The four steps in our research process are as follows (see Table 4):

- *Step 1.* Step 1 is the analysis of a hedonic pricing model with a number of game attributes to represent the related hedonic commodity.

Table 3. Correlations.

	Spending	***OppCost***	***NetEffect***	***Time***	***Access***	***Skills***	***ExperPts***	***GameLevel***
Spending	1.00							
OppCost	0.26	1.00						
NetEffect	0.70	0.34	1.00					
Time	0.26	1.00	0.34	1.00				
Access	0.24	0.72	0.31	0.72	1.00			
Skills	0.11	0.35	0.18	0.35	0.57	1.00		
ExperPts	0.21	0.47	0.23	0.47	0.56	0.28	1.00	
GameLevel	0.24	0.67	0.34	0.67	0.73	0.46	0.52	1.00

Notes: We need to know the correlations between Access and Time, since our modeling approach requires the consideration of potential instrumental variables. In addition, OppCost is computed based on the minimum wage multiplied by the amount of times a player spent in the game, so the correlation with Time is perfect.

Table 4. The Research Process in This Study.

Empirical Modeling and Estimation →		**Pricing Design and Simulation**	
1. Development of a baseline hedonic pricing model	2. Analyses of extended models to improve the robustness of the empirical results	3. Modeling game participation pricing using a game player's utility	4. Simulation of impacts of the use of a subsidy in pricing strategy for different network sizes
• Justification for the variables included • Discussion of the issues that arise around the setting and variables	• Heterogeneity, omitted variable, endogeneity, and outlier diagnosis • Value estimation for a player's game-playing time	• Modeling analysis of social game participation pricing with a price subsidy in presence of network effect	• Player subsidy simulation for early stage of game play • Differential pricing over player's life cycle in the social game

The goals of each step are:

- Step 1: Develop a hedonic pricing model for game participation. Identify the value of the attributes of the game through a measurement approach based on the hedonic price estimation.
- Step 2: Ensure the robustness of the empirical results by diagnosing and addressing key problems that arise.
- Step 3: Design a pricing scheme to complement the empirical results and extend the insights they offer.
- Step 4: Analyze the performance of a subsidy-inclusive pricing scheme via a computational simulation.

Our goal is to identify how much game players will be willing to pay based on establishing estimates for the key variables: *Access*, *Skills*, and *GameLevel*. These are intended to gauge experience, skills, and accomplishment in the game in ways that reflect the value of social interactions and a player's game accomplishments relative to others in the game. We estimate the value of a player's game-playing time by assessing the substitution effect between observed spending and the units of social game-playing time consumed.

- *Step 2.* Step 2 involves the creation of our estimation results, together with various model diagnostics that ensure their robustness. We use econometric tests to examine the stability of the coefficient estimates. The checks include heterogeneity, omitted variables and endogeneity, model reduction, and outlier diagnostics.
- *Step 3.* Step 3 entails numerical analysis of an extended analytical model to supplement the empirical work. A primary goal is to link the estimation results for the value of social game-playing time to the utility of participation when a participation subsidy can be offered, and different network effects occur in different stages (early, middle, and late life cycle) of a player's participation.
- *Step 4.* In Step 4, we suggest how to establish (1) subsidies for participation in the early stage, (2) appropriate prices based on participants' willingness to pay, and (3) time-varying prices that reflect participants' changing levels of willingness to pay in their life cycle of game participation. We also provide computational simulations to validate the proposed approach.

Empirical Analysis

We next present the results of our empirical analysis, which include the estimation of a baseline model of social game-playing time and the handling of endogeneity via an instrumental variable regression. The purpose of this estimation work is to support the valuation of social game participation, specifically game-playing time. We later present additional modeling work to establish monetary value in terms of U.S. dollars and then shift to a further discussion of how to use this information in an analytical model so that the social gaming provider can establish an effective customer life cycle–based pricing policy in the section that follows.

A Baseline Model to Value MMORPG Participation

The baseline model for this empirical research applies to a set of individuals *i* in the MMORPG:[4]

$$\ln Spending = \alpha_{Constant} + \alpha_{NetEffect} \ln NetEffect + \alpha_{Time} \ln Time \\ + \alpha_{Skills} \ln Skills + \alpha_{GameLevel} \ln GameLevel + \varepsilon.$$

In addition, there is a possibility of measurement error in the explanatory variables, as is typical in most applied settings, as well as omitted variables that our research setting did not permit us to measure (e.g., game players' wealth, available free time for game play, and the extent of the players' connectedness to other game players). The pairwise correlations involving *GameLevel*, *Access*, *OppCost*, and *Time* exhibit correlations that are less than 0.80, a desideratum in econometric analysis [27] (see Table 3).

The variable *Time* is endogenous in our model. Social game participants can make choices about how much time they wish to spend in game play, and this is likely to be tied to other unobservable or omitted variables (whether they are wealthy or have to work, have friends that enjoy computing, and so on).

Addressing Endogeneity with Extended Instrumental Variable Models

The corresponding instrumental variable model, with *Access* replacing *Time*, is[5]

$$\ln Spending = \beta_{Constant} + \beta_{OppCost} \ln OppCost + \beta_{NetEffect} \ln NetEffect \\ + \beta_{Access} \ln Access + \beta_{Skills} \ln Skills + \beta_{GameLevel} \ln GameLevel + \zeta.$$

We obtained estimates for the model in two different forms using Stata 12.1 (see Table 5). In the first estimation, the coefficients of *OppCost* and *Access* are related to a participant's game-playing time. Recall that *OppCost* is a person's opportunity cost per minute based on the relevant minimum wage. With a

Table 5. Reduced Instrumental Variable Model.

Parameters	Robust regression		GMM	2SLS
	Estimation methods			
ln *Constant*	–4.01***	–4.07***	0.321	0.321
	(0.0764)	(0.0615)	(0.4171)	(0.1858)
ln *OppCost*	–0.012			
	(0.0115)			
ln *NetEffect*	2.67***	2.671***	1.874***	1.874***
	(0.0093)	(0.009)	(0.0761)	(0.0274)
ln *Access*	0.051***	0.035***	0.183***	0.183***
	(0.0171)	(0.0112)	(0.0382)	(0.0311)
ln *Skills*	–0.008	–0.0064	–0.076***	–0.076***
	(0.007)	(0.0068)	(0.0242)	(0.0199)
ln *GameLevel*	–0.031*	–0.036**	–0.125*	–0.125**
	(0.019)	(0.0174)	(0.0639)	(0.0638)
R^2			87%	87%
Observations	775		775	775

Notes: Dependent variable = ln *Spending*. The estimation models are instrumental variables regression. All coefficient estimates are in log form. Standard errors are in parentheses. We performed additional checks for problems with endogeneity based on the application of the Durbin–Wu–Hausman (DWH) test for *Time* variable. We chose *Access* as an instrumental variable for *Time*. Based on the estimates of role different regressions, we can identify the similarity or difference between roles. Technically, we can understand the correlation of variance of error terms of role different estimations, which have similarity in some respects. Game manager always considers the balance between roles. Even though empirical results are not sufficient to illustrate the differences and similarity between every possible pair in seven different roles because of our limited data set, the approach of role different regressions allows game manager to realize the role balance. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

minimum wage in U.S. dollar terms of approximately US$2.40 per hour in Korea in 2006, a game player could have earned at least US$0.039 per minute by working in a minimum wage job and not playing the game.[6]

To correct for the issues that we have noted above, we estimated a second hedonic pricing model that omits the *OppCost* variable—the reduced instrumental variable model:

$$\ln Spending = \delta_{Constant} + \delta_{NetEffect} \ln NetEffect + \delta_{Access} \ln Access + \delta_{Skills} \ln Skills + \delta_{GameLevel} \ln GameLevel + \xi .$$

Estimation Results for the Extended Models

Most of the coefficient estimates have the expected signs. Willingness to pay to participate increases as the number of players grows. *OppCost*, the cost of playing time, was not significant though. The gains based on participant knowledge, *Skill*, and *GameLevel* were negative, since the dependent variable, *Spending*, generally decreases as gaming skills increase after some point when high competency is achieved. The coefficients of *NetEffect*, the number of game participants, indicate how well the players are able to complete the

Table 6. Reduced Instrumental Variable Model with Dummies.

	Game Stages			
Parameters	**All stages**	**Beginning stage**	**Intermediate stage**	**Advanced stage**
ln *Constant*	0.243	11.312***	3.625***	–30.023**
	(0.4123)	(0.9608)	(1.2964)	(15.043)
ln *NetEffect*	1.869***	–1.914*	–0.135	–0.354
	(0.076)	(1.1087)	(0.1669)	(0.2495)
ln *Access*	0.183***	0.474***	0.377**	0.407**
	(0.0404)	(0.1259)	(0.1508)	(0.1572)
ln *Skills*	–0.070***	–0.219	–0.028	0.026
	(0.0246)	(0.1714)	(0.0708)	(0.0857)
ln *GameLevel*	–0.087	1.901	1.158**	7.385**
	(0.0724)	(1.7251)	(0.4997)	(2.9675)
Intermediate	–0.148			
	(0.1269)			
Advanced	0.018			
	(0.1809)			
R^2	88%	12%	10%	5%
Observations	775	197	520	58

Notes: Dependent variable = ln *Spending*. The estimation model is instrumental variables GMM regression. All coefficient estimates are in log form. Standard errors are in parentheses. We classified game stages into Beginning (*GameLevel*: 1–50), Intermediate (*GameLevel*: 51–200), and Advanced (*GameLevel*: 201–251) with respect to each player's final level at the point of collecting data. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

game's tasks with other players. The fixed effects for the roles were weakly significant in our estimations, so we omitted reporting the role-dependent coefficients in Table 5.

We extended the model by adding stage dummy variables (beginning, intermediate, advanced) in order to identify the variation of the estimates over the game stages. The coefficients of the stage dummies did not have the expected signs and were not significant. Thus, we ran a separate regression for each different stage. One obvious result is the positive coefficient values of *GameLevel*, which represent more aggressive spending in the later game levels (see Table 6). The results do not show all the effects that we expected to see over the different game stages; however, the estimates of *GameLevel* establish the appropriateness of aggressive pricing at higher game competency levels. Based on this result, it may be appropriate to subsidize game participants in the early stage of their involvement and then charge them more in the latter part of their life cycle in the game.

Establishing the Value of Game Participation Time

We know that social gamers spend considerable time and effort participating in social interactions and entertainment activities. Due to the intangible benefits associated with this participation, it is hard to establish the value they receive.

By analyzing the efficiency of a user's game participation, however, it is possible to establish such an estimate for the value of participation time. This, we suggest, can be calculated by identifying the substitutability between their spending and their participation activity in the game. Based on our experience in this research, it appears that this approach is applicable to the valuation of user time in social game and social network settings.

To assess substitutability in the MMORPG context, we employed another modeling approach that makes it possible to analyze the trade-offs and establish a valuation. Our application of the modeling notation is consistent with the models we have already discussed. We now shift to an empirical model in which it is possible to gauge how players build their experience in the game, by having *ExperPts* as the dependent variable, and then seeing how they trade off *Access* (as an instrument for *Time*) and *Spending* in their game play. The model—the instrumental variable substitution model—is given by

$$\ln ExperPts = \theta_{Constant} + \theta_{Access} \ln Access + \theta_{Spending} \ln Spending$$
$$+ \theta_{NetEffect} \ln NetEffect + \theta_{Skills} \ln Skills + \theta_{GameLevel} \ln GameLevel + \mu .$$

We used a two-stage generalized method of moments (2SGMM) approach to estimate the model.[7] When game players become involved in a social game, each player's willingness to spend time and money will be different. Our approach in this research is to assess the value of game-playing time based on the different players' game roles. For example, the value of a game participant's time in the MMORPG for Role F, which was one of the most popular roles in the game, can be computed via the estimated coefficients of the instrumental variable substitution model, as follows:

$$\ln ExperPts = \underset{(0.1434)}{-2.096^{***}} + \underset{(0.0264)}{0.197^{***}} \ln Access + \underset{(0.0246)}{0.056^{**}} \ln Spending$$
$$+ \underset{(0.0471)}{-0.042} \ln NetEffect + \underset{(0.0183)}{0.495^{***}} \ln Skills + \underset{(0.0596)}{3.268^{***}} \ln GameLevel.$$

The estimated *Access* and *Spending* elasticities have the usual interpretation. We estimate that a 1 percent change in *Access* will lead on average to an approximately 0.197 percent increase in *ExperPts.* Along the same lines, a 1 percent change in *Spending* will be associated with a 0.056 percent increase in *ExperPts.* Applying the coefficients of the model to average values for *Spending* and *Access* across all game players in Role F yields the following result for the average valuation of time on the part of a representative game participant in that role:

$$\frac{\theta_{Spending}}{\theta_{Access}} \times \frac{Spending}{Access} = \frac{0.197}{0.056} \times \frac{117{,}549.24}{17{,}363.86} = 23.82 \text{ won.}$$

Thus, the value of a player's playing time in Role F for the data we used is US$0.022. The value of a social gamer's time in the other roles can be computed analogously.

The estimation of the value of a player's playing time in different game roles will be different, and it will also vary somewhat for individual players within each game role. MMORPGs are characterized by interactions among thousands of players. So each player who becomes involved in a specific role develops the skills to excel in the game tasks associated with the role to a somewhat different extent relative to other players in the same or different roles. Moreover, each game role is likely to exhibit a different level of popularity among game players.

Note that as we move from a discussion of the empirical regularities of the hedonic value that social game players may obtain during their game participation, the primary purpose of this empirical modeling is to identify useful parameter estimates so that it is possible to apply this information in the analytical modeling work that follows. This will enable us to characterize what a value-maximizing pricing strategy would look like for the social gaming services provider.

Pricing Scheme Design in Social Gaming

The typical modeling approaches evaluate how to separate different consumer segments to identify whom to give a free service to and whom to ask to pay for a service. Our premises are different. In this research, we are trying to figure out how to charge the same MMORPG players different prices based on the stage of the game they are participating in. There is no assumption here that all players are beginners, and then they all progress to intermediate and advanced levels at the same time, and so on. We have noted that the value of the time that MMORPG game players play the game is dependent on the estimation of how much money they spend and the extent of the usage they enjoy related to their accumulative experience in the game. To achieve utility from their game play with greater efficiency, social game players can acquire the necessary skills to accomplish various tasks by purchasing game tools that diminish their playing time.

One complication is that the game difficulty level increases over time as a player's game level increases. Thus, the empirical results for the value of game-playing time represent average values over time for the players' life cycle of participation in the game. A game player's valuation of game-playing time might initially be low, however, as the player learns how to play the game. The valuation will increase as the player becomes more familiar with the game and starts to have fun. Thus, it is appropriate to examine how the substitution between in-game spending and playing time change over time in the production of skills and experience points.

We did not have access to this kind of empirical data, however. We were not permitted to go beyond the collection of cross-sectional data. Nevertheless, we were able to make progress on this problem by studying the effects of differential pricing over time from the empirical results of the hedonic pricing model and an associated analytical model that reflects the knowledge we obtained in our field study.

Our empirical results shown in Table 5, which include the negative coefficient values of *Skill* and the positive coefficient values of *NetEffect*, imply that the value of game-playing time will increase as a player's game level increases. The increasing coefficient values of *GameLevel* over different game stages show that players involved in higher levels will be willing to pay more as their level increases, as shown in Table 6. The value of staying in the game will change as the player's experience and the number of other game players both increase. To explore these issues further and take advantage of the empirical findings in this research, we build and analyze a model for social game pricing from the vendor's perspective. We also develop simulation results to show the efficacy of game-playing life cycle–based differential pricing.

Model Preliminaries

Since our research involves the assessment of value of social gaming participation for an MMORPG user population, we work with averages of some of the main variables of interest in our model to reflect the potential for differences in participant valuation throughout their life cycle of game play. Vendor pricing should be based on user willingness to pay in the different levels of game play. Each social game player *i* in our model will attempt to maximize that individual's *Utility* at some level of the game, *GameLevel,* based on what benefits the player obtains from the player's own performance in the game and the network benefits that arise from the number of other gamers who are playing.[8] We refer to these variables in our model as *Performance* and *NetEffect.* We also consider the *Price* the game vendor charges for a player to participate in the game; it should be related to the value that a player is willing to pay across the different game levels. Thus, player *i*'s utility function is

$$\text{Max}\, Utility_i = f(Performance_i, NetEffect_i; GameLevel) - Price_{GameLevel}. \quad (1)$$

Our goal is to identify the impacts of *Performance* and *NetEffect* on MMORPG player utility across the different *GameLevels.* The impacts will be different in the early, middle, and later stages of a person's participation in the game. Players within the same game level are likely to have similarities—gaming skills, *ExperPts*, time spent playing, and so on. In this context, we want to work toward the specification of some basis for an optimal price for game play. This should be based on the average utility of all of the players in the same *GameLevel*. The reason we use the average utility of players in the same *GameLevel* is that, practically, the vendor cannot charge different prices to each player in the same *GameLevel*. So we need to find a price that is workable across all of the participants to the greatest extent possible. This approach is not perfect, but it improves over current practice.

This model involves a number of assumptions (see Table 7). The first is that the game vendor has full information of the average utility that game players achieve in the different game levels. This implies that $f(Performance_{GameLevel}, NetEffect_{GameLevel})$ will be exogenously determined, since the variables represent

Table 7. Modeling Assumptions.

No.	Assumptions	Definitions
1	Vendor knowledge	The game vendor will know the average value of utility for players at each of the game levels through the variables *Performance* and *NetEffect*.
2	Positive utility from performance and network effects	The average values of utility for *Performance* and *NetEffect* are positive.
3	Utility-dependent subsidy	Any subsidy for game participation offered will depend on the average utility that game players achieve in the different game levels.
4	Game level–based diminution in participation	The number of game participants decreases as they advance from the lower to the higher levels of game due to increasing game difficulty.

Notes: A common knowledge assumption for the social gaming vendor is that it will know fairly well about the level of utility achieved by a given player as the player's level of the game increases. The vendor will also have access to information on the average utility achievement of players at different game levels based on the contents of the game log files of the participants. This helps the vendor to figure out how to design and adjust the level of difficulty that players face as they play the game. This informs our specification of a player's utility and willingness to pay to play the game in Equation (1).

the average value of utility that arises from all players' performance and the network effect associated with all others who play at the game level.

A second assumption is that the utility of performance, *Performance*, at some game level will always be positive on average. This is reasonable because most game vendors usually design their games to have increasing difficulty across the different game levels. What starts out as easy becomes harder and continues to provide a challenge to participants across their life cycle of game participation.[9] This assumption is a strong one. It stresses the need for the game vendor to design the difficulty of the different game levels very carefully to minimize the departure of players. Maintaining a healthy number of game participants is a critical source of benefits for both the vendor and the participants themselves. Another aspect of our second assumption is that the utility of network effects in game play will be more strongly positive as more players participate and that this will encourage players to stay in the game and concur with the other participants' assessment of the value of social interactions.

A third assumption is that any subsidy that the vendor may offer for a player to join the game or stay in the game will depend on the average level of utility that players obtain from their performance at different levels of the game. This is also true for players who have not joined yet and may need an initial subsidy to participate; this will be determined based on the average utility of beginning game players' performance in the game.

The final assumption is that players will tend to drop out as the level of difficulty of the game increases over the different levels of play from beginning to advanced. In addition, others may drop out because of loss of interest or lack of additional challenge in the game.

Beginning gamers will benefit from vendor subsidies (a coupon to join, a bonus for achieving level-up progress, etc.). A game vendor needs to price game participation in an optimal way for players, perhaps by imposing a higher price on the play of frequent social gamers. The vendor also will benefit by establishing a basis for differentiated prices by offering subsidies when a player's willingness to pay diverges from the overall average price level in the game.

In the earlier empirical results that we presented, we estimated the average value for playing time in a way that aggregated beginning, intermediate, and advanced players' valuations. We did some work to estimate player participation time value with consideration for the different game roles they took on. A subsidy for encouraging start-up or continuing game play should be related to a gamer's willingness to pay for play across the different game levels.

The Model

We next develop and analyze a model that permits a vendor to identify an appropriate *SubsidyRate* that is in line with the average utility of the players who are participating in a given level of the MMORPG. The subsidy in this research is closely related to the utility that users achieve over different MMORPG levels. Early on in the game, it is necessary for the game vendor to attract players to participate. So the intention associated with using a subsidy is to support the new game player so the player will not have to bear the full costs of the average willingness to pay for the gaming experience over the life cycle of the player's participation at the early stage. We expect that a player's utility will come closer to the player's expected utility from the game as the game progresses, but may not rise to such a high level early in the game, and hence the subsidy is helpful.[10] The $SubsidyRate_{GameLevel}$ will be a function of game-level *Performance* and *NetEffect* across the number of game-level players, $\#Players_{GameLevel}$: $f(Performance_{GameLevel}, NetEffect_{GameLevel})$. The subsidized price then is given by $SubsidizedPrice_{GameLevel} = (1 - SubsidyRate_{GameLevel}) \cdot Price_{GameLevel}$. The value maximization function for the gamer is

$$\begin{aligned} \text{Max } Utility_{GameLevel} &= f(Performance_{GameLevel}, NetEffect_{GameLevel}) \\ &- \#Players_{GameLevel} \cdot (1 - SubsidyRate_{GameLevel}) \cdot Price_{GameLevel}. \end{aligned} \quad (2)$$

To derive the demand function for play time at each game level, each participant's utility (i.e., $Performance_i$ and $NetEffect_i$) must be represented in terms of the average utility levels among all players, as $Performance_{GameLevel}$ and $NetEffect_{GameLevel}$. When we divide both sides of Equation (2) by $f(\cdot)$, we obtain the *average utility in a given game level*:

$$\begin{aligned} &\frac{Utility_{GameLevel}}{f\left(Performance_{GameLevel}, NetEffect_{GameLevel}\right)} \\ &= 1 - \frac{\# Players_{GameLevel} \cdot \left(1 - SubsidyRate_{GameLevel}\right) \cdot Price_{GameLevel}}{f\left(Performance_{GameLevel}, NetEffect_{GameLevel}\right)}. \end{aligned} \quad (3)$$

The vendor's revenue function, as a result, will be

$$\text{Max}Revenue = \left[1 - \frac{\#\,Players_{GameLevel} \cdot (1 - SubsidyRate) \cdot Price_{GameLevel}}{f\left(Performance_{GameLevel}, NetEffect_{GameLevel}\right)}\right] \cdot \#\,Players_{GameLevel} \cdot \left(1 - SubsidyRate_{GameLevel}\right) \cdot Price_{GameLevel} \quad (4)$$
$$\text{subject to } 0 < SubsidyRate_{GameLevel} < 1.$$

Thus, the pricing scheme that we propose will include different prices in each of the three stages of a player's life cycle in the game—the beginning, intermediate, and advanced stages. Based on our field study interviews and discussions with gamers, it is reasonable to assume that the average performance-based utility for players will grow slightly in the beginning stage: it takes a beginner some time to get used to the game and begin to enjoy its qualities—but many do come to enjoy the MMORPG very much. The average performance-based utility for players is likely to grow at a more stable and faster rate in the intermediate stage of play. After a player reaches an advanced level of play—becoming an expert player in the game—there will be a diminishing rate of growth in utility from the player's game performance. However, the network effect associated with a large number of participants in the player's beginning stage of play will make the player want to stay in the game and reach the intermediate stage. This effect will probably grow weaker as the player advances, though, since our field study observations have suggested that fewer players tend to stay with the game as the level of difficulty increases. The essence of how player utility changes across the life cycle of a player's involvement in the MMORPG is captured by the contents of mathematical expressions in Table 8.

Model Analysis and Results

Figure 1 shows the stream plots for average utility in the different life cycle stages of the game. We chose values for the scales of the different parameters for which the most interesting economic behavior could be observed, not those where for which the outcome was insensitive to the various simulation values selected. We used Mathematica 8 to render the stream plots and to perform the numerical analysis.

Each different plot shows the direction and strength as the variables, *Performance* and *NetEffect*, vary. If the three plots were combined into one plot, it would look like an S-curve. It would increase, move sharply higher, more moderately higher, and then tail off and become more stable. The stream plot shape is dependent on two variables, $Performance_{GameLevel}$ and $NetEffect_{GameLevel}$, and the form of the utility function. We used two different utility functions. One is a linear utility function, $(Performance_{GameLevel} + NetEffect_{GameLevel}) \cdot GameLevel$, and the other is an exponential function, $GameLevel^{(Performance_{GameLevel} + NetEffect_{GameLevel})}$. Then we assigned specific numerical values to $Performance_{GameLevel}$ and $NetEffect_{GameLevel}$ according to our assumptions in Table 8. Each stream plot shows the local direction of utility at each (*Performance*, *NetEffect*) point.

Table 8. Player Utility by Life Cycle Stage in the Game: Beginning, Intermediate, and Advanced.

Beginning stage

$$0 < Performance_{GameLevel} + NetEffect_{GameLevel} < 1;\ 0 < Performance_{GameLevel} < NetEffect_{GameLevel} < 1$$

$$\frac{\partial f(\cdot)}{\partial Performance_{GameLevel}} > 0 \text{ and } \frac{\partial^2 f(\cdot)}{\partial^2 Performance_{GameLevel}} = 0,$$

$$\frac{\partial f(\cdot)}{\partial NetEffect_{GameLevel}} > 0 \text{ and } \frac{\partial^2 f(\cdot)}{\partial^2 NetEffect_{GameLevel}} < 0$$

Intermediate stage

$$1 < Performance_{GameLevel} + NetEffect_{GameLevel};\ 0 < Performance_{GameLevel} < 1 < NetEffect_{GameLevel}$$

$$\frac{\partial f(\cdot)}{\partial Performance_{GameLevel}} > 0 \text{ and } \frac{\partial^2 f(\cdot)}{\partial^2 Performance_{GameLevel}} > 0,$$

$$\frac{\partial f(\cdot)}{\partial NetEffect_{GameLevel}} > 0 \text{ and } \frac{\partial^2 f(\cdot)}{\partial^2 NetEffect_{GameLevel}} < 0$$

Advanced stage

$$0 < Performance_{GameLevel} + NetEffect_{GameLevel} < 1;\ 0 < Performance_{GameLevel} < 1 < NetEffect_{GameLevel}$$

$$\frac{\partial f(\cdot)}{\partial Performance_{GameLevel}} > 0 \text{ and } \frac{\partial^2 f(\cdot)}{\partial^2 Performance_{GameLevel}} < 0,$$

$$\frac{\partial f(\cdot)}{\partial NetEffect_{GameLevel}} > 0 \text{ and } \frac{\partial^2 f(\cdot)}{\partial^2 NetEffect_{GameLevel}} = 0$$

Notes: The reason *Performance* may have the highest value in the intermediate stage is that social gamers tend to be the most focused about their game-playing activities in the intermediate stage. As beginners, they sample the gaming environment and try to figure out whether it is enjoyable for them. This may be why *NetEffect* may have the highest value in the beginning stage: people need to see a lot of participation from others in order to be able to ascribe value to making their own commitment in the social game.

In the beginning stage of a player's life cycle, we expect $Performance_{Beginning}$ utility to be linear and lower in utility value, although there will be higher utility due to $NetEffect_{Beginning}$. In the intermediate stage, we expect to observe convex utility, with the highest value of utility from $Performance_{Intermediate}$ and a lower value from $NetEffect_{Intermediate}$. In a player's advanced stage of social game play, we expect to observe concave utility, with a low value of utility from $Performance_{Advanced}$ and a lower value from $NetEffect_{Advanced}$. These expectations about utility were established from our interactions with managers in our field study and are reflected in our assumptions about the general MMORPG model. The stage-based utility plots are informative for a vendor to form a strategic pricing and subsidy strategy.

Based on the assumptions, we obtained the optimal subsidy rate: $SubsidyRate^*_{GameLevel} = (2 \cdot \#Players_{GameLevel} \cdot Price_{GameLevel} - f(\cdot))/(2 \cdot \#Players_{GameLevel} \cdot Price_{GameLevel})$. From this, we can compute $Price_{GameLevel} = f(\cdot)/(2 \cdot \#Players_{GameLevel} \cdot (1 - SubsidyRate^*_{GameLevel}))$. The related optimal price to maximize the vendor's

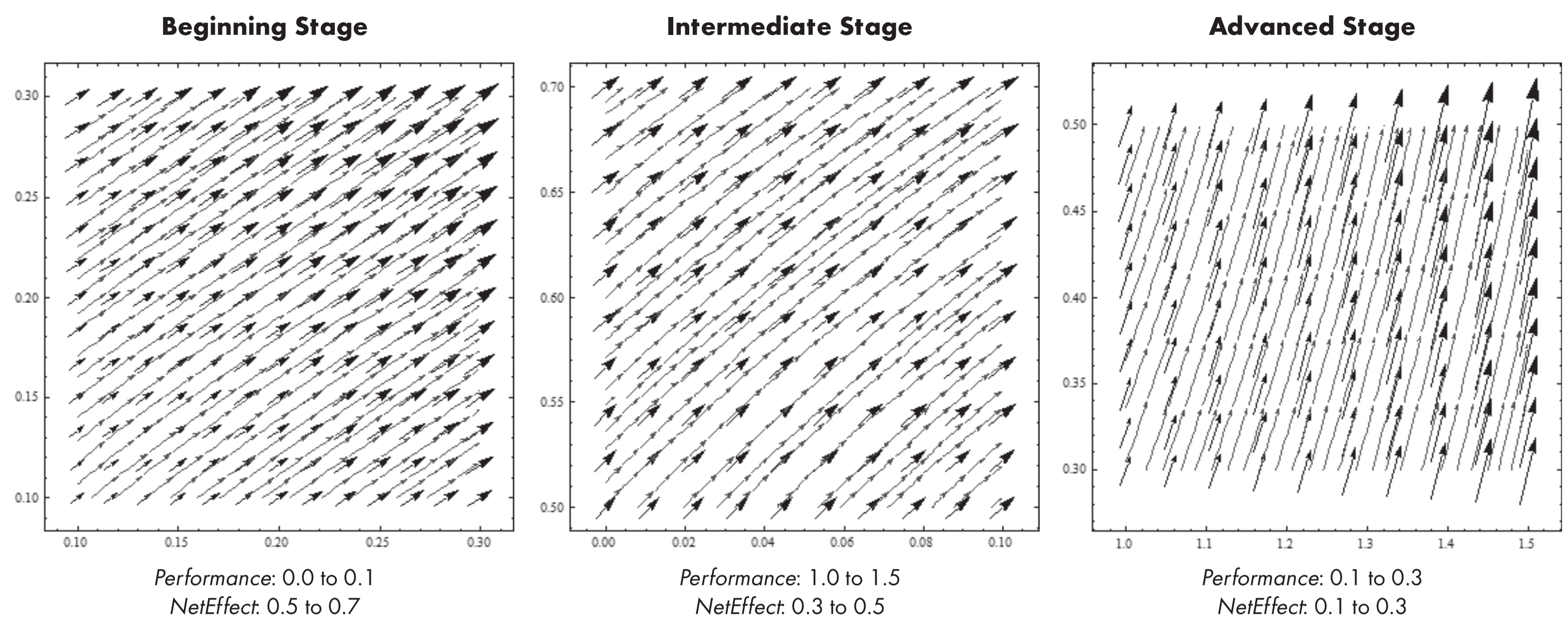
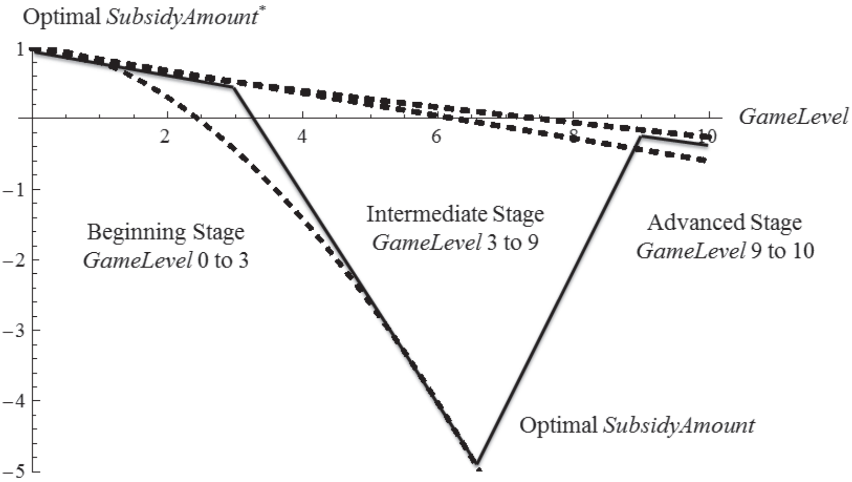


Figure 1. Stream Plots for *Performance*$_{GameLevel}$ (*x*-Axis) Versus *NetEffect*$_{GameLevel}$ (*y*-Axis)

Note: In these plots, the *x*-axis is *Performance* and the *y*-axis is *NetEffect*.



Beginning Stage	Intermediate Stage	Advanced Stage
GameLevel: 0 to 3	*GameLevel*: 3 to 9	*GameLevel*: 9 to 10
*SubsidyAmount**: 0.5 to 1.0	*SubsidyAmount**: –1 to –14	*SubsidyAmount**: -0.16 to -0.24
$Performance_{GameLevel}$: 0.1	$Performance_{GameLevel}$: 1.5	$Performance_{GameLevel}$: 0.5
$NetEffect_{GameLevel}$: 0.7	$NetEffect_{GameLevel}$: 0.5	$NetEffect_{GameLevel}$: 0.3

Figure 2. Optimal *SubsidyAmount for the Beginning, Intermediate, and Advanced Player Stages**

Notes: The *x*-axis is *GameLevel* and the *y*-axis is optimal *SubsidyAmount** or optimal *Price**. The plot is for level sets of the different *Performance* and *NetEffect* values. The plot consolidates Figures 2 and 3 to present a combined view of pricing and subsidy policy, as suggested by the numerical simulation from our model. The true ranges of *SubsidyAmount** or *Price** as computed in our numerical simulation are the same as the true ranges in Figure 2 and 3, and the functions in the figures have induced continuities, but were actually discontinuous.

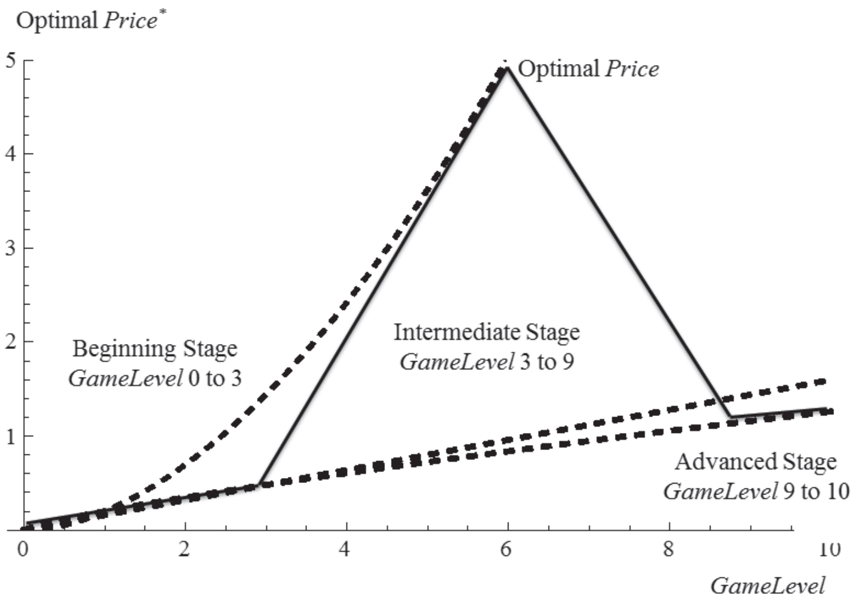
game revenue is $Price^*_{GameLevel} = f(\cdot)/(2 \cdot \#Players_{GameLevel})$ when only the subsidy level is considered. This leads us to assert:

> ***Proposition 1 (The Optimal Subsidy for Beginners Proposition):*** *A game vendor will optimally subsidize beginners if new game participants experience positive utility from the network effect of the number of players who join the MMORPG. A subsidy is a valuable means to encourage new game participants to stay in the game when they are in the beginning stage of game play by ensuring they experience positive utility.*

See Appendix B for the proof of all our propositions.

Figure 2 shows the optimal *SubsidyAmount** for game participation over the different stages and game levels that comprise them.

The optimal subsidy decreases as *GameLevel* increases at the beginning stage. After this stage, a subsidy will not be very effective in encouraging social gaming players to join the network. A negative value of the subsidy here corresponds to more aggressive and higher pricing, which will be more effective for the vendor in maximizing profit. As a result, it is important for



Beginning	**Intermediate**	**Advanced**
GameLevel: 0 to 3	*GameLevel*: 3 to 9	*GameLevel*: 9 to 10
*Price**: 0 to 0.5	*Price**: 1.5 to 16	*Price**: 1.16 to 1.26
$Performance_{Beginning}$: 0.1	$Performance_{Intermediate}$: 1.5	$Performance_{Advanced}$: 0.5
$NetEffect_{Beginning}$: 0.7	$NetEffect_{Intermediate}$: 0.5	$NetEffect_{Advanced}$: 0.3

Figure 3. Optimal *Price for the Beginning, Intermediate, and Advanced Player Stages**

Notes: The *x*-axis is *GameLevel* and the *y*-axis is optimal *Price**. The plot is for level sets of different values for the *Performance* and *NetEffect* parameters. Discontinuities in the function were connected. The true ranges of optimal *Price** as computed in our numerical simulation are shown just above.

the vendor to consider how to achieve an optimal pricing structure across the game stages. This leads us to assert:

> ***Proposition 2 (The Optimal Pricing Based on Players' Willingness-to-Pay Proposition):*** *The optimal price to charge for participation in the MMORPG will increase as a game player's utility increases, in spite of the fact that the number of players in the player's gaming network will decline as the player enters the intermediate stage.*

Figure 3 illustrates Proposition 2 by showing the optimal *Price** levels in the three different gaming participant life cycle stages. The optimal price increases at a different rate as the player's game level goes higher: slightly increasing in the beginning stage, more sharply increasing in the intermediate stage, and then linearly but not as rapidly increasing in the advanced stage. Figure 4 completes our exposition of the results by bringing together the optimal *Subsi-*

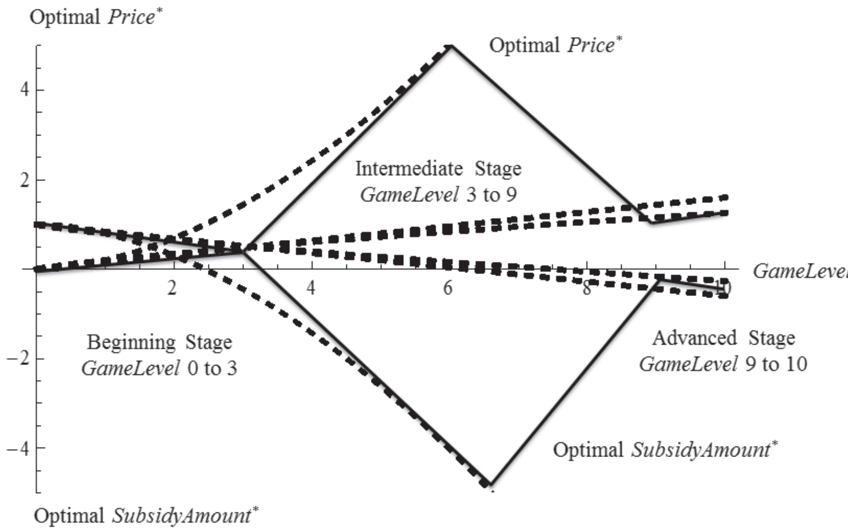


Figure 4. Consolidated View of Optimal *Price and *SubsidyAmount** Across the Player Stages**

Notes: The *x*-axis is *GameLevel* and the *y*-axis is optimal *SubsidyAmount**. The plot is for level sets of the different *Performance* and *NetEffect* values. The plot consolidates Figures 2 and 3 to present a combined view of pricing and subsidy policy, as suggested by the numerical simulation from out model. As with prior figures, the true ranges of *SubsityAmount** as computed in out numerical simulation are shown just above, and the functions in the figures have induced continuities, but were actually discontinuous.

*dyAmount** and *Price** and the relationships to the key parameters that underlie them. The reader should not misunderstand the mirror images between the *SubsidyAmount** and *Price** functions; a subsidy is a negative price.

Discussion

We next discuss some topical issues that are related to social game participation, including management and generalizability concerns as our starting point. How we can leverage the research findings from the estimation playing time in the MMORPG setting is useful for understanding value in other applied social technology platform settings. We also reflect on our modeling and empirical analysis choices and consider them relative to some of the steps depicted in the Table 4 research process of this research.

The Vendor's Perspective on an Effective Life Cycle–Based Pricing Scheme

MMORPGs represent a social gaming genre that hundreds of thousands of players can simultaneously play in online social networks. Because of the commercial popularity of MMORPGs, many game vendors have entered the market. A vendor's capability to set effective prices amid market competition is critical for success and profitability. Consumers typically react in a positive way to vendors who understand how to implement consumer value–based pricing schemes. This is true for social gaming, we believe, just as it is true for consumer segmentation with respect to mobile phone, cable television, and broadband Internet services offered by telecom firms. It also applies to digital music and movies that are offered by online sellers, and many other things.

In this study, we developed a pricing scheme based on an empirical valuation of social gaming playtime and a gamer's willingness to pay. Players typically spend a lot of time playing social games. So if the opportunity cost of a player's time in the game is estimated based on wage, the player's costs for playing the game are relatively large.[11] Players recognize the value of the time they spend, to some extent. To advance in the game, they will need to practice, which will be even more costly, so some players may choose to spend real money for game-related tools to increase their enjoyment. In this sense, we see a bridge between the real world and the gamer's spending there, on the one hand, and the higher performance that the gamer can achieve in the virtual world, on the other hand.

Estimating the value of a player's participation time in monetary terms is a useful thing for a vendor to do. We earlier suggested that the initial step to take is to formulate a baseline model that will reveal information on how much a gamer values the time spent playing in hedonic value terms. We further suggested some refinements and robustness checks to the model, so a vendor can be more confident that the baseline valuation is a reasonable basis to work from, related to the development of pricing strategy for the gamer's life cycle of participation in the social game. The additional steps of developing a model that produces an optimal set of prices for the life cycle and applying simulation and numerical analysis methods to probe the likely performance of the prices also are useful.

The steps in our approach will help to inform a vendor about its ability to implement a pricing scheme for social gamers across different game levels and the life cycle of their game participation. When a vendor can identify different levels of willingness to pay for play among beginning, intermediate, and advanced players, it will be able to maximize its profit through price-driven segmentation.

The Gamer's Perspective on Aspects of the Social Game That Create Participation Value

Social games like MMORPGs allow players to choose the roles they play in the game. Changing roles creates new interests and encourages the player to find ways to obtain a rich and varied social gaming experience. Each player's propensity to spend time or money will be different across the different game roles in an MMORPG, and a player's willingness to pay ought to reflect this also. However, it probably is not practical for the vendor to present the gamer with a price schedule for participation that is role specific, even though player perceptions of value may be role specific. This is similar to having the fans of two different baseball teams attend a game between the teams—the price that home team fans pay and the price that visiting team fans pay cannot be different, even though the fans will have different levels of willingness to pay and are likely to have different experiences as they watch the game. Prices need to be simple enough that there is no confusion on the part of the fans. Pricing is similar in the social gaming context where life cycle–based pricing seems to be a good compromise.

A related concern for gamers is their growth from beginners to experts. When experts in the game reach the end stage of the game or the final round, they will experience highly challenging tasks and will truly enjoy the gaming experience if they are committed to participating. It is also possible for the gamer to lose interest in the gaming process, however. The nature of the challenges may become increasingly familiar, or the time required to solve the problems may no longer seem worth the while. Fortunately, though, most social gaming vendors have a game manager on their staff to deal with this problem. The manager will update the game tasks that the players undertake and monitor the levels through which they progress. As a result, the game manager and the creative staff can update higher-level game tasks to be more and more attractive as a player progresses and demonstrates diminishing willingness to pay. It is important to remember that the game levels that are offered will not arbitrarily be numerous—at some point, the construction of new levels for experts will not be justifiable in cost-benefit terms due to diminishing density of demand. So it makes sense for a social gaming services vendor to recognize that having more expert players is a good thing, possibly something the vendors want to encourage with a high-end discount pricing strategy. This should increase demand among experts, extending the players' life cycle in the game and creating the possibility for some gamers to achieve social recognition from membership on the "all-time leaderboard" in the game and thus serve as the best advertisers for its hedonic value.

Another interesting aspect regarding gamers is that the games and their currency are often linked to real money, turning the social gaming setting into a market. Social gaming services vendors have been successful at supporting and leveraging human interactions in social networks. Most MMORPGs tend to be quite complex, so devoted players can achieve important accomplishments within them only by spending a lot of their free time playing the games. Other social games also can be relatively simple, so the players can obtain enjoyment without a lot of hard effort.

The key to a successful social game is to give players an option to gain something that they perceive to be of value. Players are willing to spend money to get to higher levels and to differentiate themselves from other players who are less accomplished. It is hard, however, to convert a large number of players into paying players. So in order to generate a sufficient revenue stream to stay in business, a game vendor has to try to hook a small number of players so they will begin to spend a lot of money in the game.

There may be other kinds of incentives not explored here for which it would be worthwhile to probe and understand more deeply. In cable TV, Internet broadband, and mobile phone services many approaches to retaining customers have been explored and applied. For example, with mobile phones, when the number of calling minutes used declines or a customer fails to add more minutes in a plan that requires usage-based calling time replenishment, there may be signs of impending churn. Retail telecommunications firms have set up loyalty programs, similar to bank credit card programs, that enable customers to earn rewards when they reach some predefined level of consumption. There may be business policies worth exploring for social gaming that consider this kind of approach involving playing intensity–driven rewards, or late life cycle game-play rewards for sustained involvement over time, and so on. These policies should help to retain the installed base of highly accomplished social gamers, which would be beneficial for everyone involved via network effects.

Another important consideration is the extent to which a social gaming platform involves activities that are truly, not just superficially, social. Most social games in Facebook tend to be highly social, based on the quality of the experience of Facebook users that is known in the market. Facebook makes it possible for social gamers to not have to play with all of their friends at the same time. Social games on Facebook support asynchronous player interactions over time, in the same way that much of the communication traffic Facebook supports operates. Facebook's social games are free to play but require game credits for game goods or the aid of a user's Facebook friends to get to higher levels. A gamer's life cycle in a Facebook social game, however, tends to be shorter than in other typical MMORPGs.

The Researcher's Perspective on Implementing Effective Modeling and Methods

Modeling

Effective modeling choices are critical for the support of effective managerial decisions—in this case, the construction of a price schedule across the life cycle of consumption of services on a social gaming platform. Some salient concerns in our modeling analysis are the representation of the MMORPG, its robustness with respect to the social gaming environment's structure, and the significance, depth, and frailty of the results we obtained. The value of social interactions in a social gaming setting arises from a player's experience. Players may get deeply involved, enjoy the fantasy aspects of their experience, and view their gaming experience as being hedonically valuable. People also want to be able to participate in social games in an efficient and effective manner to achieve their goals, much like a skier who wants fast skis, or a tennis player who needs a high-quality racket and a trainer, or even a music lover who demands the best headphones or speakers.

With these observations in mind, a basic premise of our approach has been to distinguish between the value of in-game social interactions and players' accomplishments within the game. Social gaming players who get into the flow of a game may become unaware of the passage of time [8]. Also, the tasks they have to complete are all characterized by some degree of learning.

Practice enhances learning efficiency, which simultaneously increases players' involvement and game enjoyment. For a beginner, playing skill in the social gaming context will be slower to build, but a skilled player will be proficient and will know the right kinds of moves and actions to make, as well as those not to make.

Hedonic models for other applied contexts often use sales information and information about payments and product attributes as a basis for valuation. We have included the network effects of other participants in the game, the time a player participates, and a player's characteristics, including flow factors and game skills, to represent the player's capacity to achieve efficiency. These factors also help in estimating the value the player places on social aspects of the gaming experience and the player's performance in the game. Thus, we believe that we have formulated a reasonable basis for developing meaningful insights that will not be frail with respect to the main elements of relevant theories that we have identified. Additional refinement and assessment is always beneficial, of course.

Data and Methods

In terms of empirical estimation it is appropriate for the reader to consider the quality of the data used for this study as well as the method choices we have made to extract useful information. Our research design tests a number of variables that we believe affect the utility that a player achieves, based on the utility of the player's participation in competition against other players and her own performance in the social game. We have chosen to represent the value of the time a person spends playing the game as a complex hedonic commodity with characteristics that make the gaming experience interesting for the player over time. The data are relatively few, cross-sectional, and only permit exploratory empirical work, however. So the importance of our work is how we achieved value estimates for game-playing time—not the exact monetary values we computed. This research is intended to be illustrative only, not definitive, even for different data sets from the same MMORPG. For a more authoritative treatment of the issues, access to much fuller panel data is required, and this would enable us to do such things as compare the value associated with different roles in the game, determine the marginal value of the things that gamers purchase to improve their playing performance, and examine how concentrated playing time versus playing time spread out over a period of months affects a gamer's performance.

Estimation of the coefficient values of the independent variables can be improved by including data on more players and a longer time period for observation—essentially an empirical extension that includes panel data. We explored this possibility; however, the game vendor is no longer operating in the market in the way it was when we originally generated and collected the data. We also can control for the highest game levels that the players reach before our observations of their play become right-censored. At present, our estimation approach cannot distinguish differences that might arise due to this. For example, players who reach a higher level may also have valued the lower levels of play more highly than other players who left the game at some earlier point.

There are other complexities in social game settings. For example, there is the issue of omitted variables and the resulting bias caused in estimating the other explanatory variables. It is appropriate to disclose this and to comment on the potential direction of the bias. For example, our data set includes information about the different game levels that players achieve, but we have not attempted to establish stratified results for players at different achievement levels. The difficulty with this is lack of sufficient observations from the game setting to make this estimation process effective. We also had no information on gamers' income and educational levels, or their total spending on gaming more.

Our observation of players' social game activities also does not represent players' complete patterns of behavior. For example, we made no effort to represent the possibility that a player could take on more than one role in the MMORPG, although this occasionally happened. Our observation suggests that there may be some degree of correlated behavior across the different roles in the game play that is occurring. One can imagine how the bias might work. For example, there are likely to be some instances in which a player will shift from one role to another to obtain a new experience, or because the player has reached a "dead end." This may be another way for the player to advance in the game. It is also possible that a player will take on multiple roles to create a role alliance that may be leveraged for further game-level advancement and improved performance. This may permit a player who chose 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, and which must be earned or purchased.

Measurement

We also made choices about proxy variables for the various constructs that we studied. Use of the opportunity cost of a player's participation time in social gaming is reasonable, though imperfect. Different game players surely will have different opportunity costs of time spent based on their own personal situations.

Hedonic pricing models typically include the characteristics of some hedonic commodity and a dummy variable for time to be used in estimation with panel data. Since our data are cross-sectional rather than in panel data form, time-varying covariates for each variable could not be estimated, which limited our ability to measure the value of a player's game participation time. Furthermore, since we were not able to extend the data set that we analyzed, we decided it would be more beneficial to extend the results through numerical analysis of the theoretical model.

Another aspect of game play that we did not attempt to measure is the influence of a player's capability to exercise an *outside option* to purchase resources for the game that are not available within the game. This is a common phenomenon in social gaming—participants develop social interactions with one another for exchange outside the game boundaries, or they may go to an externally established marketplace where it is possible to buy game-related resources. Since we do not have a way to track this scheme, our *Spending* 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, however.

There are several other aspects of the game that we did not try to measure or model in this study, because they are somewhat more complex. For example, similar durations of time in which a player participates in an MMORPG may not produce equivalent utility for different players. The time spent by a beginner to get acquainted with the gaming environment might not be as valuable as the time spent by a much more experienced player, for example. So a player's starting level may condition the value the player ascribes to the gaming experience. We think of this as a possible *starting-level effect.*

We also conjecture that a player's starting level and ending level in the game, achieved over a period of play or over several periods of play, might be associated with different levels of value for the player. For example, if one player solves tasks that permit the player to go up two game levels, as opposed to another who goes up only one level with the same amount of play, we can guess that the player who rises faster and farther will perceive higher value. Making further progress with this aspect of the game's complexity also will require panel data.

Conclusion

This study, in the form of a focused field study based on applied economics, empirical data estimation, and modeling analysis, investigates a social game-playing environment and the extent to which participants achieve value from their network activities. We began with the premise that players enjoy the social gaming experience and often lose themselves in the time they spend online. They also recognize the practical aspects of playing the game by becoming well equipped so they can be efficient and effective players. Social game playing is analogous to sports activities in which participants enjoy the social interactions they build, as well as their accomplishments vis-à-vis other players as they improve their performance. (People who play golf know what this means.) The same applies to other offline activities, such as playing a musical instrument and participating in group music activities or learning a foreign language and then visiting a foreign country. We see similar things online also—for example, playing poker in a gaming market, or doing a myriad of other things such as searching or surfing the Web with tools that power a user's experience to extraordinary efficiency while also maintaining the user's high interest and engendering a loss of awareness of the passage of time.

We employed a hedonic pricing model from economics to provide a basis in theory for this research. We also used an exploratory data set as a basis for developing a number of useful insights in this study: (1) Our theoretical model provides a basis for estimating the value of a user's social game participation. (2) We developed results for the substitution between game participation time and money spent on gaming for a participating player. (3) We found that a game player's valuation for participation is likely to be role dependent and not all of the roles are equal in terms of how players value them, but we nevertheless could establish a means to make an empirical estimate of the value of time spent playing an MMORPG.

Although we obtained some results to assess how players value their in-game social interactions and the performance improvements they achieve as their skills advance, this work is still in the exploratory stage. We 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. Nevertheless, this study is notable for the progress made in developing new conceptual and theoretical knowledge for the valuation of social-gaming mechanisms from the player's standpoint and elucidating how this knowledge can be used to help vendors do a better job of pricing their services. We view this work as a first step toward conceptualizing pricing systems for social gaming, 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 we have modeled, but we have been careful to note some of them, so the reader can gauge the value of this study, and to identify appropriate directions for further study.

We have suggested a basis for differential pricing in social gaming that is tied to the experience and different levels of willingness to pay for heterogeneous users. To accomplish this, we linked the empirical model, which produced relevant coefficient estimates for how social gamers used their time and made gains in their performance on the social gaming platform as a basis for instantiating consumer valuation and willingness to pay information, to an analytical model that produced useful results for the formulation of pricing strategy across the life cycle of social gamers' participation in the game. This innovation is unique to this research: we often see analytical models involving economic theory front-ending empirical models, but rarely have we seen the reverse in the IS literature. In this work, our ability to capture hedonic valuation information on social gamers' game participation was just what was needed to support the instantiation of the analytical model to produce sample results for the pricing of technology-enabled social gaming services.

Similar to other settings involving digital intermediation (search engines, electronic markets, group buying, and so on), early-stage game play is likely to deliver less utility and value to social gamers than later-stage play. The participants should become more adept at the required skills, and the innovativeness and attractiveness of the design of the game and its challenges should be revealed through the players' persistent use. This suggests that optimal pricing based on willingness to pay may involve an initial stage of free access or subsidized pricing, followed by implementation of a more aggressive pricing scheme once the participants' differences become more evident to the gaming vendor.

This may not mean that the most experienced players pay the most, however. Although it may be impractical to develop individual prices for people who participate, there is ample evidence to identify when social gamers need play-incentivizing discounts or monetary rewards to encourage them to continue their participation. The pricing scheme approach that we have proposed should be transparent and acceptable to the game players. Consumer value–based pricing by the game vendor should be based on who will receive the greatest value from participating, but this perspective should not be overemphasized. After all, few businesses succeed when they charge their best customers the highest prices, including print magazines, golf courses, and Internet and cable TV services. This further underscores the importance for vendors to be truly informed about the willingness to pay of social-gaming participants, so they know what prices are the "right" prices to set.

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NOTES

1. We recommend a number of helpful surveys and other broadly applicable articles. They cover various related issues, including methods for real-time computing resource provisioning for MMORPGs [44]; engagement in digital entertainment games [6]; gaming in virtual worlds and social computing [35]; game company control over virtual worlds on the Internet [47]; and creating business value [51] and making real money in virtual-world settings [42]. In addition, online gaming sites, particularly MMORPGs, can be especially interesting settings in which to conduct empirical case studies with "big data" as well as modeling work to support development of new theory. Examples of such research include the study of U.S.- and Canada-based TinySpeck's now-defunct Glitch MMORPG [29] and numerous research efforts on MMORPGs that have been conducted in Austria (Pardus) [53], China (Legends of Mi*r*) [25, 57], Japan [39], and Korea (Aion, Lineage, Lineage II) [20, 24]. University research centers and libraries are taking on new responsibilities for data curation that are making new and interesting gaming data sets available.

2. Nojima [39], in his empirical research on pricing and MMORPG participation, identified two popular pricing models in the market: monthly fees and per-item billing. His characterization of the marketplace suggests that it is possible to assign fixed prices in advance for game play, as well as differentiated prices based on observed participation after a gamer has completed play. He notes that both approaches involve risks for the gamer.

3. The online game vendor provided free online access at the initial stage of service. Six months later, the game vendor employed a monthly subscription fee

model [39]. The fee was different based on the gamer's age. The monthly fee was more expensive for adults. In July 2007, the MMORPG vendor changed its business model to a game product sales model with no subscription fees. This allowed game players to buy game money with real money and then purchase game products with game money in the MMORPG. For this data set, *Spending* means the amount of money that a game player spent to buy game-related products in the context of playing the game.

Our cross-sectional data set does not include sufficiently detailed information about group membership for each player. Thus, our empirical estimation did not permit us to identify a network effect with the implied degree of precision that additional data would have permitted. Nevertheless, we confirmed that network size is statistically correlated with the value of game participation, as should be the case.

4. To keep the modeling exposition simple, we have omitted the subscript i in this and several follow-on models.

5. We employed three different methods to estimate the hedonic pricing model. First, we conducted robust regression to minimize the influence of outliers. *OppCost* was not significant in our results. Next, we performed the Breusch–Pagan test for the presence of heteroskedasticity in the model. The results showed nonconstant variance. Thus, we estimated the model with GMM to address problems with heteroskedasticity. However, the results were no better than the results that we obtained with robust regression in terms of economic efficiency. GMM with an instrumental variable (IV) is more appropriate for estimation than simple IV regression when the data set is small, there is the possibility of muticollinearity, and the errors are heteroskedastic. We also performed the Durbin–Wu–Hausman (DWH) test for the endogeneity of *Time* variable. First, we regressed all of the regressors on the dependent variable. Second, we estimated the other independent variables to explain the *Time* variable to obtain an estimate for it. Last, we ran a regression with the other variables and the estimate of the dependent variable. By comparing the different estimates, we assessed the endogeneity of the *Time* variable and the appropriateness of the instrumental variable.

6. Minimum wages in South Korea during 2006, 2007, and 2008 were 2,840 won (~US$2.40), 3,480 won (~US$2.58), and 3,770 won (~US$2.79 in 2008). Sources such as www.korealaw.com were helpful for obtaining the numbers. For historical foreign exchange rates, a useful source is www.oanda.com.

7. Ordinary least squares (OLS) estimation uses specific distributions for random variables and establishes the model's coefficients based on the observed data. In contrast, GMM uses the *moments of random variables*—the mean and variance—and establishes coefficient estimates that are close to the moments of the population. In the process, the mean and variance of the population for a variable are replaced by the corresponding sample mean and sample variance from a population. This yields the same coefficient estimates as OLS does. GMM is useful when the distribution of random variables in a model is not known. In addition, in OLS models, when the explanatory variables are random variables and are correlated with the error term, the OLS coefficients will be biased and inconsistent. In that case, alternative estimation needs to be considered. To resolve this problem, an appropriate approach is to include an instrumental variable and then estimate the revised model through the use of a two-stage GMM (2SGMM) approach.

8. *GameLevel* represents a player's achievements in the game up to a certain point in time. It provides some useful comparative information about how a person is doing in the game relative to how others are doing. The impacts of *Performance* and *NetEffect* on user utility will be different across the different game levels. Players in the same game level, meanwhile, are likely to have similarities—in gaming skills, time spent playing, and so on.

9. There is a possibility that a player's utility will become negative if the tasks are too hard or it is too difficult to advance in the game. In simple online games like Sudoku, players sometimes ask for a hint. In more complex games like MMORPGs, they may buy a new weapon. This will likely have the effect of making their perceived

level of utility positive at the level of play in which they are involved. In general, if the average level of utility for all players at some game level is negative, the vendor will need to provide some means for individual players to obtain support so they will not leave the game. If such support is not available, players will depart, which suggests that the gaming mechanism's design needs to be better thought through.

10. We are interested in estimating the subsidy rate that is associated with the average utility of all the game players at a given *GameLevel*. Thus, we set $SubsidyRate_{GameLevel} = SubsidyRate(f(\cdot))$, where $f(\cdot) = f(Performance_{GameLevel}, NetEffect_{GameLevel})$. The new average price is $(1 - SubsidyRate_{GameLevel})Price_{GameLevel}$. Thus, the utility for a given game level will be the difference between $f(Performance_{GameLevel}, NetEffect_{GameLevel})$ and $\#Players_{GameLevel}(1 - SubsidyRate_{GameLevel})Price_{GameLevel}$.

11. Although we chose to develop the results relative to the opportunity costs of game-play time with the minimum wage for employment, the reader should recognize that this is only a rough approximation. Most people have to bear other costs, including their transportation, clothing, and other costs associated with performing the work that they do. So it is appropriate to know that the use of the minimum wage alone gives an underestimate of the true value of opportunity cost.

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Appendix A: Modeling Notation and Definitions

Notation	Definition	Comments
Time; Access	The amount of time a player spends playing the game; the number of times a player accesses the game, and the average across participating players.	The measurement of gaming time is inexact and subject to error. *Access* is a way to proxy for *Time* that is less subject to measurement error.
GameLevel	Levels of the game that characterize a player's accomplishments in the game. The levels are also described in terms of beginning, intermediate, and advanced stages.	We use game level to distinguish a user's experience and commitment to participation. The different stages are used for price differentiation.
OppCost	Player's opportunity cost per unit time spent for game play in terms of minimum wage.	*OppCost* is the maximum monetary value that users can gain by using the time to work instead of playing the game.
NetEffect	Number of players involved in playing the MMORPG; also the number of players at a specific game level.	Changes as game gains popularity, and number of players is intended to gauge the network effect of participation.
Performance	Utility obtained by a player from making progress in the game's tasks and levels.	To keep the notation simple, we use *Performance* instead of *PerformanceUtility*,
#Players	The number of online participants in the game in different game levels and stages.	The number of game players will decrease because of increasing game difficulty after the beginning stage.
Price	The price of game participation and play, reflecting different player valuations at different game levels in the empirical model; we also use this notation to indicate average price in the analytical model.	The value of average price for a game level is estimated in aggregate across users, and agreement for all the different roles and game levels.
Revenue	Revenue for the MMORPG vendor.	Based on prices set for game play and the number of participants.
Role	Players take on different game roles as they play the MMORPG.	Different roles benefit differently from different powers, skills, and weapons.
Skills; ExperPts	Skills achieved by a player; experience points gained by the user in the game for completing different tasks.	The development of skills is a way to gauge a player's accomplishments within the game, similar to experience points.
Spending	Real-world money spent by a game player in individual terms in the empirical analysis and on average across the game participants in the analytical model.	We also note that game currency is not real-world money in the MMORPG; we do not model the use of game currency.
SubsidyRate; SubsidyAmount; SubsidizedPrice	The subsidy rate in percentage terms applied to the price for game participation and play; the subsidy applied to the price in monetary terms; the price after the subsidy rate or amount has been applied.	The subsidy offered is based on the average valuation of play by game players in the early stage of their participation.

Notation	Definition	Comments
Utility	The utility of game player *i* at different game levels; the average utility of game players at a specific game level.	We expect a player's utility to change over time with game level. Also, the average utility level will change over time based on others' participation.
$\alpha, \beta, \delta, \theta, \varphi$ ($\varepsilon, \zeta, \xi, \mu, \omega$)	Coefficients for estimation and error terms for the models.	These are used in the baseline, instrumental variable, reduced instrumental variable, and instrumental variable substitution models.

Appendix B: Proofs of the Propositions

Proof of Proposition 1 (Optimal Subsidy for Beginning Gamers)

To obtain the marginal effect of the game participants' utility of $Performance_{GameLevel}$ and $NetEffect_{GameLevel}$ on the optimal subsidy, $SubsidyRate^*_{GameLevel}$, we differentiate the optimal subsidy level with respect to the two variables. This yields

$$\frac{f^{-1}\left(Performance_{GameLevel}, NetEffect_{GameLevel}\right)}{2 \cdot \# Players_{GameLevel} \cdot Price_{GameLevel}} > 0$$

because the utility function f ($Performance_{GameLevel}$, $NetEffect_{GameLevel}$) is always greater than zero. This is based on an assumption that we made related to the beginning stage of the game, that both $\partial f(\cdot)/\partial Performance_{GameLevel} > 0$ and $\partial f(\cdot)/\partial NetEffect_{GameLevel} > 0$. The difference in value decreases as the number of players decreases across the game levels after the beginning stage. Thus, the subsidy will be the greatest when a player's utility for the network effect is largest in the beginning stage.

Proof of Proposition 2 (The Optimal Pricing Based on Players' Willingness-to-Pay Proposition)

The optimal price, equal to $f(Performance_{GameLevel}, NetEffect_{GameLevel})/(2 \cdot \#Players)$, is dependent on utility $f(\cdot)$ but also the number of players in the game at a given game level. We assume that the marginal effect of $Performance_{GameLevel}$ will increase, while the marginal effect of $NetEffect_{GameLevel}$ will decrease. We further assume that the utility of $Performance_{GameLevel}$ is greater than the utility of $NetEffect_{GameLevel}$ at their averages in the game level. Thus, the utility function $f(\cdot)$ will increase at an increasing rate.

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