ESSAYS ON ONLINE GAMING COMMUNITIES

A Dissertation

by

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ABSTRACT

This dissertation investigates key issues related to online gaming communities. Across three essays, the author explores the effects of three factors—(1) social connection, (2) demarketing, and (3) game design—on game users' behaviors. The findings from the studies provide implications for theory, along with practical implications for game developers and policy makers.

In the first essay, the author examines the effect of social interactions on gamers' *in-game* purchases of two different types of products, functional and social utility products. The author uses a unique and large scale dataset from an online game—that consists of users' detailed gaming activities, their social connections and their *in-game* purchases of functional and social utility products—to examine the impact of gamers' networks on their purchase behavior. The current analysis reveals evidence of "*social dollars*," whereby social interaction between gamers in the community increases purchase of both functional and social utility products.

In the second essay, the author examines the effects on user behavior of two demarketing policy changes with regard to online and mobile games in South Korea: (1) lowering the maximum limit on *online* item purchases, and (2) restrictively allowing the use of real money to purchase items in *mobile* gaming apps. The author finds that lowering the maximum limit on online item purchases decreases the number of online gamers, and that allowing item purchases with real money in mobile games increases the number of mobile game players. The author finds that there are positive cross-channel spillover effects.

In the third essay, the author examines the *goal gradient* effects on behaviors related to attaining the goal (i.e., a game level) and purchasing virtual products in an online game. The author

provides empirical evidence that achieving game levels serve as goals. The author finds that users' efforts related to reaching a new level increases as they become closer to the new level. However, their efforts suddenly decrease right after attaining it. The author finds that while users are less likely to purchase both goal-relevant and goal-irreverent virtual items right before achieving the new level, they purchase more virtual items once they reach the goal.

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1. INTRODUCTION

The global game market had been predicted to reach the total of 108.9 billion U.S. dollars with 2.2 billion game users in 2017, and the digital game revenues formed 87% (94.4 billion U.S. dollars) of the entire market (McDonald 2017). Nowadays, the game market is considered as one of the biggest entertainment industry and the market size of the global game industry is greater than ones of movie or music industries (BusinessTech 2015). Many online communities have adopted a new pricing strategy which is called freemium by which basic features of a product or service is provided for free while premium features, services, or virtual products are charged (Kumar 2014). In the context of online games, users can access to a large portion of the game contents without any charge, and users need to pay real cash to purchase virtual goods which can help improving gaming performance or decorating virtual avatars. This strategy is called either free-to-play or in-game purchase (Wu, Chen, and Cho 2013; Mochizuki and Needleman 2016). However, game subscriptions can also drop precipitously as many games are available on free-to-play models. Thus, gaming communities struggle to devise ways that can increase user engagement in order to survive and compete effectively, and finally motivate users to make in-game purchases. At the same time, game companies also need to pay more attention to game users' welfare or health as well. With the fast growth of the game industry, the negative consequences from playing games has become serious social problems. Indeed, the World Health Organization (WHO) classified gaming addiction as a mental health condition for the first time in 2018 (Wakefield 2018). Thus, game developers need to devise tools which can protect them from gaming addiction as well as improve users' engagement and purchase behaviors.

This dissertation makes important and valuable contributions both towards theory and practice. The author explores the effects of three factors—i.e., social connection (Essay 1), demarketing (Essay 2), and game design (Essay 3)—on game users' behaviors. Three essays provide implications for theory, along with practical implications for game developers and policy makers from multiple angles—i.e., individual level, network level, and industry level. First, from a theoretical perspective, this dissertation develops and empirically examines an integrated framework that includes various factors which affect game users' behaviors. Second, from a managerial perspective, this dissertation provides implications that allow game developers to design better gaming contents and social structure which can improve users' engagement and motivate users to make in-game purchases. Finally, this research also helps policy makers and game companies to protect game users from negative consequences from playing games.

In the first essay, the author examines the effect of social connections on gamers' *in-game* purchases of two different type of products, functional and social utility products. Massively multiplayer online role player gaming (MMORPG) communities have risen steadily in popularity over the last decade. Social interactions and virtual relationships between gamers are a key aspect behind the success of these communities. The author uses a unique large scale dataset from a popular MMOPRG community—that consists of users' detailed gaming activities, their social connections and their *in-game* purchases of functional and social utility products—to examine the impact of gamers' networks on their purchase behavior. Building on theories in social psychology and social contagion literatures, the author theorizes on and study how gamers' and social network characteristics influence their susceptibility to social contagion. The current analysis reveals evidence of "*social dollars*," whereby social interaction between gamers in the community increases purchase of both functional and social utility products. The author finds that experts and "thrill seekers", i.e., gamers who engage in high risk and high reward activities exhibit less susceptibility to social contagion. Interestingly, the author finds that while greater network stability enhances the social influence effect for functional product purchases, network stability does not moderate the social influence effect for social product purchases. The results of the study have implications for both theory and practice and help provide insights on how managers can monetize social networks and use social and user information for greater engagement in gaming and online communities.

In the second essay, the author examines the effects of demarketing games in online and mobile channels. Demarketing—the process of decreasing demand for certain products or services (e.g., tobacco, alcohol, firearm) that are perceived to have a negative influence on society—is currently being widely employed in various forms of public policy, including taxation, regulation, and public education. In the game industry, demarketing tools have recently begun to be implemented to deal with negative outcomes that can result from overuse of games. Online and mobile channels are fast-growing gaming sectors, and demarketing strategies for these new channels have also been discussed and executed in diverse forms in many countries. This study assesses the effects on user behavior of two demarketing policy changes with regard to online and mobile games in South Korea: (1) lowering the maximum limit on *online* item purchases and (2) restrictively allowing the use of real money to purchase items in *mobile* gaming apps. Drawing on two unique datasets comprising online game traffic and mobile app traffic, the author estimates the effects of demarketing efforts. The author compares the change in number of game users before and after a policy change between two groups of games in a channel—a treatment group (i.e., games which are subject to the policy change) and a control group (i.e., games which are not subject to the policy change)—using the difference-in-differences estimation strategy. The author finds that lowering the maximum limit on online item purchases decreases the number of online gamers and that allowing item purchases with real money in mobile games increases the number of mobile game players. Because these games can be played in two different channels, online and via mobile devices, it is important to examine cross-channel effects of the demarketing strategies. To estimate the cross-channel effects, the author uses a difference-in-differences modeling framework, with the treatment and control groups selected from games in the channel that are not a target of the policy change. The author finds that lowering the maximum limit on item purchases in online channels also decreases the number of mobile gamers and that permitting mobile games to be purchased for real money also increases the number of online game users. Thus, the author finds that demarketing activities in one channel potentially have spillover effects on games in other channels. The author conducts a series of robustness checks and falsification tests to validate the findings. Based on the results, the author provides this study's implications for policymakers and game developers.

In the third essay, the author examines the *goal gradient* effects on behaviors related to attaining the goal and purchasing virtual products in an online game context. Intense competition in the online game industry spurs game developers to improve game design to be highly engaging to users and to encourage those users to spend more money on purchasing virtual items. Goal gradient hypothesis proposes that efforts in achieving a goal increase with proximity toward the goal. Game developers design goal-related features such as level, badge, or ranking to sustain a high level of users' engagement and motivation. Many of them also provide game contents for free, but charge for premium features such as virtual items (i.e., freemium pricing). The author provides empirical evidence that game levels, which are obtained once users' experience points reach to a threshold of each level, serve as goals. Then, as a result, users have significant

differences in their behaviors before and after achieving levels. By leveraging a unique online game dataset, the author empirically examines the goal gradient effects on goal-relevant and irreverent behaviors. The author models users' behaviors as a function of distance from a level and control variables. First, the author finds that users' efforts related to reaching a new level increases as they become closer to the new level. However, their efforts suddenly decrease right after attaining it (i.e., postgoal reset). Second, the author finds that users are less likely to purchase both goal-relevant and irreverent virtual items right before achieving the new level while they purchase more virtual items once they reach the goal. Third, if a user has experienced greater difficulty of attaining a level, that user is more likely to reduce their efforts toward in-game progression and to spend more money on virtual items after achieving a new level. Finally, as a user is more likely to collaborate with other users in the game, that user has a greater tendency to put more effort toward goal-relevant behavior and to spend less on goal-irrelevant items even after attaining a new level. The author discusses the theoretical significance of the findings and the practical implications for game design, user engagement, and freemium pricing.

2. EVIDENCE OF SOCIAL DOLLARS IN A MASSIVELY MULTIPLAYER ONLINE ROLE PLAYER GAMING COMMUNITY: ROLE OF SOCIAL CONNECTIONS, GAMER AND NETWORK CHARACTERISTICS[1]

Massively multiplayer online role player gaming (MMORPG) communities have risen steadily in popularity over the last decade. Social interactions and virtual relationships between gamers are a key aspect behind the success of these communities. In this study, the author examines the effect of social connections on gamers' *in-game* purchases of two different type of products, functional and social utility products. The author uses a unique large scale dataset from a popular MMOPRG community—that consists of users' detailed gaming activities, their social connections and their *in-game* purchases of functional and social utility products—to examine the impact of gamers' networks on their purchase behavior. Building on theories in social psychology and social contagion literatures, the author theorizes on and study how gamers' and social network characteristics influence their susceptibility to social contagion. This analysis reveals evidence of "*social dollars*," whereby social interaction between gamers in the community increases purchase of both functional and social utility products. The author finds that experts and "thrill seekers", i.e., gamers who engage in high risk and high reward activities exhibit less susceptibility to social contagion. Interestingly, the author finds that while greater network stability enhances the social influence effect for functional product purchases, network stability does not moderate the social

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[1] Part of this chapter is reprinted with permission from "Social Dollars in Online Communities: The Effect of Product, User, and Network Characteristics" by Eunho Park, Rishika Rishika, Ramkumar Janakiraman, Mark Houston, and Byungjoon Yoo, 2018. *Journal of Marketing*, 82 (1), 93-114, Copyright 2018 by the American Marketing Association.

influence effect for social product purchases. The results of the study have implications for both theory and practice and help provide insights on how managers can monetize social networks and use social and user information for greater engagement in gaming and online communities.

2.1 Introduction

With projections of over 13 billion U.S. dollars in annual revenues by the year 2017, massively multiplayer online games have gained tremendous popularity over the last decade (Superdata 2016). Massively multiplayer online role playing games (MMORPGs henceforth) such as the *World of Warcraft* have reported creating over 100 million accounts over the game's lifetime. MMORPGs lend a player the ability to assume a character or *avatar* and play the game with several players around the world. Some massively multiplayer online games are eagerly awaited such as the *Stars Wars: The Old Republic* and can quickly amass millions of subscribers within a short time after the launch of the game. *Stars Wars: The Old Republic*, in particular, generated one million subscriptions in just three days after its launch. Such game popularity can also be promptly rewarded by Wall Street. A recent article in the *Wall Street Journal* reports that *Pokeman Go*'s popularity boosted Nintendo Co.'s market valuation by nine billion dollars in just a few days after the game's release. The game provides opportunities for new sources of revenues in the form of *in-game* purchases (Mochizuki and Needleman 2016). However, game subscriptions can also drop precipitously as several games are available on free-to-play models where a user does not have to pay any subscription fee or pay to play the game. Thus, several gaming communities struggle to devise ways that can increase user engagement in order to survive and compete effectively. In this study, the author exploits the unique features of a MMORPG gaming community that is built upon player interactions in order to explore and systematically examine the role of players' social connections, player and network characteristics on their *in-game* purchase behavior.

A vast body of research has studied how an individual's behavior varies with the behavior of others in the focal individual's social network. Several studies in marketing, economics and information systems have examined how interactions among social networks have influenced new product adoption or adoption of new technology and services (e.g. Tucker 2011; Aral, Muchnik, and Sundarajan 2009). However, research on the different factors that influence how contagion spreads in different settings and contexts is still evolving. Given the numerous social platforms available today, there is increased focus on understanding how online social interactions can transform social commerce and help social media communities survive.

While many online communities aim to provide primarily digital content for their users, a growing number of communities aim to build their business model on what Meeker (2014) refers to as the three pillars of online platforms, *content*, *community* and *commerce*. For example, online platforms such as *Houzz* rely on creating content and connecting users so that users can purchase products from its site. For such communities to thrive, it is imperative that users of the community connect with each other and that social networks result in greater commerce for the online community. In this study, the author addresses these very important questions and examine how users' network interactions influence their commerce activities, i.e., purchase of virtual products.

Scholars who study social contagion have argued for a deeper understanding of the operational forces behind social contagion (Aral 2011; Godes 2011). A key focus of recent studies has been in examining the factors that moderate the effect of social contagion and shed light on the mechanisms that drive social contagion (Hu and Van den Bulte 2014). In this context of a gaming community, the author focuses on two sets of factors that can influence a user's susceptibility to his social network: user characteristics (level of expertise and willingness to take risks) and a network specific characteristic (network stability). Thus, the second objective in this study is to examine the moderating role of *time-varying* user specific and user-network specific characteristics on the effect of social contagion in online communities.

To accomplish the objectives, the author leverages a novel dataset from a MMORPG community. MMORPGs are a blend of role-playing video games and massively multiplayer online games. MMORPGs facilitate communication and interaction between users and often, users, frequently called gamers,[2] team up with other gamers to play games. MMORPGs often involve users' purchase of "in-game" products in exchange for real-world currency. In this online gaming community, users can purchase two different types of virtual products, functional and social utility products. While functional utility products help improve the in-game performance of the gamer during play, social utility products are strictly hedonic and may help a gamer gain social currency (such products help in signaling taste, virtual appearance, etc.) without improving a gamer's actual performance in the online game. Another interesting feature of MMORPGs is the character progression system by which gamers earn experience points and use those points to reach higher character "levels." Gamers can also, at their discretion, engage in high-risk strategies to progress faster and earn experience points. This feature of MMORPG helps the author gauges the effect of time-varying gamer-specific skill levels and their ability to take risks to get more points. Furthermore, gamers team up with many different gamers, changing alliances at will, which leads to a significant variation in network stability both across users and across time. The above-mentioned features of this MMORPG community make it an ideal context to examine the effect of social networks on users' purchase behavior.

[2] Henceforth the author uses the terms users and gamers interchangeably.

Several earlier studies have relied on survey or geographic proximity to infer social contagion, however, access to social networking sites has enabled researchers to observe actual interactions between actors (Nitzan and Libai 2011; Tucker 2011). In this gaming community, the author observes *actual* interactions between users and the author relies on these interactions to measure social contagion. Social contagion literature has identified several challenges in the identification of social influence from observational data. One of the thorniest issue is that of homophily, also referred to as endogenous group formation, whereby actors with similar tastes tend to form social networks. The author follows all the prescriptions of the recent studies to handle these issues (Nair, Manchanda, and Bhatia 2010; Hartmann et al. 2008; Ghose, Han, and Iyengar 2012) and perform a battery of robustness checks to rule out alternative explanations.

This analysis reveals evidence of "*social dollars*," whereby social interaction between gamers in the community increases purchase of both "in-game" functional and social utility products. However, the author finds a greater contagion effect for social utility product purchases as compared to functional utility products. The author finds that players with a greater level of game expertise and thrill seekers are less susceptible to contagion. Finally, the author finds that while more stable networks strengthen influence over gamers' purchase of functional utility products, network stability does not moderate the social contagion effect over gamers' purchase of social utility products.

This study makes several contributions to both theory and practice. While several studies have documented social contagion effects in different contexts (e.g., Nitzan and Libai 2011; Tucker 2011), there is scant evidence in current research on the effect of social contagion on *within community* purchases or commerce activities. From a theoretical perspective, recent studies based on lab experimental data have suggested that the mere presence of other brand supporters in social media communities can influence purchase intentions (e.g., Naylor, Lamberton, and West 2012). This study uses actual social interactions and users' purchase data to provide much needed evidence on the influence of networks in generating "*social dollars*" for online communities.

Secondly, most of the studies on social contagion have either focused on functional or utilitarian products or focused on only one type of product. However, an extensive body of research shows that consumer behavior differs across different types of products (e.g., Dhar and Wertenbroch 2000). This data allows the author to study contagion across two different types of products thus enabling the author to provide insights into the underlying mechanisms that drive contagion. In this gaming context, gamers may display both utilitarian and hedonic behaviors. Whereas utilitarian gamer behavior may be more rational and performance or goal-driven, hedonic behavior may embody a notion of fun, excitement and gaining social status among peers. Thus, depending upon the type of product, the author argues for and finds differential contagion effects across the two types of products. These results are not only new contributions to the literature on social interactions in online communities but also yield relevant managerial implications for managers of niche communities that are based on consumers' interests in specific type of products.

The results on the moderating effects of *time-varying* user-specific and network-specific characteristics on users' susceptibility to social contagion add to the recent studies that have focused on examining the moderating factors and providing explanations for why contagion occurs (Hu and Van den Bulte 2014). From a managerial perspective, the author establishes the impact of social connections in online communities on social commerce, i.e., commerce activities such as user purchase behavior facilitated by social media platforms. While many communities are trying to leverage online social networks to engage and motivate users to make purchases, there is scant evidence on the monetization of social networks. Based on the results, the author offers insights for managers on implementing user segmentation strategies and strategically managing user networks across different types of products.

2.2 Research Context

The setting of massively multiplayer online role-playing games or MMORPGs is ideally suited to examine the effect of social contagion on users' purchase behavior in online communities. MMORPGs are a genre of online games that support a large number of gamers in an environment in which they participate simultaneously and interact with each other (Wikipedia contributors 2018). More specifically, MMORPG is defined as "*graphical two-dimensional (2-D) or three-dimensional (3-D) RPGs played online, allowing individuals, through their self-created digital characters or 'avatars', to interact not only with the gaming software but with other users*" (Steinkuehler and Williams 2006, p. 886). It is estimated that in 2013, the size of the global game market was 75.5 billion U.S. dollars and MMORPGs had a 20% market share (NEWZOO 2014). Prior literature in the area of information systems suggests that gamers' motivations to play MMORPGs include a sense of achievement, social interaction and immersion (Yee 2006) and that gamers prefer MMORPGs not only for their technological features but also for the social experience (Jin and Sun 2015). MMORPG users, on an average, spend 22 hours per week in the online gaming environments (Yee 2006).

Typically, online gaming platforms adopt a "free-to-play" or a "freemium" pricing model. Users can create a personalized "avatar" and play a significant portion of the game content without paying. However, online games earn revenues when gamers spend actual money to buy virtual products. In MMORPGs, typically there are two types of virtual products that gamers can buy. Functional utility products (e.g., virtual energy drinks or safety cards) help gamers play better, garner more experience points and progress faster through the levels of a given game. For example, in this focal game, a focal gamer loses “health points” when his/her virtual avatar is hit by monsters. Once an avatar’s health points reach zero, the avatar becomes temporarily incapacitated and it receives penalties such as a temporary inability to play and a deduction in points. However, if the gamer buys an energy drink, his/her avatar gains points instantaneously and can resume playing. Social utility products include virtual clothes and decorative items (e.g., jewelry, accessories or clothes) that users can buy to adorn their avatars. Gamers often take their avatars very seriously, even considering virtual avatars as an idealized or experimental representation of themselves in the virtual world; thus, to facilitate self-enhancement goals, many gamers attempt to make their own avatar look special or different from the others (Yee and Bailenson 2007). These products do not help gamers play better and earn points.

While purchase of social utility products by a focal gamer are easily observed by other gamers, purchase of functional utility products can only be inferred from the performance of a focal gamer. For example, gamers can immediately observe an avatar donning jewelry but they have to infer that an avatar consumed an energy drink that enabled it to come alive and start suddenly playing better. However, because the functional products typically cause a dramatic change in performance (e.g., a focal gamer who is unable to play suddenly resumes playing), such inferences are relatively clear and easily made. Gamers gain experience points and progress in levels by beating monsters or by completing missions. In MMORPGs, gamers can collaborate and communicate with each other to fight against monsters or complete missions. Within a group, gamers can communicate and exchange information, providing a mechanism by which gamers in a group might have a mutual influence on each other’s playing style and purchases of virtual products.

From the firm's perspective, massively multiplayer online games can involve large development and testing costs and need to be managed by investing in and increasing reliable server capacity (Marchand 2016). Thus, sales of virtual products are a critical source of revenue for these games and vital for their survival. To sum, the focal MMORPG enables the author to observe social interactions between gamers in the online community, variation in gamers' skill levels, and evolution of network structure over time and in-game purchases. This setting is thus conducive to studying the impact of social contagion on users' in-game purchase behavior and providing much needed insights for content managers into developing viable online gaming communities.

2.3 Research Background

2.3.1 Social Contagion

Scholars in marketing, sociology, economics and science have been interested in the phenomenon of social contagion as it plays a key role in the diffusion of new products, ideas and behaviors. Earlier studies in the area of social contagion relied either on geographic proximity between actors to infer social contagion between actors (e.g., Bell and Song 2007; Manchanda, Xie, and Youn 2008) or on surveys to construct the social network between users (Manchanda, Xie, and Youn 2008; Nair, Manchanda, and Bhatia 2010; Iyengar, Van den Bulte, and Valente 2011). Online communities, however, offer the ability to *observe* interactions between users, thus enabling a researcher to construct a focal actor's social network instead of relying on geographic proximity or surveys. For example, in this context of MMORPG, the author can observe if two gamers teamed up to play against monsters or to complete missions.

A rich set of studies in marketing have established that social contagion, also referred to as peer or word of mouth effect, plays an important role in the diffusion of new products (Roberts and Urban 1988). Social contagion is effective in the spreading of ideas and behaviors as it helps reduce perceived economic and/or social risk. Whereas economic risk stems from the quality uncertainty associated with new products, social risk stems from an individual's need for social reassurance wherein the individual takes into account how others in the network might judge him or her based on the individual's choices (Prasad 1975). Knowing or observing the actions of other individuals reduces this perceived uncertainty and can also help mitigate social risk. In this online community, observing the actions (i.e., purchases of functional and social utility products) of other individuals with whom a focal gamer interacts would help reduce the social risk associated with the purchase of both functional and social utility products.

Van den Bulte and Lilien (2001) argue several mechanisms facilitate social contagion in the adoption of an innovation, such as awareness, social learning or informational transfers, social normative influences, competitive pressures, and direct or indirect network externalities. In this online gaming community, a focal gamer's interactions with other gamers who buy virtual products can trigger some of these same mechanisms through which contagion can take place. Recall that functional utility products help a focal gamer play better and social utility products are items that a focal gamer can "wear" to decorate his/her avatar. Thus, through in-game interactions with others, a focal gamer can become aware of these virtual products and learn about the performance or the social status-improving benefits of these products. Such online interactions can also instill a sense of competitive pressure thus triggering social contagion. For functional products, gamers can particularly feel the pressure to buy upon observing their peers buying these products and enhancing their gaming abilities. For purchases of social utility products, social normative pressures ("keeping up with the Joneses") are likely to kick in that prompt a gamer to don his/her avatar with these products that maintain or increase the social status of the avatar. Based on these arguments, the author presents the first set of hypotheses:

H_{1a}: *A focal gamer is more likely to purchase functional utility products when the focal gamer's friends have done so recently*.

H_{1b}: *A focal gamer is more likely to purchase social utility products when the focal gamer's friends have done so recently*.

2.3.2 Impact of User and Network Characteristics on Susceptibility to Social Contagion

Studies show that user and network characteristics can moderate the social contagion effect (e.g., Aral and Walker 2014). In this context, gamer characteristics such as gamer expertise and network characteristics that reflect the stability of the network of a focal gamer would influence social transmission. The author discusses these next.

2.3.2.1 Experts

A gamer's level of expertise reflects the depth of domain related knowledge he/she possesses. This can be critical in influencing the amount of social information transfer that occurs. An expert gamer is likely to know the different aspects of a game, the various characters or monsters the gamer is likely to encounter and the level of skill that will be needed to defeat these monsters or progress to more advance levels. As Ericsson (2006, p. 685) states, "*extensive experience of activities is necessary to reach high levels of performance*." A beginner gamer, on the other hand, needs to spend a considerable amount of time to understand the different aspects of a game and focus on actions and activities that reduce mistakes. Thus, learning from immediate peers can prove to be invaluable for gamers lacking in expertise. Prior research also suggests that individuals with a higher level of expertise may have higher levels of confidence (Trafimow and Sniezek 1994) in their abilities and thus, may be less likely to be subject to influence from their peers. As beginners (the "newbies" in gamers' parlance) lack gaming expertise, they may be more prone to searching for ways to enhance their social status in the community. Learning about social utility products from peer purchases of such virtual products can hence be incredibly beneficial for them. Based on these arguments, the author proposes that social influence effects for in-game purchases of both functional and social utility products will be diminished for experts and propose the following hypotheses:

H_{2a}: *The greater the expertise level of a focal gamer, the weaker is the effect of social contagion on the gamer's purchase of functional utility products.*

H_{2b}: *The greater the expertise level of a focal gamer, the weaker is the effect of social contagion on the gamer's purchase of social utility products.*

2.3.2.2 Thrill Seekers

Rogers (2003) argues that the key characteristics of those who adopt innovations early (the "innovators") are adventurousness and willingness to take risks in the face of uncertainty. In the seminal paper on diffusion of innovations, Bass (1969) suggests that innovators are less likely to be influenced by others. There is evidence in the literature on diffusion of innovations that uncertainty avoidance is correlated positively with the coefficient of imitation (e.g., Yaveroglu and Donthu 2002; Tellis, Stremersch, and Yin 2003). Thus, risk preference is a key factor in how innovation or information about innovation spreads. Whereas risk-seekers tend to be influencers and early adopters in the diffusion process, late adopters tend to be more susceptible to the forces of social contagion.

MMORPGs provide gamers with a virtual world in which individual gamers can create their own identities and experience the "thrill" and excitement of activities that are otherwise not available to them in the real world (Chappell et al. 2006; Yee 2006). Studies in psychology define "thrill seeking" as the desire to engage in activities that involve speed or danger (e.g., Zuckerman, Eysenck, and Eysenck 1978). In a MMORPG, individual gamers can engage in several such activities. For example, Yee (2006, p. 309) states that MMORPGs involve, "*selling virtual weaponry and real estate for a living, coordinating fifty people in a dragon-slaying expedition over a period of 5 hours, marrying someone you'll never meet, and switching gender for several hours at a time*." These activities are either impossible to take part in the real world or they are laden with a lot of risk and thus they provide boundless excitement to gamers. Hence, gamers can particularly be prone to seeking thrill and engaging in more high-risk and high-reward activities.

From the perspective of social transmission of information, due to their preference for adventure and danger related activities, thrill-seekers will be less likely to conform to social norms or learn from others in their network. They will also exhibit a lower susceptibility to social normative pressures and thus will be less susceptible to social contagion. Based on the above arguments, the author proposes the following:

H_{3a}: *The greater the thrill-seeking preference of a focal gamer, the weaker is the effect of social contagion on the gamer's purchase of functional utility products.*

H_{3b}: *The greater the thrill-seeking preference of a focal gamer, the weaker is the effect of social contagion on the gamer's purchase of social utility products.*

2.3.2.3 Network Stability

A key feature of online communities is that interactions between users are often dynamic which makes a gamer's network structure unstable. For a gaming community, dynamic interactions are even more relevant as gamers often play games for the social benefits such as building relationships, deriving satisfaction from engaging in teamwork etc. (Yee 2006; Billieux et al. 2013). Some recent studies have explored how network characteristics such as tie strength and structural embeddedness influence the flow of information within a network (Aral and Walker 2014; Ghose, Han, and Iyengar 2012). While tie strength refers to the intensity of interaction between peers, structural embeddedness refers to the extent to which individuals share common ties or peers (Granovetter 1985). However, in this gaming community, unlike prior studies, a gamer can choose who he/she plays with and thus a gamer's network can be quite dynamic. Thus, the author investigates how the stability of a gamer's network may influence the strength of social contagion in this context.

Network stability refers to the extent to which a focal actor's network retains the same connections over time (Bien, Marbach, and Neyer 1991). The underlying concept of a focal actor's network stability is driven by the repeat interactions that a focal user has with peers or friends. Tucker (2011) examines the effect of network stability on network externalities related to the adoption of new video conferencing technology and suggests that the effect of instability is not clear. Unstable networks can induce a lot of uncertainty about future interactions or communication patterns which could both enhance or mitigate the social contagion effect depending upon how individuals respond to uncertainty (Tucker 2011).

In this MMORPG, greater network stability between a gamer and his/her network of friends implies that a focal gamer is able to consistently play with a core group of friends (Dunn, Cutting, and Fisher 2002). Through these repeated interactions, gamers can learn about each other's skill levels and may feel the desire to compete and showcase their skill levels resulting in an increased purchase of functional utility products in response to friends' purchases. A stable network may also increase contagion for social utility products as gamers may feel more comfortable and secure in responding to their friends' choices of social utility products. However, a more stable network may also give less opportunity to gamers to interact with and be influenced by *new* players leading to a mitigation of the social contagion effect. This may be particularly true for social utility products as gamers may respond more to new friends in order to gain an increased social status in the beginning of a relationship. Thus, the author believes that the effect of network stability on gamers' response to social contagion is an empirical question. However, for the purpose of testing, the author offers the following hypotheses:

H_{4a}: *The greater the stability of a focal gamer's network, the greater is the effect of social contagion on the gamer's purchase of functional utility products*.

H_{4b}: *The greater the stability of a focal gamer's network, the greater is the effect of social contagion on the gamer's purchase of social utility products*.

Figure 1 illustrates the proposed conceptual framework.

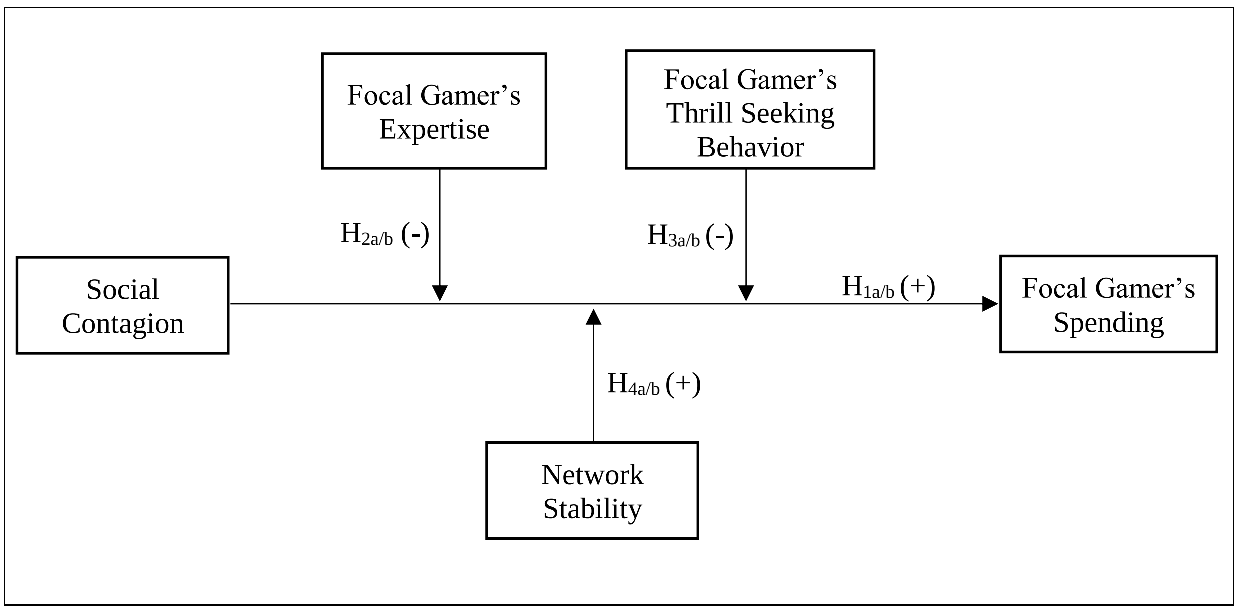


Figure 1. Conceptual Framework

2.4 Data

2.4.1 Research Setting

The author uses data from a popular MMORPG which was launched in South Korea in 2010. The Korean online game market is one of the largest in the world with revenues of 2.5 billion

U.S. dollars in 2013 (Davis 2014). The author has access to individual gamers' log data, which captures all actions taken by each gamer, including the purchases made. The estimation data spans a total of eighteen weeks. Given that gamers can join at different points of time and given that not all of the gamers log in to play during the data time period, for the purposes of model tractability, the author applies the following two criteria to select the gamers: (1) the author works with gamers who registered in the second month of the launch of the focal game and (2) who played the game at least once a month over the data time period of 18 weeks. For the purpose of the analysis, the author excluded the first month of data (after the launch of the game) from the analysis to allow for a "settling period" as online games often experience systematic errors and corrections during the first few weeks. The above filtering steps yielded a sample of 623 gamers. Thus, the estimation sample contains the login, gameplay activities and purchase decisions of 623 gamers over a period of 18 weeks. The total number of gamers who played with these 623 gamers over the data time period is 21,742.

The MMORPG, as do most MMORPGs, has a skill-based progression system. Gamers earn experience points, the unit of measurement in many MMORPG games, by completing missions or defeating enemies (e.g., monsters) and progress through various levels; gamers can also lose points if they do not play well. For example, if a gamer's virtual avatar were to get hit by monsters, the gamer would lose points. As a gamer gains experience points, the gamer's virtual character "levels up,"[3] and progress to a new level comes with benefits such as new abilities and improved statistics. This, in turn, lets the gamer's character get stronger and enables the gamer to participate in more difficult tasks (e.g., fighting stronger monsters or completing more difficult

[3] Once a gamer reaches a predetermined amount of experience points, his or her character proceeds to the next level.

missions). While gamers can play some of the games for free, the online game earns revenues when the gamers spend real currency to buy virtual products. As mentioned earlier, gamers can buy two types of products: a) functional utility products such as health drinks or safety cards that help them fight against monsters and play better, or b) social utility products which include items such as jewelry and clothes that gamers can use to decorate their avatars.

2.4.2 Dependent and Independent Variables

2.4.2.1 Gamer Spending

The unit of analysis is at the individual gamer-weekly level. The focus is on understanding the impact of social influence on a focal gamer's level of spending in buying virtual products. Given that there are two types of virtual products— functional utility products and social utility products— the author has two dependent variables, $Spending_{it}^{Functional}$ and $Spending_{it}^{Social}$. These variables capture the spending (in Korean Won)[4] of a focal gamer *i*'s purchase of functional and social utility products at week *t* respectively. The author notes that gamers can access the basic game content without paying and thus the author has a high preponderance of zeros in the dependent variables. The author handles this issue explicitly in the methods section. Conditional on a gamers' decision to purchase virtual products, the author notes that the spending variables exhibit positive skewness. To alleviate this issue, the author log transforms the spending variables.

2.4.2.2 Social Contagion

Following extant research (Iyengar, Van den Bulte, and Valente 2011; Ghose, Han, and Iyengar 2012), the author operationalizes social contagion by the spending level of a gamer's friends. Specifically, the author defines a gamer *i*'s social contagion at time *t* by the *sum* of amount

[4] 1 U.S. Dollar is equal to 1,155.6 Korean Won (as of June 7, 2016).

spent by the gamer's friends at time *t-1*. As the author noted earlier, a gamer can team up with other gamers to fight monsters. Based on the collaboration history between gamers, the author classifies two gamers as friends if they collaborated in a game prior to the focal time period. There are three important things to note about the operationalization of social contagion. First, the operationalization is based on *observed* interactions between a focal gamer and his/her friends. Second, the author works with a (one period) lagged measure of contagion (as opposed to contemporaneous) to avoid the "reflection problem" (Manski 1993). The author elaborates on the identification issues in the following section but very briefly, the lagged measure helps the author identify the effect of friends' purchase behavior on the purchase behavior of the focal gamer from the effect of the focal gamer's purchase behavior on the purchase behavior of his friends. Third, social contagion can be due to both recent and past spending behavior of a focal gamer's friends. To accommodate this possibility, the author formulates a stock version of the contagion variable as follows (à la Nerlove and Arrow 1962):

$$Contagion_{it}^{k} = \sum_{j} (Spending_{ijt}^{k}) + \lambda Contagion_{it-1}^{k} \tag{2.1}$$

where $Spending_{ijt}^{k}$ is the spending of a gamer *i*'s friend *j* at time *t* on product type *k* (*k*: functional and social utility products). λ is the carry-over parameter associated with spending.[5]

2.4.2.3 Experts

The author operationalizes a gamer's level of expertise based on his/her experience points. As gamers gain (lose) experience points when they defeat a monster (or get defeated by a monster),

[5] For the sake of model parsimony, the author does not estimate λ. The author found via grid-search method λ of value .6 to be the best fitting. The author performs additional robustness checks in the paper as well.

the context and data allow the author to measure variation in a gamer's expertise level over time. Because high scores indicate high expertise, the author labels this variable "Pros" for ease of exposition in the model. Given that gamers' experience points can vary over time and that total points that a gamer accumulates can change with the number of times they have logged in to play, the author operationalizes $Pros_{it}$ as the ratio of total points earned by a user *i* at week *t* to the frequency of his participation (logins) at time *t*.

$$Pros_{it} = \frac{\text{Total Experience Points}_{it}}{\text{Login Frequency}_{it}} \tag{2.2}$$

2.4.2.4 Thrill Seeker

Thrill seekers are individuals who have a higher preference for danger and adventure. In this MMORPG, before engaging with a monster, a gamer can see the monster's level, infer the monster's ability to attack and defend, and then decide whether to fight it. If a monster's level is greater than that of the focal gamer, the gamer cannot defeat the monster easily. However, if the gamer were to successfully defeat the monster, the gamer has the opportunity to gain more points. Hence, the author defines $Thrill\ Seeker_{it}$ as the ratio of the number of higher level monsters fought by a gamer to the total number of monsters fought by the gamer *i* at time *t*.

$$Thrill\ Seeker_{it} = \frac{\text{Number of Higher Level Monsters Fought}_{it}}{\text{Number of Total Monsters Fought}_{it}} \tag{2.3}$$

2.4.2.5 Network Stability

Network stability measures the extent to which a focal user's network of friends changes over time (Bien, Marbach, and Neyer 1991). Following recent studies (Tucker 2011), the author operationalizes a focal user's network stability as the ratio of the number of friends a gamer has played with before and plays with at time t to the total number of unique friends in the gamer's network. Accordingly, the author defines network stability as follows:

$$NetworkStability_{it} = \frac{\text{Number of past friends playing with the focal user } i \text{ at time } t}{\text{Total number of unique friends in focal user } i\text{'s network at time } t\text{-1}} \quad (2.4)$$

where the numerator indicates the number of friends (i.e., friends a focal gamer has played with in the past) who are playing with the focal user at time t and the denominator represents the total number of unique friends who have played with the focal gamer i until the previous time period (t-1).

2.4.3 Control Variables

The author controls for various gamer-specific, gamer-network-specific, game-related and demographic characteristics in the model. The gamer specific control variables are the following: the number of logins by the focal gamer (denoted by $Login\ Frequency_{it}$), the total size of a gamer's network at any given time operationalized by the total number of friends who play with the gamer at week t ($Number\ of\ Friends_{it}$). Following the arguments in recent literature (Nair, Manchanda, and Bhatia 2010; Hartmann 2010), the author created a gamer-network specific variable to account for correlated unobservables, factors that can simultaneously affect all the gamers in a gamer's network. Specifically, by accounting for the purchase behavior of friends of friends of a focal gamer who are *not* friends of the focal gamer ($Friends\ of\ Friends_{it}$), the author controls for factors that affect all gamers in a gamer's network. The author elaborates on this variable in the following section. The author created this variable for the two types of virtual products, functional and social utility products. The focal MMORPG is a role-playing game and hence a gamer can select an *avatar* type or a job from the following four options: Magician, Archer, Thief, or Warrior. The author created game related dummy variables (denoted by Job_i) for the basic characteristics of the avatar that a gamer chooses.[6] Finally, the author also controls for the age and the gender of the gamers.

In Table 1, the author presents the list, operationalization, and summary statistics of all the variables.

2.5 Econometric Model

Before the author presents the main model, the author discusses several econometric challenges that researchers who work with observational data have to overcome in establishing the effect of social contagion.

2.5.1 Identification Challenges

Studies that examine social influence using observational data like the current dataset face the challenge of identification in terms of differentiating the social contagion effect from the effect of confounding factors. Prior literature in economics has identified three sources of confounding factors, namely, endogenous group formation, correlated unobservables, and simultaneity (Manski 1993). Among these issues, endogenous group formation is the thorniest issue for researchers who work with observed behavioral data. In the following paragraphs, the author elaborates on these issues and explain the prescriptions expounded in the recent literature (Hartmann et al. 2008; Nair, Manchanda, and Bhatia 2010; Ghose, Han, and Iyengar 2012) to address these issues.

2.5.1.1 Endogenous Group Formation

Endogenous group formation or homophily refers to the possibility that individuals with similar tastes or preferences are more likely to form a group. In this context, gamers who prefer to spend money and decorate their avatars (by purchasing social utility products) may form groups

[6] The author notes that once a gamer chooses his/her character's job, he /she cannot change it.

to play with each other. In such a scenario, the effect of a gamer's friends' purchase behavior on the gamer's purchase behavior may not be driven by social contagion but may be due to homophily. Several solutions have been developed to address the issues of endogenous group formation (Nair, Manchanda, and Bhatia 2010; Hartmann et al. 2008; Hartmann 2010; Ghose, Han, and Iyengar 2012). The key is to leverage panel data and account for endogenous group formation by using either individual user level fixed effects (Nair, Manchanda, and Bhatia 2010) or random effects (Hartmann 2010). The argument is that both fixed and random effects formulations help capture unobserved common tastes by accounting for user level unobserved heterogeneity. The author uses individual-gamer level random effects.

2.5.1.2 Correlated Unobservables

The second identification challenge is the issue of correlated unobservables, which may drive purchase behavior of all the gamers simultaneously. For example, gamers who play together during a sports event (such as the soccer World Cup) may be all equally excited and may increase their in-game purchase behavior following or during this big event. This increase then is likely to be driven by the exogenous event that the group of gamers experienced together and should not be inferred as social contagion. Correlated unobservables are driven by exogenous time period specific shocks and studies suggest that these can be accounted for by incorporating time fixed effects (Nair, Manchanda, and Bhatia 2010). The author thus has time fixed effects in the model.

Variable Name	Description of the Variable	M	SD	Min	Max
Dependent Variables					
$Spending_{it}^{Functional}$	User *i*'s spending on functional utility products at time period *t*	652	3,707	0	126,800
$Spending_{it}^{Social}$	User *i*'s spending on social utility products at time period *t*	596	3,093	0	67,600
Independent Variables					
$Contagion_{it}^{Functional}$	Cumulative (stock measure) sum of spending on functional utility products by a focal user *i*'s friends at time period *t*	14,850	46,191	0	927,626
$Contagion_{it}^{Social}$	Cumulative (stock measure) sum of spending on social utility products of a focal user *i*'s friends at time period *t*	15,798	39,031	0	534,546
$Experts_{it}$	A ratio of a focal user *i*'s total experience points to frequency of play logins at time period *t*	5.65	14.50	0	262
Thrill $Seeker_{it}$	Ratio of number of higher level monsters fought to the total number of monsters fought by the focal user *i* at time period *t*	.15	.23	0	1
$Stability_{it}$	Ratio of number of past friends with whom the focal gamer plays (at time *t*) with to the total number of unique friends of the focal user *i* (at time period *t-1*).	.35	.40	0	1
Control Variables					
Friends of $Friends_{it}^{Functional}$	Average spending of the friends of focal gamer *i*'s friends (who are not friends of the focal gamer) on functional utility products at time period *t*	3,753	5,520	0	64,046
Friends of $Friends_{it}^{Social}$	Average spending of the friends of focal gamer *i*'s friends (who are not friends of the focal gamer) on social utility products at time period *t*	4,235	5,793	0	87,600
Login $Frequency_{it}$	A focal user *i*'s number of logins at time period *t*.	14.82	34.71	1	1,184
Number of $Friends_{it}$	Number of a focal user *i*'s friends at time period *t*.	5.75	12.08	0	132
$Job1_i$ (Magician)	=1 if user *i*'s virtual job is Magician; 0 otherwise	.21	.40	0	1
$Job2_i$ (Archer)	=1 1 if user *i*'s virtual job is Archer; 0 otherwise	.30	.45	0	1
$Job3_i$ (Thief)	=1 1 if user *i*'s virtual job is Thief; 0 otherwise	.22	.41	0	1
Age_i	Age of user *i*	25.72	12.67	3	74
$Gender_i$	=1 if user *i* is Female; 0, otherwise	.44	.50	0	1
Notes: Spending, Contagion, and Friends of Friends are in Korean Won. 1 US dollar is equal to 1,155.6 Korean Won (as of June 7, 2016). The unit of Experts is 10^7. Number of observations = 7,847 across 623 gamers.					

Table 1. Variable Operationalization and Summary Statistics

Although time fixed effects help the author account for shocks that affect *all* the gamers at a given point of time, the author also would like to account for other unobserved factors at the (gamer) *network and time* level. Following prior studies (e.g., Nair, Manchanda, and Bhatia 2010) the author employs the "difference-in-difference" approach and construct the purchase behavior of those gamers who are *not* in a focal friend's network. Since the author can map the social network of all the gamers, the author measures $Friends\ of\ Friends_{it}^{k}$, the purchase behavior of gamers (of product type *k* at time *t*) who are *not* in a focal gamer *i*'s network as a variable to control for unobserved network and time specific correlated unobservables. The variable $Friends\ of\ Friends_{it}^{k}$ helps absorb all unobserved time and network specific shocks to purchase behaviors that are common to all gamers in a gamer *i*'s network. Given that gamers can choose from different avatars with specific roles or jobs in the game (e.g., Magician, Archer, Thief, and Warrior), and because gamers who choose similar jobs might purchase similar items, the author also incorporates avatar type-specific dummy variables to account for correlated unobservables.

2.5.1.3 Simultaneity

The next issue that confronts researchers who use observational data to model social contagion is simultaneity, also referred to as the reflection problem (Manski 1993). The issue arises because the effect of social contagion can be difficult to identify if individuals in the same group affect each other's behavior simultaneously. In order to separate the effect of a gamer's purchase behavior on his/her friends' purchase behavior from the effect of the gamer's friends' purchase behavior on the purchase behavior of the focal gamer, following prior literature, (e.g., Hartmann et al. 2008; Ghose, Han, and Iyengar 2012), the author uses lagged values of a gamer's friends' purchase behavior to operationalize social contagion.

2.5.2 Final Model Specification

The author models the effect of social contagion and the moderating effects of gamers' expertise level, thrill-seeking preference and network stability on users' purchase behavior. The author needs to account for two issues in the model formulation. First, the dependent variable, gamers' spending level, is censored as it is only observed when it is greater than zero. Second, gamers do not buy virtual products in all the play sessions and thus the author has a preponderance of zeros in many time periods. To address both these issues, the author formulates a Tobit model of gamers' spending behavior (Amemiya 1973). Based on the conceptual framework (see Figure 1) and the identification related issues discussed earlier, the author presents the model of gamers' spending behavior as follows:

$$\begin{aligned}\ln Spending_{it}^{k*} = {} & \ln Contagion_{it-1}^{k} \times (\beta_1 + \beta_2 Pros_{it} + \beta_3 Thrill\ Seeker_{it} + \beta_4 Stability_{it}) \\ & + \beta_5 Pros_{it} + \beta_6 Thrill\ Seeker_{it} + \beta_7 Stability_{it} \\ & + \beta_8 Login\ Frequency_{it} + \beta_9 Number\ of\ Friends_{it} \\ & + \beta_{10} \ln Friends\ of\ Friends_{it}^{k} \\ & + \beta_{11} Job1_i + \beta_{12} Job2_i + \beta_{13} Job3_i + \beta_{14} Age_i + \beta_{15} Gender_i \\ & + \varphi_i^k + \upsilon_t^k + \varepsilon_{it}^k \end{aligned} \tag{2.5}$$

where $\ln Spending_{it}^{k*}$ is the latent variable of $\ln Spending_{it}^{k}$ which indicates individual *i*'s observed spending on product type *k* (*k*: functional and social utility products) at time *t*. The author notes that the author uses a log-transformation on all the spending related variables, $Spending_{it}^{k}$, $Contagion_{it-1}^{k}$, and $Friends\ of\ Friends_{it}^{k}$, since all of these spending variables are skewed.[7] The author refers the readers to the previous section for notation of independent variables used in

[7] The author added one to the *Spending*, *Contagion*, and *Friends of Friends* before employing the (natural) log-transformation to avoid taking the logarithm of 0 (Snedecor and Cochran 1967, p. 329).

Equation 2.5. φ_i^k is the individual, product type specific random effect term that helps account for unobserved individual heterogeneity. υ_t^k is the set of time (product specific) fixed effects. ε_{it}^k is the error term associated with the model. The author estimates two separate models for each type of product (functional and social utility products).

As discussed earlier, the latent dependent variables are observed only for values greater than zero and are censored otherwise. Thus, the author formulates the measurement equations for the observed variables, ($\ln Spending_{it}^k$) as follows:

$$\ln Spending_{it}^k = \begin{cases} \ln Spending_{it}^{k*} & \text{if } \ln Spending_{it}^{k*} > 0 \\ 0 & \text{otherwise} \end{cases} \tag{2.6}$$

The likelihood function of the proposed Tobit model for a gamer *i*'s spending behavior for product type *k* (L_i^k) is:

$$L_i^k = \int_{-\infty}^{\infty} \left\{ \prod_{(t|y_{it}^k>0)}^{T_i} \frac{1}{\sigma_\varepsilon^k} \phi\left(\frac{y_{it}^k - x_{it}^{k'}\beta^k - \varphi_i^k}{\sigma_\varepsilon^k} \right) \times \prod_{(t|y_{it}^k=0)}^{T_i} \Phi\left(\frac{-x_{it}^{k'}\beta^k - \varphi_i^k}{\sigma_\varepsilon^k} \right) \right\} \phi\left(\frac{\varphi_i^k}{\sigma_\varphi^k} \right) d\varphi_i^k \tag{2.7}$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ are the probability density function (pdf) and the cumulative distribution function (cdf) respectively of the standard normal distribution, y_{it}^k are the dependent variables, x_{it}^k is the set of independent variables, β^k refers to the vector of parameters to be estimated, φ_i^k distributed $\mathrm{N}(0, \sigma_\varphi^k)$ is the individual specific random effects (for the two types of virtual products, denoted by *k*), σ_ε^k is the standard deviation of the error term (ε_{it}^k) in Equation 2.5, and T_i refers to the total number of weeks the gamer *i* logged in. The author estimates the proposed model (Equation 2.7) via maximum likelihood estimation.

2.6 Results

2.6.1 Model-Free Analysis

Before the author presents the results from the estimation of the proposed model, the author offers model-free evidence of the effect of contagion on gamers' spending behavior. As part of the model-free analyses, the author presents plots of social contagion and gamers' spending on functional and social utility products. As can be seen from Figure 2, as the friends' spending level increases, a gamer's average spending on both functional and social utility products increases. To ascertain the role of the moderating variables in detail, the author splits the data—based on the median value of the relevant moderating variable—and segment the gamers into "high" and "low" types for each moderating variable. In Figure 3, the author presents the variation in spending for the high and the low levels of the three moderating variables for both the functional and the social utility products in Panel A and Panel B respectively.

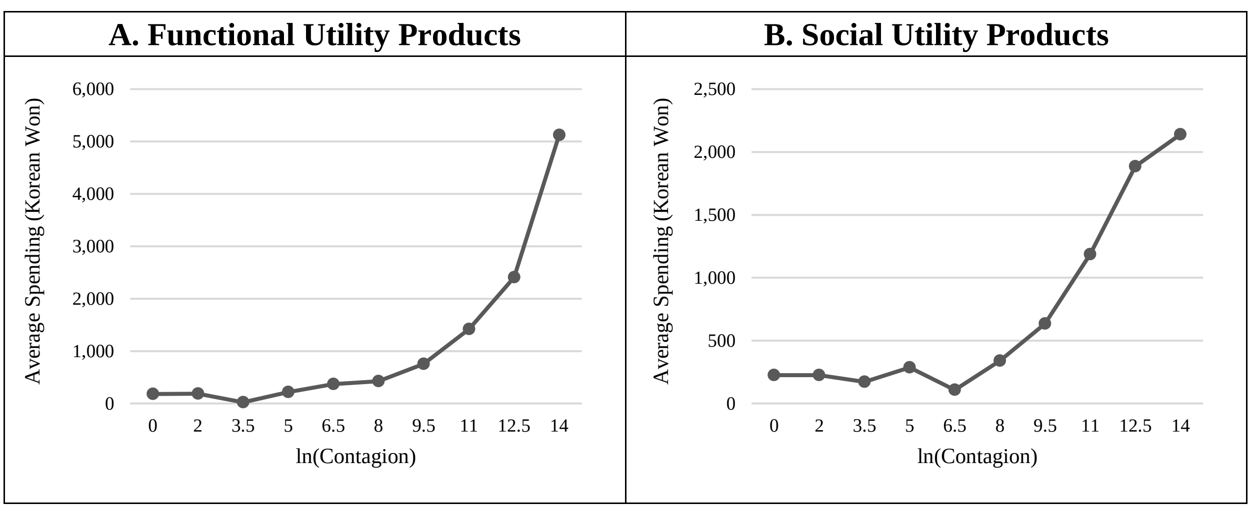


Figure 2. Model Free Evidence: Main Effect of Social Contagion on Spending

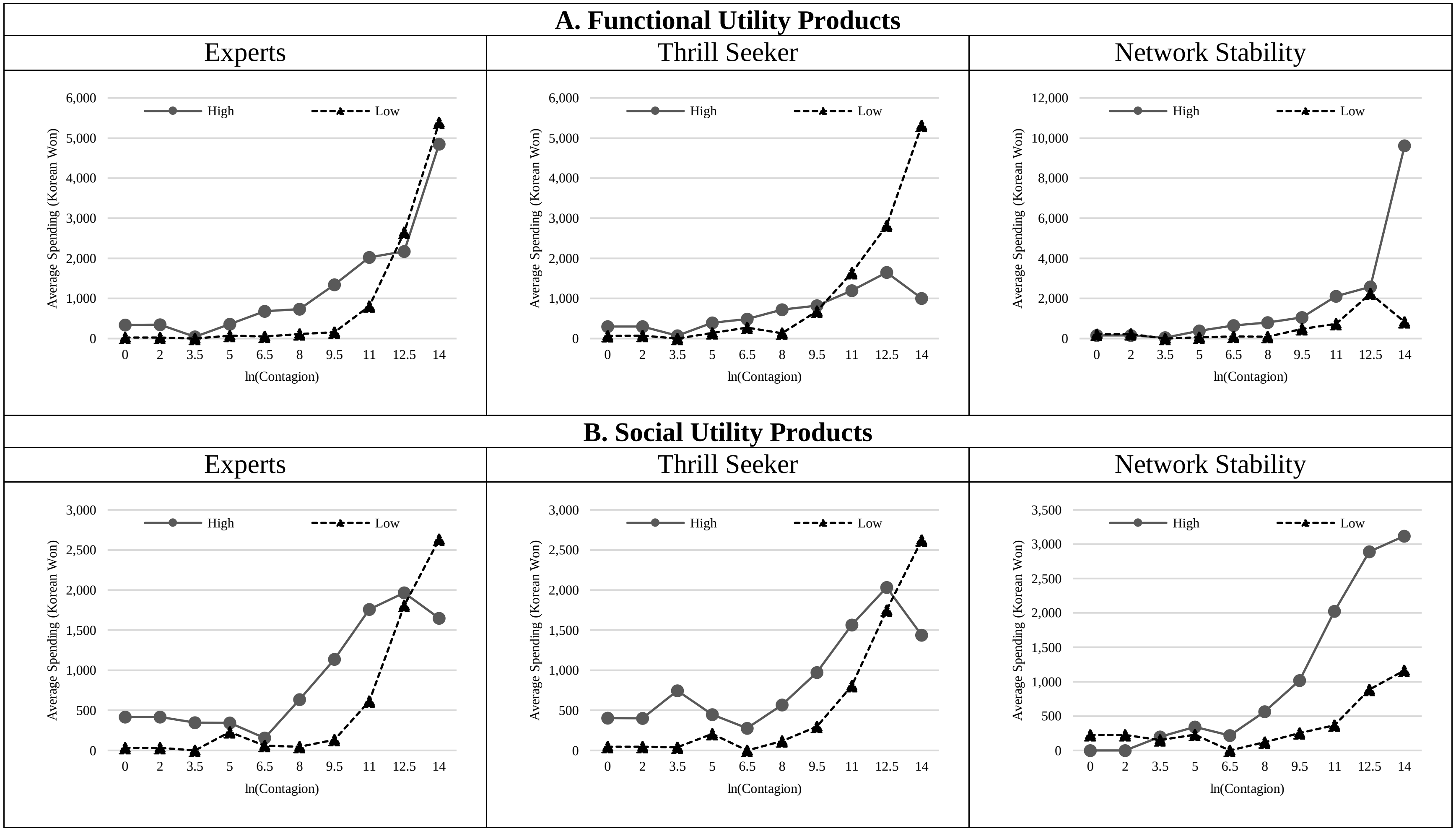


Figure 3. Model Free Evidence: Moderating Effects of Experts, Thrill Seeker, and Network Stability

It is evident from the figures that on average, gamers with greater expertise (i.e., the "Pros") spend more on purchases of both types of products. However, the rate of increase in spending when there is an increase in contagion is greater for gamers with a lower level of expertise. This suggests that gamers' expertise level could negatively moderate the relationship between social contagion and gamers' spending. The author finds similar patterns between gamers' thrill seeking levels and their susceptibility to contagion, i.e., the model free analyses suggest that gamers' thrill seeking behavior might negatively moderate the relationship between social contagion and gamers' spending behavior. Finally, with respect to network stability, for low levels of social contagion, the author does not find much difference between the spending behaviors of gamers with high and low network stability. However, for higher levels of social contagion, a difference in spending behavior between gamers with high and low network stability begins to emerge.

2.6.2 Parameter Estimates

Table 2 provides the fit statistics of a series of alternative models (Models 1 to 5) and the proposed model (Model 6). The author starts with the basic model (Model 1) of spending behavior as a function of only control variables. Model 2 builds on Model 1 as the author also accounts for the main effect of social contagion. From Models 3 to 5, the author subsequently adds one interaction term at a time before adding all the interaction terms, which yields the proposed model (Model 6). The author notes that all the models account for time-period dummies, individual-level random effects and other variables that help address the identification challenges discussed earlier. The proposed model has the best fit as compared to the other alternative models in terms of log-likelihood, Akaike information criterion (AIC), and likelihood-ratio (LR) test.

Model	Description	Log-Likelihood	LR test (vs. Model 6)	AIC
A. Gamer Spending Behavior: Functional Utility Products				
Model 1	Gamer spending behavior as a function of control variables only.	-3,253.64	χ^2(d.f.=4) = 41.99***	6,569.28
Model 2	Variables in Model 1+ Contagion variable	-3,247.71	χ^2(d.f.=3) = 30.12***	6,559.41
Model 3	Variables in Model 2+ Moderating effect of experts.	-3,237.62	χ^2(d.f.=2) = 9.95***	6,541.24
Model 4	Variables in Model 2+ Moderating effect of thrill seeker	-3,245.27	χ^2(d.f.=2) = 25.24***	6,556.54
Model 5	Variables in Model 2+ Moderating effect of network stability	-3,244.15	χ^2(d.f.=2) = 23.00***	6,554.29
Model 6 (Proposed Model)	Variables in Model 2+ Moderating effects of experts, thrill seeker and network stability	-3,232.65	-	6,535.29
B. Gamer Spending Behavior: Social Utility Products				
Model 1	Gamer spending behavior as a function of control variables only.	-3,004.99	χ^2(d.f.=4) = 36.75***	6,071.98
Model 2	Variables in Model 1+ Contagion variable	-2,996.78	χ^2(d.f.=3) = 20.34***	6,057.56
Model 3	Variables in Model 2+ Moderating effect of experts.	-2,989.90	χ^2(d.f.=2) = 6.58**	6,045.81
Model 4	Variables in Model 2+ Moderating effect of thrill seeker	-2,993.27	χ^2(d.f.=2) = 13.33***	6,052.55
Model 5	Variables in Model 2+ Moderating effect of network stability	-2,995.83	χ^2(d.f.=2) = 18.44***	6,057.66
Model 6 (Proposed Model)	Variables in Model 2+ Moderating effects of experts, thrill seeker and network stability	-2,986.61	-	6,043.22

* $p < .1$, ** $p < .05$, *** $p < .01$

Notes: Likelihood Ratio (LR) tests compare the model fits of the full model to ones of other models. AIC = Akaike information criterion. All models account for time period dummies and players' unobserved heterogeneity.

Table 2. Model Fit

In Table 3, the author presents the parameter estimates of the proposed model and other alternative models. Since the proposed model (Model 6) has the best fit, for the sake of brevity, the author discusses the parameter estimates of the proposed model only. The author finds that social contagion has a positive and significant effect on gamers' purchase of functional and social utility products. The author thus finds support for H_{1a} and H_{1b}. The author further finds that the coefficient of the interaction between social contagion and gamer expertise is negative and significant for both types of virtual products. This suggests that gamers' expertise negatively moderates gamers' susceptibility to contagion and thus supports H_{2a} and H_{2b}. The results also suggest that gamers' thrill seeking behavior negatively moderates the relationship between contagion and gamers' purchase behavior. This implies that gamers who have greater preference for thrill and adventure are less susceptible to contagion; this finding supports H_{3a} and H_{3b}. Lastly, the author finds that whereas network stability has a positive and significant moderating effect on contagion for gamers' purchase of functional utility products, the author does not find evidence to suggest that network stability moderates the effect of social contagion on gamers' purchase of social utility products. The author discusses the theoretical and practical implications of these results in detail in the discussion section.

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
A. Functional Utility Products												
Variable	**Estimate**	**SE**	**Estimate**	**SE**	**Estimate**	**SE**	**Estimate**	**SE**	**Estimate**	**SE**	**Estimate**	**SE**
ln(Contagion)	-	-	.399***	(.117)	.608***	(.128)	.546***	(.136)	.269**	(.126)	.602***	(.149)
ln(Contagion)×Experts	-	-	-	-	-.695***	(.153)	-	-	-	-	-.638***	(.153)
ln(Contagion)×Thrill Seeker	-	-	-	-	-	-	-.636**	(.287)	-	-	-.601**	(.291)
ln(Contagion)×Stability	-	-	-	-	-	-	-	-	1.405***	(.522)	1.344**	(.521)
Experts	2.490***	(.510)	2.210***	(.514)	9.210***	(1.620)	2.180***	(.513)	2.270***	(.514)	8.660***	(1.620)
Thrill Seeker	4.502***	(1.358)	4.693***	(1.354)	3.744***	(1.365)	8.541***	(2.186)	4.337***	(1.356)	7.145***	(2.232)
Stability	-3.029**	(1.372)	-.587	(1.535)	.595	(1.561)	-.402	(1.535)	-1.345	(1.559)	-.069	(1.587)
Login Frequency	.028***	(.006)	.026***	(.006)	.025***	(.006)	.026***	(.006)	.028***	(.006)	.026***	(.006)
Number of Friends	.175***	(.025)	.158***	(.025)	.161***	(.025)	.152***	(.025)	.150***	(.025)	.147***	(.025)
ln(Friends of Friends)	.599***	(.095)	.538***	(.096)	.514***	(.096)	.538***	(.096)	.518***	(.096)	.496***	(.095)
Job1	-.848	(1.460)	-.668	(1.449)	-.457	(1.431)	-.629	(1.446)	-.754	(1.421)	-.530	(1.406)
Job2	.367	(1.289)	.515	(1.276)	.643	(1.260)	.509	(1.227)	.610	(1.250)	.715	(1.236)
Job3	-3.359**	(1.594)	-3.025**	(1.584)	-2.721*	(1.566)	-3.051*	(1.584)	-2.962*	(1.552)	-2.710*	(1.537)
Age	.100**	(.042)	.090**	(.042)	.083**	(.042)	.087**	(.042)	.089**	(.041)	.080**	(.041)
Female	1.814*	(1.022)	1.889*	(1.013)	1.683*	(1.001)	1.920*	(1.012)	1.816*	(.993)	1.657*	(.983)
B. Social Utility Products												
ln(Contagion)	-	-	.543***	(.137)	.743***	(.150)	.749***	(.160)	.453***	(.151)	.828***	(.181)
ln(Contagion)×Experts	-	-	-	-	-.685***	(.181)	-	-	-	-	-.618***	(.183)
ln(Contagion)×Thrill Seeker	-	-	-	-	-	-	-.809**	(.305)	-	-	-.723**	(.308)
ln(Contagion)×Stability	-	-	-	-	-	-	-	-	.689	(.495)	.591	(.496)
Experts	2.890***	(.546)	2.630***	(.546)	9.650***	(1.930)	2.570***	(.544)	2.670***	(.546)	8.950***	(1.950)
Thrill Seeker	5.368***	(1.447)	5.343***	(1.444)	4.698***	(1.451)	10.797***	(2.496)	5.180***	(1.447)	9.518***	(2.538)
Stability	-2.322	(1.447)	1.939	(1.779)	3.082*	(1.830)	2.109	(1.800)	1.352	(1.829)	2.618	(1.892)
Login Frequency	.040***	(.007)	.037***	(.007)	.037***	(.007)	.036***	(.007)	.038***	(.007)	.036***	(.007)
Number of Friends	.163***	(.026)	.140***	(.027)	.143***	(.027)	.132***	(.027)	.138***	(.027)	.134***	(.027)
ln(Friends of Friends)	.807***	(.107)	.755***	(.107)	.728***	(.107)	.752***	(.107)	.743***	(.107)	.718***	(.107)
Job1	-1.321	(1.552)	-1.126	(1.530)	-.978	(1.521)	-1.036	(1.533)	-1.115	(1.514)	-.900	(1.512)
Job2	.275	(1.348)	.281	(1.326)	.457	(1.320)	.313	(1.327)	.337	(1.312)	.518	(1.309)
Job3	-3.562**	(1.686)	-3.327**	(1.664)	-2.990**	(1.655)	-3.326**	(1.668)	-3.305**	(1.647)	-2.997*	(1.646)
Age	.045	(.044)	.033	(.044)	.029	(.044)	.030	(.044)	.033	(.044)	.026	(.044)
Female	2.538**	(1.081)	2.643**	(1.066)	2.505**	(1.060)	2.664**	(1.068)	2.601**	(1.055)	2.501**	(1.054)

* $p < .1$, ** $p < .05$, *** $p < .01$

Notes: The unit of Experts is 10^7. Standard errors in parentheses. All models account for time-period dummies and players' unobserved heterogeneity.

Table 3. Parameter Estimates: Effects of Social Contagion

2.7 Robustness Checks

The author performs robustness checks to insure that the core results pertaining to contagion are robust to alternative operationalizations of the social contagion variable. First, instead of operationalizing contagion as purchase behavior of all the friends of a user, the author separates contagion stemming from the purchase behavior of "old" versus "new" friends. The author classifies a gamer as an "old friend" of a gamer if the former played with the latter prior to the focal time period. The author classifies a gamer as a new friend if the focal gamer played with the particular gamer friend for the first time (in a given time period). The author presents the results in Table 4. The author finds that the main effect of contagion that stems from the purchase behavior of old friends on a focal gamer's purchase of functional and social utility products is positive and significant. In terms of contagion that stems from the purchase behavior of new friends, the author finds that whereas new friends have a significant and positive effect on a focal gamer's purchases of social utility products, new friends do not have a significant effect on the purchases of functional utility products.

Second, instead of taking into account all of the lagged purchases of a focal gamer's friends, the author separates the lagged purchases into recent versus past purchases (up to three lagged intervals of *t-1*, *t-2* and *t-3*). The author presents the results in Table 5. The author finds that social contagion has a positive and significant effect on gamers' purchases of functional and social utility products even after separating the purchase behavior of a gamer's friends into three distinct time periods. As expected, the author finds that recent purchase behavior of friends is more effective as compared to past purchase behavior of friends. Taken together, the results of these robustness checks suggest that —regardless of source (old versus new friends) and temporal classification (recent versus past) of social contagion—friends' spending behavior has a significant impact on gamers' spending behavior.

A. Functional Utility Products					
	Main Effects			Full Model	
Variable	**Estimate**	**SE**		**Estimate**	**SE**
ln(Contagion from Old Friends)	.465***	(.107)		.868***	(.158)
ln(Contagion from Old Friends)×Experts	-	-		-.420***	(.122)
ln(Contagion from Old Friends)×Thrill Seeker	-	-		-.751**	(.382)
ln(Contagion from New Friends)	.160	(.123)		.187	(.169)
ln(Contagion from New Friends)×Experts	-	-		-.370**	(.171)
ln(Contagion from New Friends)×Thrill Seeker	-	-		-.086	(.340)
Experts	1.960***	(.514)		8.390***	(1.520)
Thrill Seeker	5.716***	(1.370)		7.191***	(2.161)
Stability	-1.473	(1.527)		-.585	(1.545)
Login Frequency	.024***	(.006)		.022***	(.006)
Number of Friends	.151***	(.025)		.144***	(.025)
ln(Friends of Friends)	.530***	(.096)		.501***	(.095)
Job1	-0.541	(1.435)		-0.250	(1.415)
Job2	0.422	(1.267)		0.491	(1.249)
Job3	-2.972*	(1.573)		-2.619*	(1.553)
Age	0.083**	(0.042)		0.070*	(0.041)
Female	1.969**	(1.006)		1.746*	(0.992)
Log likelihood	-3,239.84			-3,223.37	
B. Social Utility Products					
ln(Contagion from Old Friends)	.377***	(.113)		.342**	(.163)
ln(Contagion from Old Friends)×Experts	-	-		-.125	(.133)
ln(Contagion from Old Friends)×Thrill Seeker	-	-		.313	(.374)
ln(Contagion from New Friends)	.337**	(.138)		.660***	(.186)
ln(Contagion from New Friends)×Experts	-	-		-.517**	(.203)
ln(Contagion from New Friends)×Thrill Seeker	-	-		-.792**	(.354)
Experts	2.380***	(.551)		8.080***	(1.830)
Thrill Seeker	6.107***	(1.456)		9.386***	(2.439)
Stability	1.038	(1.751)		2.283	(1.792)
Login Frequency	.035***	(.007)		.033***	(.007)
Number of Friends	.133***	(.027)		.092***	(.029)
ln(Friends of Friends)	.760***	(.107)		.632***	(.087)
Job1	-1.106	(1.512)		-1.002	(1.515)
Job2	0.297	(1.310)		0.253	(1.312)
Job3	-3.351**	(1.647)		-3.275**	(1.590)
Age	0.026	(0.044)		0.016	(0.044)
Female	2.612**	(1.055)		2.475**	(1.053)
Log likelihood	-2,993.41			-2,984.32	

* $p < .1$, ** $p < .05$, *** $p < .01$

Notes: The unit of Experts is 10^7. All models account for time dummies and unobserved heterogeneity.

Table 4. Effect of Old versus New Friends on Spending Behavior

	Functional Utility Products			Social Utility Products	
Variable	**Estimate**	**SE**		**Estimate**	**SE**
ln(Friends' Spending$_{t-1}$)	.182**	(.087)		.246***	(.091)
ln(Friends' Spending$_{t-2}$)	.177**	(.086)		.153*	(.089)
ln(Friends' Spending$_{t-3}$)	.106	(.084)		.146*	(.087)
Experts	2.090***	(.518)		2.520***	(.550)
Thrill Seeker	5.052***	(1.390)		6.063***	(1.481)
Stability	-1.704	(1.467)		-.395	(1.602)
Login Frequency	.026***	(.006)		.035***	(.007)
Number of Friends	.148***	(.026)		.123***	(.028)
ln(Friends of Friends)	.523***	(.098)		.683***	(.110)
Job1	-.769	(1.471)		-1.492	(1.544)
Job2	.296	(1.297)		-.0001	(1.335)
Job3	-2.760*	(1.598)		-3.488**	(1.682)
Age	.091**	(.042)		.042	(.044)
Female	1.752*	(1.028)		2.565**	(1.076)
Log likelihood	-3,113.93			-2,816.05	

* $p < .1$, ** $p < .05$, *** $p < .01$

Notes: The unit of Experts is 10^7. Standard errors in parentheses. All models account for time-period dummies and players' unobserved heterogeneity.

Table 5. Effect of Friends' Lagged Spending on Spending Behavior

2.8 Discussion

Massively multiplayer online role-playing games have been gaining in popularity and exhibiting steady growth for much of the last decade. It is now known that it is not just young males that play these games but that the demographic profile of a gamer is more complex and comprises people from several different demographic groups (Williams, Yee, and Caplan 2008). A key feature of these MMORPGs is that while they are mostly available as "free to play," game managers have created several features to entice gamers to purchase different types of virtual products. The author undertakes an empirical examination to understand how gamers' social networks influence these in-game purchases. The author uses a unique and large scale individual user-level activity data from a massively multiplayer online role-playing gaming (MMORPG) community to examine the effect of gamers' social interactions, gamer and network characteristics on the actual purchase behavior of users in this virtual gaming community.

2.8.1 Theoretical Implications

This study examines and applies different perspectives from psychology, sociology and gaming behavior to help understand social influence in online gaming communities. While social contagion or peer effects have been well-established in the context of offline communities, an emerging stream of research in marketing, economics and information systems focuses on social information transmission and the underlying mechanisms in online communities (e.g., Aral, Muchnik, and Sundarajan 2009). This upswing in interest has merit because, unlike earlier studies that relied on self-reported measures or geographic proximity to infer social contagion, access to social networking sites has enabled researchers to observe actual interactions between individuals (Nitzan and Libai 2011; Tucker 2011).

With the increased popularity of online social platforms, website managers are continuously designing features that harness the power of online social interactions to stimulate social commerce activities (Pöyry, Parvinen, and Malmivaara 2013). However, there is limited research on the economic consequences of online social interactions among users of an online community. The findings show that social interactions significantly facilitate social commerce activities. Importantly, the author finds substantial peer effects in the purchases of two different types of products, functional and social utility products. Specifically, the author finds that the social contagion effect is greater for gamers' purchase of social utility products as compared to their purchase of functional utility products. This suggests that social normative forces that motivate an individual to conform to the group have a stronger presence in the focal MMORPG community. Prior research suggests that individuals diverge from others in product domains that can effectively communicate their desired social identity (Berger and Heath 2007). In this gaming community, a gamer's identity is tied more strongly towards game performance and while social contagion operates over both functional and social utility product domains in this study, the author observes greater effects for social utility products suggesting gamers' desires to conform more in contexts where identity signaling is inconspicuous.

Prior contagion research has heavily focused in contexts such as new product adoption (e.g., Iyengar, Van den Bulte, and Valente 2011) where risk mitigation is seen as a major force driving social contagion. Thus, product domains where risk is minimal such as the current dataset (virtual products are not very expensive in this MMORPG community) have received less attention. However, as social commerce has taken off and shows no signs of abatement, it is important to understand how contagion forces may differentially operate for different products depending on individual motivations to communicate or create a desired identity in a particular online community. Thus, the results add new insights to existing research and help extend the scope of current research in understanding the driving forces of social transmission of information.

The author also finds that certain individuals are more susceptible to contagion. Specifically, experts and thrill seekers are less vulnerable to social contagion. These results are in conformity with the earlier discussion where the author explains how individuals who seek to create a distinct and a unique self-identity may exhibit less sensitivity to peer behavior. Experts and thrill seekers are likely to be focused on improving their own games and in seeking differentiation from other players. Novices (the "newbies") and non-thrill seekers are more likely to seek heightened social interaction benefits that help them experience the virtual world in its entirety with others and in the process, they are more likely to be susceptible to social contagion. Indeed, research in online gaming cites three prominent motivations of gamers – achievement, immersion and social benefits (Yee 2006). The results suggest that depending upon the primary motivation for playing the game, users are likely to exhibit differential response to social contagion forces. These findings are new to the literature and help understand how different motivation forces may work to strengthen or mitigate social contagion.

Networks are a conduit for transmission of information and hence network interactions determine how individuals in a network will influence each other. The nature of influence itself often depends upon how these network interactions take place. Thus, network properties such as how close relationships are, how many common relationships exist etc. may help decipher how and why information gets transmitted (Aral and Walker 2014; Tucker 2011). A key feature of the gaming community is that a gamer's network is dynamic as a gamer chooses whom he or she will play with in a time period. Thus, new ties can be added and old ties can be easily abandoned in this community. The author exploits this feature of the community to study how stability of a network will influence social contagion. The findings suggest that while contagion is strengthened over functional product purchases, stability of a network does not influence contagion over social product purchases. Thus, repeated interactions with the same group of players helps intensify contagion for products that help gamers' increase their performance and meet achievement goals in the game. Social utility products, in the community, help gamers gain visibility and recognition by donning their avatars with jewelry etc. Thus, while the size of the network matters for these products, influx of new friends or exit of existing friends does not seem to influence the extent of influence. These results are new to the literature as there is no study that addresses the question of differential impact of network characteristics on social influence across different product domains.

2.8.2 Practical Implications

The findings from this study highlight that managers of online communities can benefit from monetization of social networks and that social contagion can entice gamers to increase purchases of virtual products. This is an important finding as website and content managers often face a difficult choice between increasing more features for users and investing in building a social network. While the focus is on MMORPGs, the author limits the scope of the practical implications of this study to managers of online gaming communities but acknowledge that some of these prescriptions will be applicable in several other social online communities as well.

The use of online gaming platforms has been steadily increasing and the results suggest evidence of *social dollars* in these communities. In other words, the author finds that social interactions between users of an online community have direct economic outcomes for community managers. In order to compare the size effects of social contagion, following McDonald and Moffitt (1980), the author computes the elasticities of social contagion on gamers' purchase behavior. The author calculates the elasticity of contagion, the percentage change in user spending due to a 1% increase in contagion, conditional on a focal user's decision to purchase.[8] The author finds that the elasticities of contagion for functional and social utility products are .053 and .069 respectively. Thus, although social contagion has a positive and significant effect on a user's purchase of both functional and social utility products, elasticity results suggest that contagion has a greater effect on users' purchase of social utility products as compared to users' purchase of functional utility products. This suggests that to enhance sales of products within an online

[8] Recall that the proposed Tobit model of gamers' purchase behavior has two components: a) a model that captures whether a gamer would spend or not and b) the level of spending conditional on a gamer's spending being more than zero. The author computes conditional elasticity which is the percentage change in spending behavior with a 1% change in contagion, conditional on users spending more than zero.

community, managers must create social networks such that user purchases are prominently visible to their networks. Further, engaging in differential pricing of social and functional utility products can also enhance sales in the community.

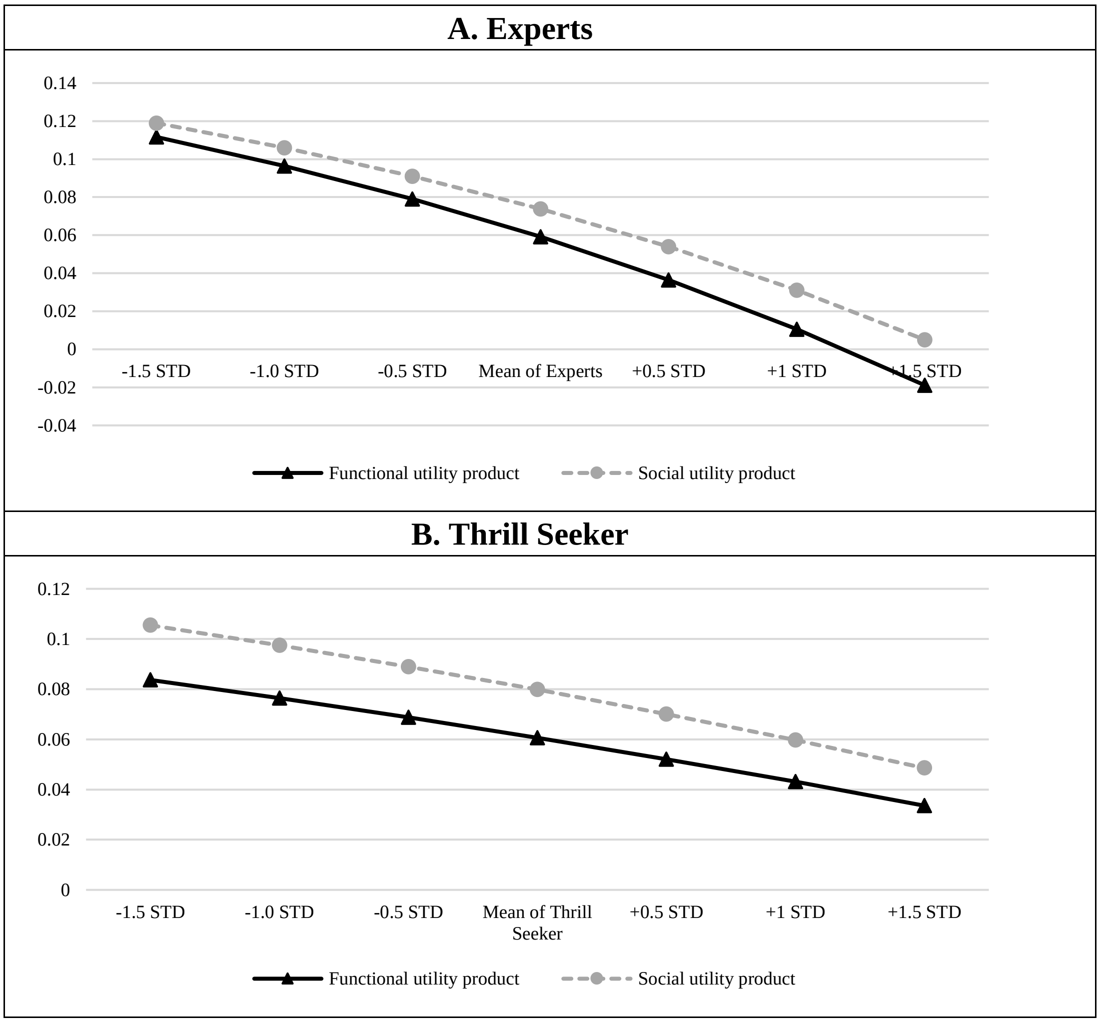
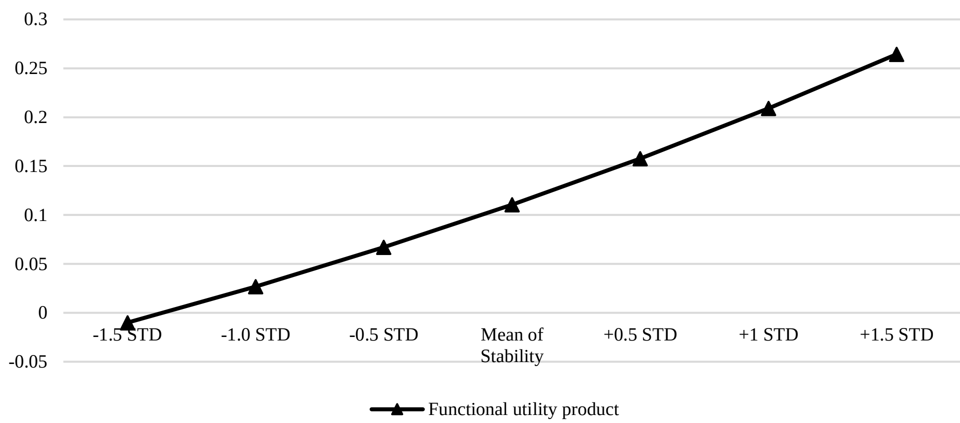


Figure 4. Elasticities of Contagion: of Experts, Thrill Seeker, and Network Stability



Notes: Reported elasticities are conditional (on users spending more than zero) elasticities. Since network stability does not significantly moderate the effect of contagion for social utility products, we do not report the elasticities for these products in Panel C.

Figure 4. Continued

The findings also suggest that gaming content managers must target gamers based on their gaming activity and network characteristics. The author presents the variation in elasticities for the range of the three moderating variables—expertise, thrill-seeking and network stability—in panels A, B, and C of Figure 4, respectively. The author computes the change in elasticities based on a range of ± 1.5 standard deviation for each of the three moderators. As can be seen from the figure, the elasticity of contagion for the two products decreases with gamers' expertise and thrill-seeking behavior. This suggests that managers of the gaming community should facilitate greater social interactions for "newbies" and for gamers who do not actively engage in "high-risk/high-reward" plays. The author also finds that the elasticity of contagion for functional utility products increases with network stability. This suggests that managers of gaming communities should target gamers with a stable set of friends for potential cross selling of game related products.

To sum, this study highlights that there are substantial benefits from harnessing the power of social networks and these vary depending upon the type of products a community produces, user and network characteristics. Thus, it is essential to understand the unique aspects of a particular community and its users, users' goals and motivations to formulate strategies that can effectively engage users and manage social networks to yield greater returns.

2.9 Limitations and Directions for Future Research

While the author observes detailed purchase behavior and interactions between gamers of the focal online gaming community, the results of this study are based on only one online gaming community. The author believes that it is important to conduct detailed empirical examination of the impact of social networks in several different contexts and the author urges researchers to look into other platforms such as music sharing, purchase behavior in retail settings etc. in order to develop a deeper understanding of the social contagion phenomenon in these settings. In this study, the author relies on the differential effect of contagion across the different types of products, user and network characteristics to argue for the different mechanisms that drive social contagion. While the author took a series of cautionary steps and conducted a number of robustness checks, the author acknowledges that the author works with observational data to infer the effect of social contagion and thus the study may suffer from the issues associated with deriving inferences from purely observational data. The author hopes that future studies can conduct field experiments (à la Aral and Walker 2011) to ascertain the effect of contagion on purchase behavior as well as use experimental study settings to uncover the different mechanisms that drive contagion. Despite these limitations, the author hopes that this study spurs future inquiries into the effect of social networks in online communities in general and online gaming communities in particular.

3. EFFECTS OF DEMARKETING GAMES IN ONLINE AND MOBILE CHANNELS

Demarketing—the process of decreasing demand for certain goods and services that are perceived to have a negative influence on society—is widely employed in various forms, including taxation, regulation, and public education. Especially in the game industry, demarketing tools are implemented to protect game players from addiction. Online and mobile media are fast-growing gaming sectors, and demarketing strategies for these new channels have also been discussed and executed in diverse forms in many countries, especially in East Asia. This study assesses the causal effects on user behavior of two demarketing activities with regard to online and mobile games in South Korea: (1) lowering the maximum limit on *online* item purchases, and (2) restrictively allowing the use of real money to purchase items in *mobile* gaming apps. Drawing on two unique datasets on online game traffic and mobile app traffic, the author estimates the effects of demarketing efforts by adopting a difference-in-differences estimation strategy. The author finds that lowering the maximum limit on online item purchases decreases the number of online gamers, and that allowing item purchases with real money in mobile games increases the number of mobile game players. Examining the cross-channel effects of demarketing strategies, the author finds that lowering the maximum limit on item purchases in online channels also decreases the number of mobile gamers, and that permitting mobile games to be purchased for real money also increases the number of online game users. Thus, the author finds that demarketing activities in one channel potentially affect games in other channels, in which case the actual results of demarketing are questionable. The author conducts a series of robustness checks and falsification tests to validate the findings. Based on the results, the author elaborates on the study's implications for policymakers and game developers.

3.1 Introduction

The World Health Organization (WHO) classified gaming addiction as a mental health condition for the first time in 2018 (Wakefield 2018), and the International Classification of Diseases (ICD) has announced that it will include gaming disorder in its next version.[9] Addiction related to playing games has recently become a serious issue, especially given the evolution of the Internet and mobile technologies. Not only are online and mobile games easy to access; many also offer free access for game players. Consequently, game users today are at a greater risk of developing addiction than previously, and indeed, increasingly more cases of gaming addiction among people of all ages and social groups have been reported around the globe. Gaming addiction can cause various impacts at a personal and societal level, including financial, health, and mental problems. For example, in Ohio, a 17-year-old boy caused death and injury to his parents after they forced him to stop playing Halo 3, a popular Xbox shooting game (Williams 2015). In China, two newborn babies were sold by their parents to subsidize their in-game purchases on spears and shields (Kosoff 2014). From an economic perspective, the addiction to games not only influences individuals' finances, but is also associated with socioeconomic factors**.** According to Cho et al. (2018), the social costs of caring for game addicts may be greater than the total benefits of the game industry. In some countries, such as South Korea, compared to other types of addiction (i.e., drug, alcohol, and gambling addictions), game addiction is considered to be the most serious, and the strongest contributor to the reduction of social welfare (Matthew 2014). Hence, the implementation of demarketing tools or government regulations may be a solution for protecting game users from addiction.

[9] The last version of the ICD was completed in 1992, with the new guide due to be published in 2018.

Recently, to reduce social problems arising from gaming and protect individual users from gaming addiction, policymakers and politicians have considered applying demarketing tools within the online and mobile game industries. For example, Vietnamese and South Korean governments have implemented an online game curfew that bans young players' access to games from night (e.g., midnight) to morning (e.g., 6 AM).[10] In 2018, US president Donald Trump proposed to implement regulations on violent games (Morris 2018). It is believed that violent games may have contributed to mass murders such as the recent shooting at a high school in Parkland, Florida.

The abovementioned governmental regulations and policy changes are considered to fall under demarketing, defined as the use of marketing tools and techniques to lower demand for a specific good or service (Kotler and Levy 1971). Public entities or private companies employ demarketing strategies for various purposes, such as, to improve the sustainability of public goods (Varadarajan 2014; Kasulis, Huettner, and Dikeman 1981), protect (certain) customers from using impure or dangerous products (Gundlach, Bradford, and Wilkie 2010; Inness et al. 2007), or manage the perceived quality of products (Miklós-Thal and Juanjuan 2013). Even though demarketing has been studied in prior literature, there is a dearth of research on the relative effectiveness of demarketing across the 4Ps (i.e., marketing mix variables). Especially in the context of online and mobile games, to the best of the author's knowledge, no research has empirically examined the effect of demarketing, even though many governments have recently regulated this industry. In addition, in the context of addictive behaviors (e.g., abuse of alcohol,

[10] This is also known as shutdown law or Cinderella law. Young people are forbidden from playing online games from 10 PM to 8 AM in Vietnam, and from midnight to 6 AM in South Korea.

drugs, or gaming), it is difficult to make accurate predictions about the consequences of demarketing activities (e.g., Inness et al. 2008; Harris and Chan 1999).

Hence, understanding the effects of demarketing activities should be of great importance for policymakers and companies. Policymakers should be cautious in passing new laws for goods and services, as demarketing strategies can drastically change the industry structure, or potentially have unexpected consequences. From the perspective of gaming companies, comprehending the impacts of new demarketing strategies on gamers' behavior can be a pressing matter in devising marketing strategies and minimizing the negative effects of new policies, while not damaging the purpose of demarketing. However, compared to customers' behavior with other products, gamers' behavior can be more unpredictable due to addictive features in games (Inness et al. 2008; Harris and Chan 1999), and unexpected problems arising from policy changes (Wang, Lewis, and Singh 2016; Zhen et al. 2015; Schopper 2002). With regard to addictive goods, a few researchers have empirically examined the effect of demarketing in the tobacco (Wang et al. 2017; Harris and Chan 1999; Inness et al. 2008) and alcohol industry (Duffy 1983; Dee 1999). However, to the best of this author's knowledge, no study has investigated the effect of demarketing on gaming behaviors. Moreover, little is known on the impact of regulations on users' behaviors and firms' performance in the gaming industry. Thus, the first objective of this study is to measure the effects of demarketing in the gaming industry on the marketer's and game users' behaviors.

Changes or events in one channel can also affect customers' behavior in other channels (e.g., Xu et al. 2014; Janakiraman, Lim, and Rishika 2018). Similarly, demarketing efforts in one channel can directly and indirectly affect games in channels that were not targeted. The cross-channel effect depends on the relationship between the channels, as well as on the characteristics of the events. If two channels have similar functionalities, they can be considered as substitute channels. (Moriarty and Moran 1990). On the other hand, if two channels have complementary capabilities, they can supplement each other (Avery et al. 2012). In terms of the characteristics of events, prior literature has studied the cross-channel effects of channel addition (e.g., Soysal and Krishnamurthi 2016; Xu et al. 2014), price change (e.g., Gong, Smith, and Telang 2015), and data breach (e.g., Janakiraman et al. 2018). However, no study has investigated the cross-channel effect of demarketing activities. Doing so is very important, as these effects are unintended results that marketing managers and policymakers did not aim for, and as they may not know which cross-channel effects demarketing has on other channels. Especially in the game industry, there are different types of channels in which game users can play games, including online and mobile, as well as traditional console channels, and thus the cross-channel effects of demarketing could be a key issue. The second objective of this study is therefore to examine the cross-channel effects of demarketing efforts in the game industry.

In this research, the author employs two game-week level datasets, which cover all games in South Korea's online and mobile app market. The author identifies the effect of demarketing by employing difference-in-differences (DID), which is a popular empirical method for measuring the effects of a treatment of interest on outcome variables. In the absence of experimental data, DID has been broadly used in natural experimental settings such as this study. In this case, one type of game was selected as the target of the policy interventions, while other games were not subjected to the policy changes. The author considers the target games of the policy change as a treatment group and other games as a control group. By checking the parallel paths between the two groups in the model-free evidence section, the author shows that both groups in the model had parallel trends.

The results show that lowering the maximum limit on purchasing online game items decreases the number of online game users by 15.1%. In addition, demarketing has a positive spillover effect in the mobile channel, in which it reduces the number of active players of similar types of games by 52.0%. The author thus finds evidence of significant effects of demarketing efforts in both the focal and the alternative game channels. Similarly, when policymakers allowed purchasing mobile game items with real money, the number of weekly active mobile-game users increased by 56.9%. The author also observed a cross-channel spillover effect from the mobile channel to the online channel. Additionally, the increase in the availability of the mobile games increased the number of online game users by 14.4%. The author conducted various robustness checks and falsification tests to show that the core results are valid.

This study makes the following contributions to literature. First, it helps understand how demarketing works by examining its actual effects, which only a limited number of researchers have empirically studied to date. Second, the study presents empirical evidence showing the unintended consequences of demarketing. By providing evidence of the potential consequences of demarketing in alternative channels, the study sheds light on the fact that literature in the field of demarketing needs to consider the effects of demarketing not only on targeted individuals or industries, but also on those that were not initially considered as targets.

The chapter is organized as follows. In the next section, the author provides a brief background on the game industry and reviews previous research on the effect of demarketing and policy changes in the game industry. The author subsequently presents the theoretical framework of this study and provides an overview of the research setting as well as details of the data. This is followed by a presentation of the econometric model, after which the author provides the results of the model. The author also presents the results of the various robustness checks and falsification tests that were performed. The author concludes the paper with a discussion and a consideration of the study's implications.

3.2 Conceptual Background

In this section, the author first introduces related studies in marketing and subsequently shows how this study contributes to the stream of literature on demarketing and public policy.

3.2.1 Demarketing

According to the American Marketing Association, demarketing is defined in two ways. From the firm perspective, demarketing is "*a term used to describe a marketing strategy when the objective is to decrease the consumption of a product*." On the other hand, in the social marketing context, it is defined as "*the process of reducing the demand of products or services believed to be harmful to society.*" Thus, it can be considered to comprise both marketing strategies and policy changes aimed at restricting the availability of a good or service (see also for e.g., Lefebvre and Kotler 2011). In this research, the author studies governments' demarketing efforts and the author considers them as social demarketing.

Regarding the social marketing context, prior literature has examined how demarketing can be used to foster environmental sustainability by eliminating consumption of certain products, reducing consumption of certain other products, and redirecting consumption from ecologically more harmful to less harmful substitute products (e.g., Varadarajan 2014), and protect consumers from using socially dangerous or impure products (e.g., Gundlach, Bradford, and Wilkie 2010; Inness et al. 2007). The main entities undertaking demarketing activities are private companies, non-profit organizations, and governmental agencies. Even though demarketing has been studied in the field of marketing, its effectiveness is still questionable (Pechmann et al. 2003), and there are a limited number of studies that empirically measure its effect. Especially in the context of online and mobile games, there exists no research examining the effect of demarketing, even though many governments have regulated the industry to protect customers from game addiction. This paper investigates the effect of two demarketing activities in online and mobile games. First, the author studies the effect of lowering the limit of item purchase in online games. Second, the author studies the effect of allowing the use of real currency for item purchases in the mobile game channel, which the author considers to a demarketing activity, as it sets maximum limits.

3.2.2 Effect of Limiting Online Games on Online Game Users' Behavior

Prior literature in marketing, public policy, and economics shows that demarketing can contribute to a reduction in consumption (e.g., Hamilton 1972; Kotler 2011; Varadarajan 2014). Governments and private companies have implemented various types of demarketing strategies across the 4Ps (i.e., product, price, place, and promotion), which have indeed lowered the demand for certain goods and services. However, each demarketing strategy has a different mechanism, though all eventually achieve the reduction in the demand for or consumption of a specific good or service. For example, increasing the availability of substitute products (e.g., public transportation) or promoting them induces people to choose the alternative instead of the original product (e.g., private car driving), which potentially has negative effects on both individual customers and society (e.g., Wright and Egan 2000; Varadarajan 2014). Imposing higher taxes on products (e.g., sugary drink tax, cigarette tax, etc.) also decreases the demand for a product by increasing the cost of purchasing it (e.g., Baltagi and Levin 1986; Zhen et al. 2014). Restricting consumption spaces (e.g., designating smoking area at work or granting gambling permissions to licensed casinos only) makes customers consume specific goods and services in designated spaces (e.g., Evans, Farrelly, and Montgomery 1999; Thalheimer and Ali 2003). Finally, public campaigns or warning labels about harmful goods such as cigarettes, alcohol, and so forth change customers' behaviors and attitudes toward specific products (e.g., Grinstein and Nisan 2009; Pechmann et a. 2003; Andrews et al. 2004).

In this research, the author studies the effects of demarketing activities in South Korea's online and mobile games in South Korea. The South Korean government restricts the amount of purchases of virtual items or the amount virtual money that can be used to play board games. Especially for board games, a player cannot play a game without virtual money, as betting with it is necessary to play these games. Thus, the setting a maximum, decreases the availability of the product. According to prior literature (Musalem et al. 2010), the unavailability of a product may lead to a reduction in demand. Lowering the maximum amount of virtual items a user can purchase is a way of limiting a game's availability. Thus, it can be expected that lowering the maximum amount of purchasing items decreases the demand for the games targeted by the policy change.

3.2.3 Effect of Limiting Online Game on Mobile Game Users Behavior

Prior literature in the field of marketing shows that product availability has a significant influence not only on the demand for the focal product that is unavailable, but also on the demand for alternative products (Anupindi, Dada, and Gupta 1998; Musalem et al. 2010). Similarly, in the context of cross-channel shopping, the availability of a channel may affect customers' purchasing patterns across channels (e.g., Ansari, Mela, and Neslin 2008; Forman, Ghose, and Goldfarb 2009; Xu et al. 2014). However, the alternative channel may substitute or complement the focal channel depending on the relationship between the channels' features (Avery et al. 2012; Xu et al. 2014). The alternative channel could cannibalize demand in the focal channel if many characteristics or capabilities of the two channels closely match each other (Deleersnyder et al. 2002). However, if the alternative channel provides different functionalities or supplements the characteristics of the focal channel, customers may take advantage of both channels instead of migrating from one to another (Avery et al. 2012). Especially as the mobile channel has unique features, including high mobility, it can play a significant role as a complementary channel to both the online and offline channels (Shankar et al. 2010).

In addition to the differences between two channels, within the context of this study, the products in the two channels had different features, which may strengthen the gaming services' complementary effects in each channel. According to Lam (2007), people play games with different motivations or values, such as to win money (i.e., monetary value), enjoy excitement or challenge (i.e., hedonic value), or interact with friends and family (i.e., social value). In the current cases, users played mobile games for their hedonic or social value, whereas they played online games for monetary and other values. Thus, playing games without any betting options in the mobile channel may not be a perfect substitute for playing games in the online channel; rather, it can be considered as a complementary service for players who want to enjoy similar types of games anywhere and anytime. Based on this discussion, the author considers how the negative effect of demarketing on the online channel may spill over to the mobile channel.

3.2.4 Effect of Allowing Mobile Games on Mobile Game Users' Behavior

The second policy change this study examines is mobile game deregulation, which is currently beginning to allow the use of real money for betting in mobile games, while item purchase with real currency was unavailable before this policy change was implemented in South Korea. This policy change in the mobile channel became effective six months after the first policy change in the online channel. As the same limit in the online channel is applied in the mobile channel, this policy change can also be viewed as a demarketing activity. Prior literature studying public policy across various contexts mainly focuses on the effect of regulation, such as how increasing taxes (e.g., Zhen et al. 2013; Inness 2007), restricting advertising (e.g., Hamilton 1972), or restricting areas of consuming or purchasing products (e.g., Evans et al. 1999; Thalheimer and Ali 2003) contributes to lessening the demand for products. A limited number of papers examine the effect of deregulation (e.g., Brown, Rucker, and Thurman 2007; Jarrell 1984; Nicholas 1998). The major focus in most of the existing literature is the effects of deregulation on industry-level performance, such as production (Brown et al. 2007) or stock market trade (Jarrell 1984). However, a limited number of studies examine customer-level reactions or demand perspectives.

The second policy change toward allowing item purchase with real currency can be considered as a way of increasing product availability in a channel or introducing a product in a new channel, both of which help customers access the product more easily. Existing customers who already use the product in the other channel and new customers who have not yet tried the product in the other channels, but prefer the newly available channel are expected to begin to consume the product in the new channel. Thus, once a product becomes available in a channel, existing customers are likely to consume more of it in that channel and new customers are also likely to join the channel to play the game.

3.2.5 Effect of Allowing Mobile Games on Online Game Users' Behavior

The introduction of a product in one channel can affect demand for the product in another channel (Ansari, Mela, and Neslin 2008; Forman, Ghose, and Goldfarb 2009; Xu et al. 2014). As discussed above, the impact of a channel addition depends on the relationship between the two channels (Avery et al. 2012; Xu et al. 2014). If the new channel's features are similar to those of the existing channel, the new channel may be viewed by customers as a substitute for the existing channel (Moriarty and Moran 1990). On the other hand, if the new channel can provides functions that the existing channel lacks, the new channel is expected to become complementary to the existing channel and ultimately increase the demand for the product in both channels (Avery et al.

2012). Regarding the relationship between the mobile and online channels, prior literature shows that two channels are complementary to each other (Bang et al. 2013; Wang et al. 2015; Xu et al. 2014). Therefore, the author assumes that permitting item purchase with real cash in the mobile channel increases the number of game users in the online channel as well.

3.3 Methods

3.3.1 Research Setting

In this research, the author estimates the impact of demarketing activities in South Korea's game industry, thereby specifically examining the effect of two different policy changes in online and mobile card and board games, including Go-Stop (a Korean card game), poker, and other games with gambling features. To play these games, game users need to purchase virtual currency to use in betting. In online and mobile channels, other types of games are also available, such as role-playing games, shooting games, arcade games, and so forth. While users play those games, they also purchase virtual items with real cash to improve their gaming performance or decorate their avatars.

One policy intervention is designed to regulate the online game only, while the other was implemented as a mean to control the mobile-app-game industry. The first is a reduction in the maximum amount of virtual items and money a customer can purchase in online card and board games. The limitation was changed from 500,000 Korean Won (approximately 500 USD) in a month to 300,000 Korean Won (approximately 300 USD) [11] across all online card and board games, according to the Game Industry Promotion Act (Presidential Decree No. 24865). In South Korea,

[11] 1,000 Korean Won is approximately equal to 1 US dollar.

all online users must provide their resident registration number[12] to join a (gaming) website, which helps the government and game companies to observe players' item purchases within and across websites. The purpose of the gaming policy intervention is to protect citizens from gaming addiction, even though the government still allows playing games or purchasing in-game items to a certain extent. This new policy was made effective on April 21, 2014. Most online and mobile games provide basic game content free of charge, but game users purchase in-game items which they can virtually use or consume. For example, shooting-game players purchase advanced firearms to beat enemies easily and improve their performance in the game, role-playing gamers buy energy drinks to improve virtual avatars' health status, and web-board gamers buy virtual game money to bet stakes in the game. Of all online games, card and board games with gambling features are the target of this new policy, as the government considers them as having the potential to lead to additional social problems, if users wager sums of money as large as those wagered in casinos. Especially for card and board games, "virtual currency" is necessary to play (i.e., to bet money). Thus, changing the maximum amount from 500,000 to 300,000 Korean Won is indeed a reduction in the availability of these games, even though the government still allowed such online games with real money betting. This new policy may have a greater effect especially on the behaviors of game players who habitually spend or intend to spend more than 300,000 Korean Won in a month.

The second policy change regards mobile card and board games, and became effective on October 31, 2014: six months after the first policy change discussed in this study. The South

[12] It is the unique identification number assigned to each citizen and issued by the government, similar to national identification numbers in other countries. A user is required to provide the valid number to create an online account including gaming website.

Korean government began to allow people to purchase virtual items with real cash for mobile card and board games, as it had allowed for online games, and setting the same maximum amount as for online games, namely 300,000 Korean Won. Before this new policy was implemented, mobile card and board gamers were able to play the games without virtual items, meaning that real money betting was only allowed in online card and board games until October 31, 2014, while it was not allowed in mobile games. Thus, people began to spend money and bet on mobile games with the limitation of 300,000 Korean Won per month.

These two policy changes can be considered as treatments that influence the online and mobile card and board games they targeted. Hence, other types of games, which were not subject to these policy changes, form the control group. The author uses two datasets, each of which includes weekly statistics for all online and mobile games in South Korea, respectively. These datasets include not only card and board games, but also other types of online and mobile games.

3.3.2 Identification Strategy

Studies examining the causal effects of these policies may encounter identification challenges in disentangling the treatment effects from other confounding factors. Prior literature in the fields of marketing, economics, and public policy have employed *difference-in-differences* (DID) methods to rule out potential problems in measuring policy changes (Angrist and Pischke 2009; Wooldridge 2002).

3.3.2.1 Difference-in-differences

To estimate the effects of demarketing activities in the game industry, the author uses a DID estimation strategy. Difference-in-differences is a quasi-experimental design used to estimate the causal effect of a treatment or intervention by choosing an appropriate counterfactual from the longitudinal data on the treatment and control groups. The goal of the estimation with DID is to accurately measure the effect of a policy change on the groups targeted by it. By using the DID method, the author can measure the effect of a policy change (i.e., treatment) on game-level performance after the intervention (i.e., post period). Specifically, the author compares the pre- to post-intervention change in outcomes of interest for the treated group that was subjected to the new policy, relative to a comparison group (i.e., control group) that was not targeted by it.

In applying the DID method, it is important to construct a relevant control group (versus the treatment group) in order to obtain accurate measures of causal effects. In theory, the outcomes of the comparison group indicate what would have happened to the treatment group if no treatment had been implemented. Thus, the control group needs to satisfy a number of criteria to be a good counterfactual to the treatment group. The most important is that the treatment and control groups have a parallel trend (or common trend), meaning that the average change in the outcomes of the control group corresponds to the (counterfactual) change in the treatment group if no intervention was implemented.[13] If the treatment and control groups do not share a common trend in the outcome of interest, the pre- to post-intervention comparison between them cannot be made. Once the common trend between the two groups before the treatment's implementation is identified, it is reasonable to assume that the control group's outcomes of interest after the intervention indicate what would have happened in the treatment group if no treatment had been carried out. Thus, it is essential in applying the DID method to confirm whether there was parallel trend between the treatment and control groups. This requirement again emphasizes that researchers need to select appropriate control groups to accurately measure the causal effects of interventions.

[13] In the robustness section, the author tests the parallel trend. If multiple time periods are available in the pre-treatment period, parallel trend assumption can be tested with the pre-treatment trends between the treatment and control groups. From the result of the robustness check, the author finds the parallel trend between treatment and control groups.

The treatment group in this study consists of the set of games targeted by the policy changes, namely card and board games with gambling features, while the control group consists of the set of games that were not subjected to these policy interventions. As discussed above, the control group needs to have a parallel trend with the treatment group. In this case, the control group is the set of online or mobile games that were not targeted by the two policy changes. In the main analysis, the author classifies all games that were not subjected to the policy changes as control groups.[14] In addition, in the robustness check section, the author reselects the analysis sample and the estimate models.

3.3.3 Analysis Sample

To estimate the effect of demarketing in online and mobile game channels, the author uses game-week level datasets from panels of online gaming centers and mobile-app-game players, respectively.

3.3.3.1 Online Game Statistics Data

The online game performance dataset was collected across 4,000 PC rooms[15] in South Korea. PC rooms are Internet game centers where visitors pay an hourly rate to play online games.[16] The dataset was collected by an online game analytics company in South Korea, namely Gametrics.[17] In this dataset, the performance of all online games is observable, ranging from arcade, shooting, and role-playing games to card and board games. This online game dataset

[14] In the analysis sample, the author includes games which are observable over the entire analysis period. Due to technical issues or data privacy issues, the author cannot observe some games' statistics at some points of time.
[15] As of 2017, 20,000 PC rooms are operating in South Korea (Zhou 2018). The current dataset covers approximately 20% of this market.
[16] In general, an hourly charge ranges from 500 to 1500 Korean Won (0.5 to 1.5 USD). The median number of computers in a PC room is over 70.
[17] http://www.gametrics.com/

contains the number of users who played a game, the average number of hours they spent playing it, the game's ranking, and so forth. As the aim of this study is to estimate the effects of two policy changes at different times, the author selected two sets of analysis samples from the dataset. The author compares the outcome of the treatment group to that of the control group before and after the policy intervention. Each pre- and post-policy period contains 12 weeks. Thus, each sample includes observations of both the treatment and control groups over a total of 24 weeks: 12 weeks in the pre-intervention period and 12 weeks in the post-intervention period.[18] Due to technical problems or data-privacy issues, all or parts of the statistics on some of the games were unavailable. Thus, the author uses statistics on games only if they were accessible for the entire 24-week period. The author numbers with zero the week in which the new policy became effective and did not include that week's observations in the analysis. The first analysis comprises 53 treated games and 133 control games, while 44 treated games and 242 control games serve to estimate the effect of the second treatment.

3.3.3.2 Mobile Game Statistics Data

The second dataset in this study is a mobile-app-game database that was collected by another data collection agency in South Korea, namely AppRanker.[19] The author observes the number of weekly active users who played the mobile-app game in the Android market in South Korea, the app download rate, the average time spent on mobile apps per week, and so forth. Mobile-app games have various game genres. As with the online game sample, the author selected gaming apps of which the statistics are observable over the entire 24 weeks, and the analysis

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[18] In the analysis sample, the author does not include the week that a policy becomes effective.
[19] http://www.appranker.co.kr

samples exclude the observations at week 0. For the first analysis, the sample consists of 44 treatment and 303 control games. For the second analysis, the sample consists of 50 treated games and 509 control games.

3.3.4 Operationalization of Variables

The dependent variable of interest is the number of people who played a game. As explained in the previous section, the author uses two different datasets: one with online game statistics and one with mobile game statistics. In the online game dataset, the number of players is measured as the number of people who played the game across 4,000 PC rooms in South Korea. The author obtained an *hourly* average number of unique users who played at least one session of an online game during one week. In the mobile game dataset, the number of users is measured as the number of people who used a mobile-app game at least once during one week. These datasets include *all* online and mobile games that were operating in 2014.

The author notes that the analysis samples are game-week level aggregate datasets over a total of 24 weeks: 12 weeks before and 12 weeks after each policy change.[20] Based on the games' ranking at 13 weeks before the policy change, the author selected both the treatment and control groups from the online and mobile game datasets.[21] Thus, for each policy change, the author obtained two analysis samples, each selected from online and mobile datasets, respectively, and both including treatment and control groups. The list of variables, operationalizations, and descriptive statistics are shown in Table 6.

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[20] Between two policy interventions, there was an approximately 6-months gap. Thus, to avoid overlapping analysis time periods for policy changes, the author selected 3 months (i.e., 12 weeks) for pre and post time periods.
[21] The author selected games based on information before the period of the analysis samples.

Variable	Operationalization	Obs	M	SD	Obs	M	SD
		Policy 1: Limiting Item Purchase in Online Channel			Policy 2: Allowing Item Purchase in Mobile Channel		
NumUser^o	Weekly average number of users who played the online game at the same time during an hour in the PC rooms.	4,464	1,463	8,514	6,864	967	6,946
NumUser^m	Number of users who played the game via mobile app during a week among 100,000 panel.	5,616	37,836	208,867	13,416	66,538	299,157

Table 6. Operationalizations and Summary Statistics (by Game and Week)

3.3.5 Econometric Analyses

The models capture the effects of the policy changes on the number of game users. To do this, the author employs the DID method.

3.3.5.1 Effect of the Policy Change on the Number of Game Users

The dependent variable is the number of users who played game *j* in channel *c* (i.e., online or mobile) during time *t*. The author takes the logarithm of the variable because of its skewedness. Following prior studies that employing the DID technique (Angrist and Pischke 2009; Kumar et al. 2016; Shi et al. 2017), the author formulates the main model, which accounts for the impact of a policy change on the number of gamers:

$$\ln(NumUser_{jt}^{c}) = \beta_1 Treatment_j^c \times Post_j^c + \mu_j^c + \tau_j + \varepsilon_{jt}^c \qquad (3.1)$$

where $Treatment_j^c$ is a treatment group which is equal to one if game *j* in channel *c* is a board game and zero otherwise. $Post_j^c$ is a dummy variable with a value of one if time *t* is after the policy change and zero if it is before the policy change. The model also includes game fixed effects (μ_j^c), time fixed effects (τ_t), and idiosyncratic error terms (ε_{jt}^c). The focal coefficient in the model is β_1, which captures the effect of a policy intervention on changes in the number of users of treated games across the pre- and post-policy intervention periods compared to those of the control group.

3.3.5.2 Cross-channel Spillover Effect of the Policy Change

In addition to measuring the effect of a policy change on games in the channel targeted by it, the author also examines its effect on games in other channels to find cross-channel spillover effects. The equation is similar to that employed to measure the effect on games in the focal channel. Instead of estimating the effect on games in the focal channel of the policy change (denoted by c), the author estimates the effect of the policy change in the other channel (denoted by c'). In this case, the author considers card and board games in other channel (c') as the treated group and other types of games in this channel (c') as the set comprising the control group. The equation is written as follows:

$$\ln(NumUser_{jt}^{c'}) = \beta_1 Treatment_j^{c'} \times Post_j^{c} + \mu_j^{c'} + \tau_t + \varepsilon_{jt}^{c'} \quad (3.2)$$

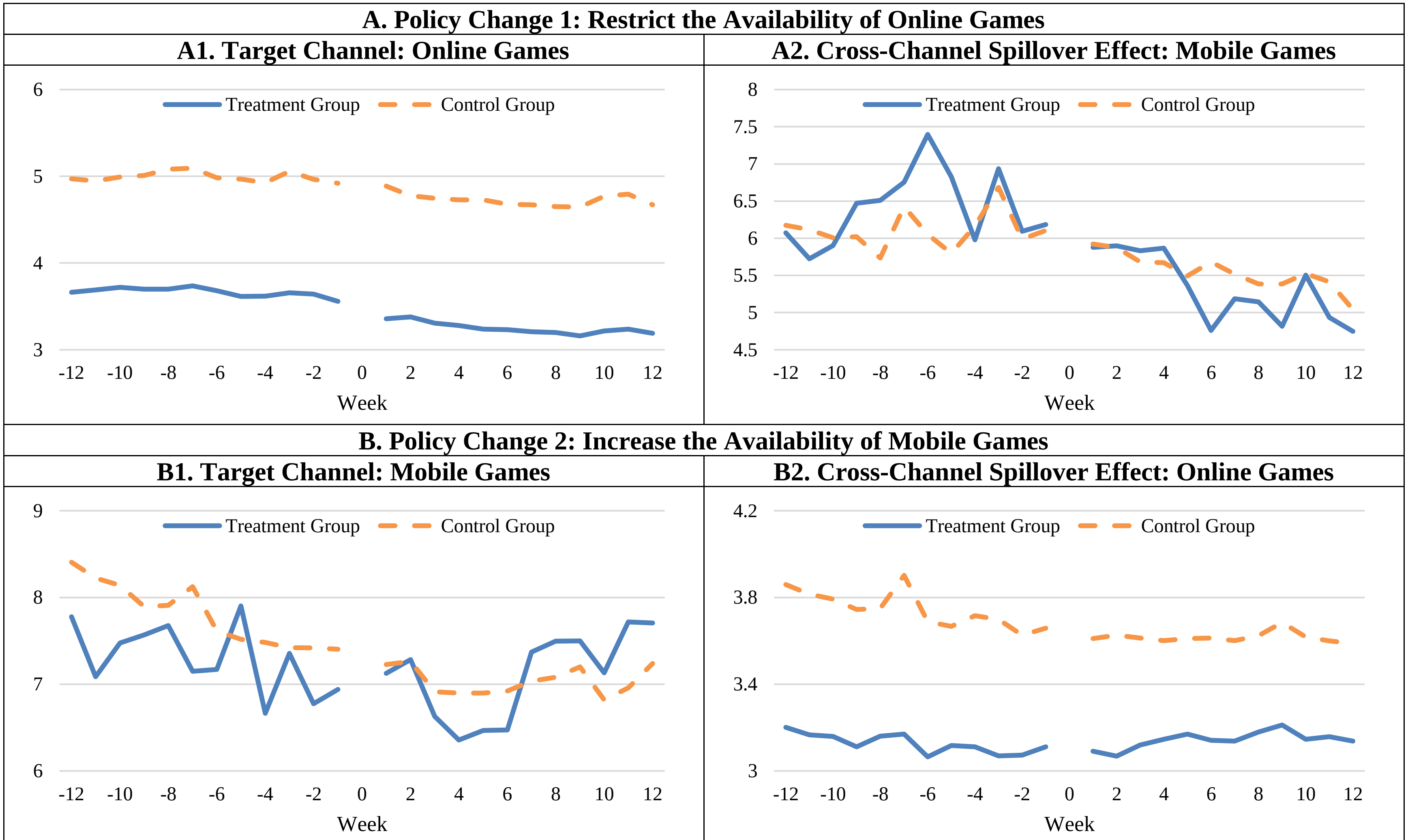
where c is the channel targeted by the policy intervention and c' is the non-target channel of the new policy intervention.

3.4 Results

3.4.1 Model-Free Evidence

Before presenting the results of the proposed DID models, the author provides the model-free evidence, which shows the effect of the policy changes on the outcome variables. In Figure 5, the author plots the relative average of the outcome variables between the treatment group (solid line) and the control group (dashed line) before and after the policy change. Based on the outcome value at week -12 (i.e., 12 weeks prior to the policy change), the author calculates the relative values at the following weeks while setting the relative value at week -12 to 1 by the nature of the measurement. Weeks -12 to -1 indicate the 12 to 1 weeks before the policy change, week 0 is the week in which the new policy became effective, and weeks 1 to 12 represent the 1 to 12 weeks after the new policy intervention. In Panel 1 of Figure 5, the model-free evidence for the first policy change (limiting the availability of online games) and the model-free results for the second policy change (increasing the availability of mobile games) are shown in Panel 2. As shown in Panel A1 of Figure 5, the number of users of the treated games *declined* between the pre- and post-policy change periods relative to that of the other games. Panel A2 provides the cross-channel spillover effect of online game regulation on mobile games. It suggests that the number of users of the treated mobile games slightly *increased* after the policy change compared to that of the control mobile games.

With regard to the effect of the second policy change (i.e., increasing the availability of mobile games), Panel B1 of Figure 5 plots the relative number of users for the treated and control mobile games. The figure suggests that the number of gamers for the treated mobile games *increased* steadily over time after the second policy became effective compared to other mobile games. Next, the author examines the cross-channel effect of increasing the availability of mobile games on games in the online channel. Panel B2 shows a slight *increase* in the outcome variable of treated online games compared to that of other types of online games.



Note: These figures show overall trend of logged average number of users between treatment group (——) and control group (– –) over time.

Figure 5. Model Free Evidence: Logged Number of Game Users over Time between Treatment and Control Groups

3.4.2 Parameter Estimates

The results of the model-free evidence support the claim that policy changes have a causal effect on the focal channel and a cross-channel spillover effect on the alternative channel. While the model-free findings provide clear evidence of the policy's effects on the focal channel, only weak evidence of its cross-channel effect was found. By estimating the proposed models, it proved necessary to further investigate the effects of the policy changes.

Variables	**DV: ln(*NumUsers^o*)**
Treated Game × Post	-.151*** (.057)
Post	-.306*** (.045)
Constant	4.599*** (.021)
Game Fixed Effect	Yes
Week Fixed Effect	Yes
# of Games	186
# of Obs	4,464
Notes: Standard errors in parentheses are clustered at game level. p-value: *** < .01; ** < .05; * < .1	

Table 7. Effects of Limiting Online Item Purchase on Online Games

Table 7 provides the estimation results of the effects of a policy change on games in the focal channel, and the results in Panel B show the cross-channel spillover effects. The author employs cluster standard errors at game level to account for the serial correlation, as suggested by the prior literature (e.g., Bertrand, Duflo, and Mullainathan 2004). Limiting the availability of online card and board games indeed decreases the number of online users of the targeted games.

Specifically, the policy change reduced the number of gamers in the targeted online games by 15.1%. With respect to the cross-channel spillover effect, the author also finds a significant effect of limiting the availability of online board games on the performance of mobile card and board games, as shown in Table 8. Taken together, the author finds that limiting the availability of online card and board games had a significant effect on the number of users in the targeted games in the online channel and a positive cross-channel spillover effect on the mobile card and board games.

Variables	**DV: ln(*NumUsers*^{m})**
Treated Game × Post	-.520* (.314)
Post	-1.089*** (.245)
Constant	6.160*** (.155)
Game Fixed Effect	Yes
Week Fixed Effect	Yes
# of Games	347
# of Obs	8,328
Notes: Standard errors in parentheses are clustered at game level. p-value: *** < .01; ** < .05; * < .1	

Table 8. Cross-channel Effects of Item Purchase on Mobile Games

Regarding the effect of the second policy change (increasing the availability of mobile card and board games), Tables 3.4 and 3.5 present the estimation results of the DID models for the number of game users in the mobile and online games, respectively. Table 9 shows that increasing the availability of mobile card and board games actually increases the number of mobile card and board gamers, specifically by 56.9%. With respect to the cross-channel effect of the second policy change on the number of online card and board gamers, Table 10 suggests that allowing mobile card and board games to use real money for betting also increases the number of users, specifically by 14.4%.

Variables	DV: ln($NumUsers^m$)
Treated Game × Post	.569** (.288)
Post	-1.126*** (.178)
Constant	8.357*** (.113)
Game Fixed Effect	Yes
Week Fixed Effect	Yes
# of Games	559
# of Obs	13,416
Notes: Standard errors in parentheses are clustered at game level. p-value: *** < .01; ** < .05; * < .1	

Table 9. Effects of Allowing Mobile Item Purchase on Mobile Games

Variables	DV: ln($NumUsers^o$)
Treated Game × Post	.144*** (.030)
Post	-.260*** (.041)
Constant	3.745*** (.024)
Game Fixed Effect	Yes
Week Fixed Effect	Yes
# of Games	286
# of Obs	6,864
Notes: Standard errors in parentheses are clustered at game level. p-value: *** < .01; ** < .05; * < .1	

Table 10. Cross-channel Effects of Allowing Mobile Item Purchase on Online Games

3.5 Robustness Checks

The author performs a series of robustness checks and falsification tests to verify that the core results shown in the previous section are robust.

3.5.1 Parallel Trend Check

In addition to showing the model-free evidence of the effect of policy changes on the outcome variables of the two groups, i.e., the treatment and control groups, the author notes that Figure 5 shows the parallel trend between the two groups before the new policy interventions. The author finds an almost identical trend between the two groups across all panels, meaning the dataset satisfies the most important assumption in the DID setting (i.e., the parallel trend or parallel assumption). It suggests that other types of games, which were not affected by the new policy changes, may be a good control group for the focal games that were directly or indirectly targeted by the policy changes in the same channel.[22]

3.5.2 Alternative Estimation Strategies: Synthetic Control Method

The main DID model in this study provides the average change before and after a policy intervention in the outcome variable of the treated group compared to that of the untreated group. Even though the author was able to observe quite parallel trends between the treatment and control groups during the pre-treatment period, as shown in the model-free evidence in Figure 5, it is still uncertain whether the control group reproduces the counterfactual outcome that the treatment group would have generated without the policy interventions. To address this issue, the author employs a synthetic control method (Abadie and Gardeazabal 2003; Abadie et al. 2010) as a robustness check, thereby suggesting an alternative way of constructing a control group for each

[22] In the robustness section, the author employs different selection methods to construct control groups.

treated game by choosing and weighting units in the control group. Abadie et al. (2010) claim that the synthetic control method is a data-driven procedure that serves to select appropriate comparable units, and it has recently been used in various fields, including marketing (e.g., Chesnes et al. 2017; Tirunillai and Tellis 2017), economics (e.g., Kleven et al. 2013; Bohn et al. 2014), and public health (Kreif et al. 2016; Branas 2011).

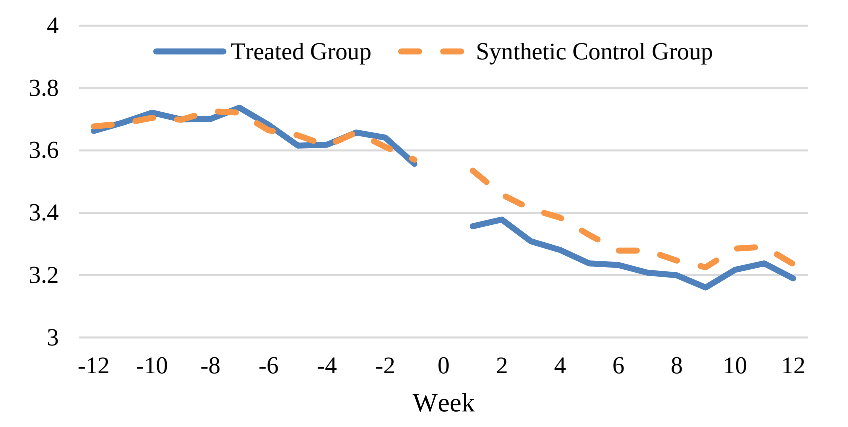
The purpose of the synthetic control method is to select a vector of weights, which minimizes the distance between the outcome of the treated group and that of the weighted control group. For each treated game, the author finds synthetic control games. The author posits that Y_1 is a vector of the outcome values of the treatment group in the pre-policy period and that Y_0 is a vector of the outcome values of the control group in the pre-policy period. As previously mentioned, the objective of the synthetic control method is to find weight vectors (W), which can be found by solving the following distance function (please see Abadie et al. 2010 for details):

$$\min_{W} \sqrt{\left(Y_1 - Y_0 W\right)' V \left(Y_1 - Y_0 W\right)} \tag{3.3}$$

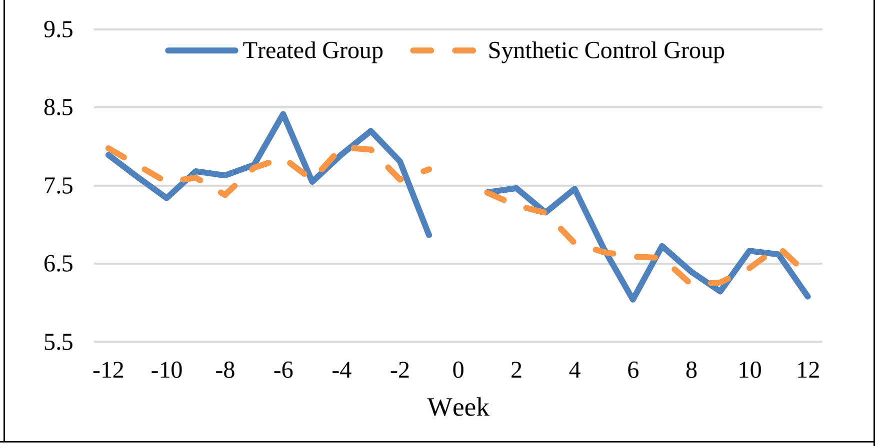
where V is a symmetric positive semidefinite matrix that assigns weights in accordance with the relative importance of the pre-policy outcomes (i.e., Y_1 and Y_0). Similar to W, the author determines V, which minimizes Equation 3.3. Again, to determine W and V, the author uses pre-policy period data only and subsequently calculated the average treatment effect using W, V, and the outcome values in the post-policy period. In Figure 6, the author presents the average logged outcome variables between the treatment group (——) and the synthetic control group (- -) over time, and the difference between the two groups is interpreted as the average treatment effect on the treated group. The author finds very similar results to those of the model-free evidence and main DID estimation.

A. Policy Change 1: Restrict the Availability of Online Games

A1. Target Channel: Online Games

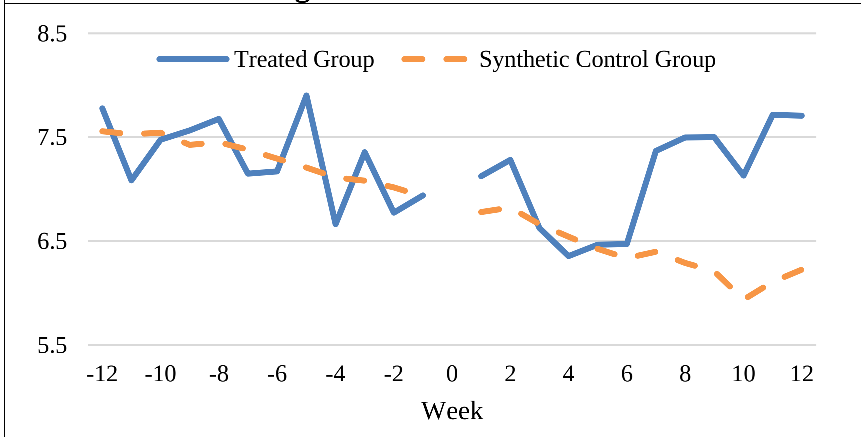


A2. Cross-Channel Spillover Effect: Mobile Games

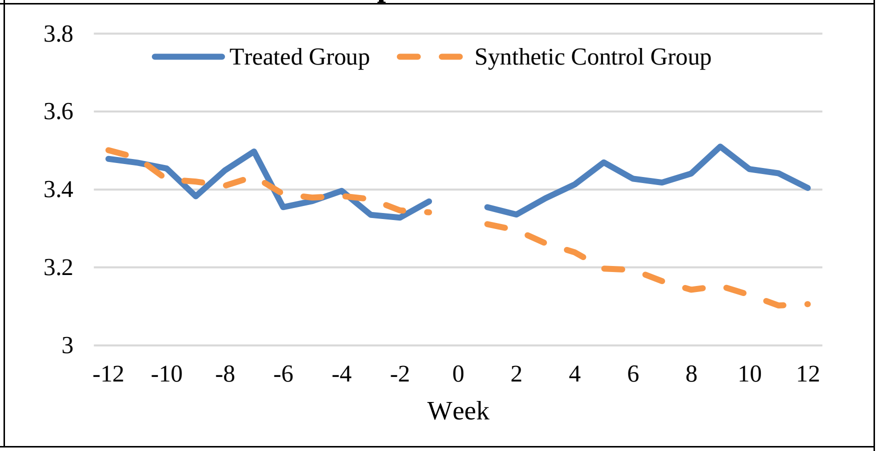


B. Policy Change 2: Increase the Availability of Mobile Games

B1. Target Channel: Mobile Games



B2. Cross-Channel Spillover Effect: Online Games



Note: These figures show logged average number of users between treatment group (——) and synthetic control group (– –) over time. Based on the value at week -12 (i.e., 12 weeks before a policy change).

Figure 6. Logged Number of Users over Time: Treated versus Synthetic Control Groups

3.5.3 Randomly Selected Control Group

The author had earlier considered all games which were not target of the policy changes as the control group. Instead of using all other games as a control group, the author uses different selection methods as a robustness check. To be specific, the author randomly selects 100 games from the entire control group. In Table 11, the author presents the results of the model with the randomly selected control group. The author finds that the results with the new control group are still consistent with the results in the main analysis.

	Policy 1: Limiting Item Purchase in Online Channel		**Policy 2: Allowing Item Purchase in Mobile Channel**	
Variables	**DV: ln(*NumUsers^o*)**	**DV: ln(*NumUsers^m*)**	**DV: ln(*NumUsers^m*)**	**DV: ln(*NumUsers^o*)**
Treated Game × Post	-.185*** (.058)	-.614* (.344)	.961** (.367)	.136*** (.033)
Post	-.254*** (.043)	-.806*** (.400)	-1.668*** (.419)	-.241*** (.043)
Constant	4.454*** (.019)	6.150*** (.252)	8.061*** (.234)	3.558*** (.020)
Game Fixed Effect	Yes	Yes	Yes	Yes
Week Fixed Effect	Yes	Yes	Yes	Yes
# of Games	153	144	144	150
# of Obs	3,672	3,456	3,456	3,600
Notes: Standard errors in parentheses are clustered at game level. p-value: *** < .01; ** < .05; * < .1				

Table 11. Randomly Selected 100 Games in Control Groups

3.5.4 Alternative Measures: Mobile App Download Rate

Instead of using the number of users as the main dependent variable, the author estimates the model with other dependent variables, especially with respect to the mobile-app games, for which the author uses the "mobile app download rate" as an alternative dependent variable. This measured the percentage of mobile phone users who downloaded or installed a mobile app within the total number of users in the panel. The cross-channel effect of the first policy change on mobile games was not significant, which suggests that the first policy indeed did not increase the number of (actual or consistent) mobile card and board game users. However, by including the download rate, the author could test whether (new) users at least attempted to play mobile games after the first policy change.

DV: ln(*Downroad_Rate*^{m})	**One Post-Policy Dummy**		**Three Post-Policy Dummies**	
	Policy 1	**Policy 2**	**Policy 1**	**Policy 2**
Treated Game × Post	.294 (.236)	.904*** (.341)	-	-
Treated Game × Post_Month1	-	-	.378** (.155)	.514** (.260)
Treated Game × Post_Month2	-	-	.208 (.282)	1.000** (.403)
Treated Game × Post_Month3	-	-	.294 (.289)	1.199*** (.422)
Post	-.951*** (.204)	-1.748*** (.258)	-	-
Post_Month1	-	-	-.883*** (.184)	-.974*** (.182)
Post_Month2	-	-	-.941*** (.205)	-1.775*** (.244)
Post_Month3	-	-	-.951*** (.206)	-1.771*** (.263)
Constant	2.962*** (.126)	4.372*** (.126)	2.962*** (.126)	4.372*** (.126)
Game Fixed Effect	Yes	Yes	Yes	Yes
Week Fixed Effect	Yes	Yes	Yes	Yes
# of Games	347	559	347	559
# of Obs	8,328	13,416	8,328	13,416

Notes: Standard errors in parentheses are clustered at game level. All coefficients are in 10^{-3}. In the first model, the author uses a time dummy which captures post-policy period as the author did for the main analysis. In the second model, three time dummies which indicate three different months after policy change.
p-value: *** < .01; ** < .05; * < .1

Table 12. Effects on Mobile App Download Rate

As shown in Table 12, the first policy change caused an increase in mobile board game users' download rates at the first month after the policy change. Thus, the results of the mobile-app download rate suggest that users made more attempts to play mobile card and board games after the policy change, even though the first policy change actually decreased the number of active mobile card and board game users, as shown in Table 8. Regarding the second policy change, the author finds that both the mobile-app download rates and the number of active mobile game users increased over time after the policy intervention, as shown in Table 12.

3.5.5 Falsification Test: Placebo Effect Test

In the main model, the treatment group comprised games that were targeted by the policy changes and the control group comprised other types of games. In the DID estimation, it is important that the control group is not affected by the treatment (i.e., that there are no spillover effects). This helps to assume that the control group is not influenced by the policy intervention and subsequently enables accurately measuring the effect of the policy changes. To check the validity of this assumption and the construction of the treatment and control groups, the author estimates a DID model with a "fake treatment" group (i.e., placebo effect test). The author randomly divides the games in the control group into two sub-groups: a "fake treatment" group, which had a placebo treatment, and a control group. The author assumes that the "fake treatment" group was subjected to the policy change and ran a DID estimation with the new treatment and control groups. The results of this model are shown in Table 13. The author does not find any significant effect of policy interventions with the new sets of treatment and control groups, which indicates that the original construction of treatment versus control groups was valid.

	Policy 1: Limiting Item Purchase in Online Channel		Policy 2: Allowing Item Purchase in Mobile Channel	
Variables	**DV: ln(*NumUsers*^{o})**	**DV: ln(*NumUsers*^{m})**	**DV: ln(*NumUsers*^{m})**	**DV: ln(*NumUsers*^{o})**
Treated Game × Post	.022 (.064)	.322 (.203)	-.172 (.179)	.032 (.044)
Post	-.311*** (.071)	-1.291*** (.282)	-1.082*** (.207)	-.281*** (.050)
Constant	4.972*** (.026)	6.173*** (.165)	8.406*** (.117)	3.860*** (.029)
Game Fixed Effect	Yes	Yes	Yes	Yes
Week Fixed Effect	Yes	Yes	Yes	Yes
# of Games	133	303	515	236
# of Obs	3,192	7,272	12,360	5,664
Notes: Standard errors in parentheses are clustered at game level. p-value: *** < .01; ** < .05; * < .1				

Table 13. Placebo Effect Test

In summary, all of the findings from the robustness checks with alternative measures, model specifications, falsification tests, and the alternative construction of the treatment group suggest that the results regarding the causal effect of policy changes are robust.

3.6 Discussion

Firms, governments, and public organizations have become increasingly interested in the welfare of customers, including concern for their mental health and physical risks. Demarketing strategies have been implemented in various contexts to minimize potential social problems related to the use of certain products. However, little is known about the actual effect of demarketing on consumers' behaviors. The author conducted an empirical investigation to understand how demarketing activities affect customers' behaviors. The author employed unique product-level datasets covering entire online and mobile games in South Korea to empirically scrutinize the effect of demarketing on games in the target channel, as well as its unintended consequences in the alternative channel.

This study contributes to the literature on demarketing by examining its actual effects and helping to understand how demarketing works. Currently, only a limited number of research studies have empirically scrutinized the effects of demarketing. Even though the author investigates the effects of specific demarketing strategies in a particular context, the overall theoretical framework the author provides in this study may be generalizable to other settings as well.

Additionally, only a few prior studies consider the potential unintended consequences of demarketing, even though it can affect subjects or products that were not targeted by it. By providing evidence of the potential unintended consequences and mechanisms of demarketing activities, the author also indicates that literature in demarketing needs to consider not only its main effects on targeted individuals or industries, but also its effects on groups that were not initially considered as targets. In this study, the author considers the potential unexpected outcomes in other channels. The author provides evidence of spillover effects in products in non-targeted channels and explains the underlying mechanisms of the unintended consequences in different channels, based on the relationships between channels.

The findings also provide insights relevant for policymakers and business practitioners. As demarketing strategies are nowadays widely implemented in various contexts, the author suggests that both marketing managers and policymakers should be careful in devising and reacting to demarketing. Based on the findings, the author provides them with the following practical guidance.

In this study, the author finds that demarketing, which either reduces or increases a product's availability, works as intended by policymakers. However, one of the most important findings of this study is that the effects of demarketing can spill over to similar or identical products in other channels. Specifically, limiting the availability of products in the online channel decreases the demand for those products in the mobile channel, as well as in the online channel. On the other hand, increasing the availability of products in the mobile channel increases the number of game users in both the mobile and online channels. From the perspective of policy makers, this finding indicates that they also need to consider similar products in different channels, as new policy changes may unintentionally negatively affect the industry in other channels, or lead it to flourish. Hence, prudent decisions should be made especially if there are alternative products or channels in the market. From the perspective of business managers, this study indicates they should be aware of the fact that, depending on the substitutive or complementary relationships between channels, demarketing may affect products in non-targeted channels as well. Companies should understand the ecosystem of multiple channels and be aware of the potential effects of demarketing or public policy changes even though they were intended for products in other channels.

3.7 Limitations and Directions for Future Research

Although this study contributes to the literature in marketing as the first study which empirically examines the effects of demarketing in the context of the online and mobile games, still there is room for improvement in follow-up studies. First, even though South Korea is the leading country in the digital game industry, the current study examines demarketing in South Korea only. Similarly, demarketing has been employed in different industries including tobacco, alcohol, and drugs. If cultural and contextual differences could be accounted in the future works, it would be very helpful to comprehensively understand how demarketing strategies work. Second, this study focuses on one type of demarketing strategy. However, managers or policy makers can devise different demarketing strategies across the 4Ps. Hence, future studies should examine the effects of various demarketing activities on changes in customers' behavioral patterns and firms' performance. By doing so, researchers can help managers and policy makers find the right demarketing strategies for different products, customers, and industries. Third, there could be other alternative game channels or products while this study focused on the digital game context including the online and mobile channels due to the limitation of the current datasets. If additional datasets are available, future research will be able to discuss further about the cross-channel or cross-product effects. Finally, the author uses product-level observational datasets in the current study. Using individual-user level data and experimental data will help future researchers comprehend the underlying mechanism of behavioral changes of game users. In spite of these limitations, the author believes the current study contributes to both academia and practitioners especially in understanding the effects of demarketing and its potential unintended consequences. In addition, the author hopes this paper can be a great spur for future research which will study the effects of demarketing and digital games.

4. GOAL GRADIENT EFFECTS ON USERS' ENGAGEMENT AND PURCHASE BEHAVIORS IN AN ONLINE FREEMIUM SETTING

Intense competition in the online game industry spurs game developers to improve game design to be highly engaging to users and encourage those users to spend more money on purchasing virtual items. In this study, the author examines goal-gradient effects on behaviors related to attaining goals and purchasing virtual products in an online game context. The goal-gradient hypothesis proposes that efforts toward achieving a goal increase with proximity to the goal. Game developers design goal-related features such as levels, badges, or rankings to sustain a high level of user engagement and motivation. Many also provide game contents for free, but charge for premium features such as virtual items (i.e., freemium pricing). The author provides empirical evidence that game levels, which are obtained once users' experience points reach a threshold of each level, serve as goals. As a result, users have significant differences in their behaviors before and after achieving levels. By leveraging a unique online game dataset, the author empirically examines goal-gradient effects on goal-relevant and goal-irreverent behaviors. The author models user behaviors as a function of distance to a level and control variables. First, the author finds that users' efforts related to reaching a new level increases as they move closer to the next level. However, users' efforts suddenly decrease right after attaining the goal (i.e., post goal reset). Second, users are less likely to purchase both goal-relevant and goal-irreverent virtual items immediately before achieving the new level, but purchase more virtual items once they reach the goal. Third, if a user has experienced greater difficulty to attain a level, that user is more likely to reduce efforts toward in-game progression and spend more money on virtual items after achieving a new level. Finally, as a user is more likely to collaborate with other users in the game, that user has a greater tendency to exert more effort toward goal-relevant behavior and spend less money on goal-irrelevant items even after attaining a new level. The author discusses the theoretical significance of the findings and the practical implications for game design, user engagement, and freemium pricing.

4.1 Introduction

Online communities struggle to boost user engagement with their content or motivate users to spend money on within-community purchases. Many of these online communities—such as news websites, online games, and mobile apps—provide content without any charge, but generate profits by selling additional and premium features (i.e., freemium[23]). In the context of online communities, designing a community with proper tools that improve user engagement and increase purchase behavior should be an important objective. Indeed, online community managers have adopted features such as rankings, badges, and levels to increase user engagement and purchase behavior. These features serve as a goal that users want to achieve and providing a goal can increase user attention and effort in the community (e.g., Heath et al. 1999; Locke and Latham 2002).

According to goal setting theory, having goals activates individuals to increase their effort, leads to greater persistence, and directs attention toward goal-relevant activates (e.g., Heath et al. 1999; Locke and Latham 2002). In addition, scholars have argued that effort invested in achieving a goal increases with proximity to the goal, i.e., *goal gradient effects* (e.g., Hull 1932; Kivetz, Urminsky, and Zheng 2006). Thus, these goal gradient effects offer can explain why subjects exert more effort as they move closer to achieving a goal. In a classic experiment that tested goal gradient

[23] See Kumar (2014) for details about Freemium pricing.

effects, Hull (1934) found that rats ran gradually faster as they moved from the starting point of the straight alley to the food. This effect has been extensively investigated with animals (e.g., Anderson 1933; Brown 1948). Recently, marketing literature (e.g., Kivetz et al. 2006; Dreze and Nunes 2011) has investigated these effects in the context of reward setting. However, outside reward setting, goal gradient effects have been understudied. Furthermore, this issue having important theoretical and practical implications for online communities which use goal-achievement designs to increase user engagement and purchase behavior. Specifically, user behavior can vary depending on relative status from achieving a goal in online communities. Thus, understanding the interplay between goal-related design and user behavior becomes critical as communities pursue strategies to boost user participation and purchases. With this relevant problem in mind, the first objective of this study is to systematically examine how relative distance from achieving a goal affects user content participation and within-community purchase behavior.

Jhang and Lynch (2015) have demonstrated that people exert greater effort on goal-relevant activities as they move closer to achieving a goal, whereas individuals are less likely to show more effort on goal-irrelevant behavior. There are different types of game user engagement and purchase behavior, which could be related to achieving a goal. Companies provide different types of content and premium products, and some behaviors are related to achieving a goal and some premium products are also associated with accelerating achievements (e.g., reaching a goal) in the online community. So far, however, most of the goal related literature has focused on one type of behavior or, at least, different types of behavior in one dimension. In the current study, the author examines how the goal gradient effect could differ across different types of user engagement and purchase behavior. In addition, how goal gradient effects can vary across purchasing different types of products is also investigated. Thus, the second objective of this study is to assess how goal gradient effects differ between varying types of behavior.

Most goal-related or goal-gradient effect literature has focused on how achieving a goal increases an individual's effort until the goal is reached and has demonstrated that effort increases as people move closer to a goal. Recently, some literature has investigated behavior after a goal is achieved, i.e., post-goal resetting (e.g., Dreze and Nunes 2011; Goswamin and Urminsky 2017). Post-goal resetting posits that people suddenly decrease their efforts on goal-directed behavior once they obtain a goal. Dreze and Nunes (2011) revealed that in the context of reward settings with recurring goals, people reset their behavior after they achieve a goal. However, most previous literature investigating post-goal resetting has focused on one type of goal-relevant behavior. No study, to the best of the author's knowledge, has examined post-goal resetting in goal-irrelevant behavior. Thus, the third objective of this study is to examine different patterns of post-goal resetting between goal-relevant versus goal-irrelevant behaviors.

Goal-gradient effects could vary depending on personal or situational factors (e.g., Klein et al. 1999; Wright 1992; Zhang et al. 2017). Especially, patterns of the post-goal resetting could be influenced by user experiences when achieving a goal. Prior literature has demonstrated that goal commitments may vary depending on task or goal difficulty (e.g., Wright 1992; Presslee et al. 2013) or social influence (e.g., Klein et al. 1999; Zhang et al. 2017). However, prior literature has focused on the moderating effects on goal engagement or commitment. Thus, the last objective of this study is to identify moderating factors which affect post-goal resetting behavior.

The author uses a novel dataset from an online game community to accomplish the objectives of the current study. The focal game is a role-playing game in which a game user raises a virtual character over time by beating monsters and completing missions. Most role-playing settings have goal-related features called “level-based progression”. Once users defeat monsters or complete missions, they gain experience points and can then move to the next level once they accumulate a certain number of these points. This focal game is free, as are most online games. Thus, if a user spends time fighting against virtual monsters, that user can level up their avatar from level one to two, and two to three, and so forth. In this online gaming community, users can purchase two different types of virtual products: functional and decorative products. Functional products help improve the gamer user’s in-game performance during play, whereas decorative products are purely for fun or image and may help the game user accumulate social currency without improving the gamer’s actual performance in the online game. Another interesting game feature is virtual reality and social interaction between users. Once a user logs into the game, that user can see the virtual spaces where they can move from one place to another. Users can also chat or interact with other players and thus, can spend time not only completing missions but also on simply being in the virtual worlds or socializing with other gamers. Furthermore, gamers team up with many other different gamers and change alliances at will. In the current study, the author could track all a game user’s activities, in-game playing, purchasing, and team-working behavior, allowing investigation of the effect of achieving a goal (in this context, a level) on user engagement and purchasing behavior.

The author analyzes user engagement and purchasing behavior before and after achieving a new goal (level). The author jointly estimates models of three dependent variables since user engagement and spending money on functional and decorative products can be correlated. First, the author finds that user effort related to reaching a new level increases as individuals become closer to the new level. However, these efforts suddenly decrease immediately after attaining the next goal (i.e., post-goal reset). Second, the author finds that while users are less likely to purchase both goal-relevant and irreverent virtual items immediately before achieving a new level, users purchase more virtual items once they reach the goal. Third, if a user has experienced greater difficulty attaining a level, that user is more likely to reduce their effort for in-game progression and spending more money on virtual items after achieving a new level. Finally, because a user is more likely to collaborate with other users in the game, that user has a greater tendency to exert more effort for goal-relevant behavior and spend less on goal-irrelevant items even after attaining a new level.

This study's findings provide important theoretical and practical insights. From a theoretical perspective, this study is one of the first to examine the effects of a goal on goal-related versus non-goal-related behaviors before and after achieving the objective. In addition, the author also examines factors that can weaken or strengthen the effects of goal achievement. Concerning contributions for practitioners, in the context of freemium pricing strategies, the author demonstrates how game design or online communities increase user engagement and ultimately, boost sales. Moreover, this research provides insights that can maximize the effect of community designs.

The remainder of the manuscript is organized as follows. The author first presents the relevant literature on the effect of achieving a goal on user engagement and purchase behavior. In the following section, the field settings, data description, and variable operationalization are provided. The author then describes the proposed econometric model and presents the results. A series of robustness checks are presented, and finally, the author concludes with a discussion and implications.

4.2 Theoretical Background

4.2.1 Goal-Pursuit and Goal-Gradient Effects

A goal is defined as the object of an action (Locke and Latham 1990) or representation of desired states (Austin and Vancouver 1996). Previous literature has demonstrated that having a goal can lead to higher performance in various settings (e.g., Locke and Latham 1990; Zimmerman, Bandura, and Martinez-Pons 1992; Bagozzi and Dholakia 1999). Goal setting theory (e.g., Heath et al. 1999; Locke and Latham 2002) proposed four goal mechanisms that help individuals prioritize tasks: 1) goals make individuals pay more attention to goal-relevant activities and less on goal-irrelevant activities; 2) goals activate individuals to increase their effort; 3) goals lead to greater persistence; and 4) goals activate cognitive knowledge and skills that help individuals attain goals.

The goal-gradient hypothesis proposes that the motivation and persistence to attain a goal (i.e., goal pursuit) can increase with proximity to the goal (e.g., Hull 1932; Kivetz et al. 2006). Initially, this hypothesis was tested with animals in behavioral science and these studies demonstrated that animals ran progressively faster as they moved from a starting point toward food (e.g., Hull 1934; Anderson 1933; Brown 1948). Recently, this effect has been empirically examined with customers in the field of marketing (e.g., Kivetz, Urminsky, and Zheng 2006; Dreze and Nunes 2011). Prior literature (e.g., Atkinson 1957; Heath et al. 1999) provides explanations for the underlying reasons of these goal-gradient effects. Atkinson (1957) argues that motivation to obtain the goal is reinforced as the expectation of gaining positive outcomes increases. Heath et al. (1999) employed prospect theory to explain the goal-gradient effect with diminishing sensitivity, i.e., the marginal utility from performing each action increases as the distance to the goal decreases.

Thus, the author also expects that game users gradually increase their efforts to achieve a goal as they move closer to the goal in the game.

4.2.2 Goal-relevant versus Goal-irrelevant Behaviors

Most goal-gradient studies have focused on one type of activity that becomes more inspiring with the progress of reaching the goal (e.g., Kivetz et al. 2006; Dreze and Nunes 2011). Recently, Jhang and Lynch (2015) examined different patterns of goal-relevant versus goal-irrelevant behaviors depending on the distance to the goal. These authors found that people pay more attention on goal-directed activities as they move closer to achieving a goal, while the same individual pays less attention on non-goal-directed activities. Goal-setting theory (Heath et al. 1999) has explained that people are more likely to focus on goal-relevant activities compared to goal-irrelevant ones once they have a goal, and this tendency is reinforced as people progress closer to the goal. Gilbert et al. (1998) have argued that goal-irrelevant behavior is less attractive for people who are closer to finishing the tasks required to obtain the goal. In the context of education, Rothkopf and Billington (1979) revealed that students can better learn and concentrate on goal-relevant materials than goal-irrelevant materials. In an automobile-driving task, Locke and Bryan (1969) demonstrated that people could improve their performance on dimensions with specific goals but could not improve performance on some aspects if these facets did not include goals. In the context of an online game setting, there are different types of behavior that a game user can perform, including beating monsters or decorating avatars. Some actions are directly related to making progress and achieving a goal, whereas some are not explicitly related to the goals. The author expects that distance to a goal in the game makes a difference in patterns between goal-relevant versus goal-irrelevant behaviors.

4.2.3 Post-goal Resetting

In addition to the main effect of goal gradient, demonstrating that efforts increase as a person moves closer to the goal, and some recent studies have investigated behavior after achieving a goal (e.g., Dreze and Nunes 2011; Goswami and Urminsky 2017). Dreze and Nunes (2011) examined behavior after a goal was achieved (i.e., post-goal reset) when there were recurring goals. These authors found that consumer efforts on goal-related tasks suddenly declined after obtaining the goal (i.e., post-goal resetting). This post-goal resetting indicates that people readjust their efforts on goal-relevant behavior once they achieve a goal and their status is far from achieving the next goal. Similarly, Pink (2011) has claimed that people are less engaged with incentivized behavior after the incentive has expired compared to cases when the incentive has not been offered from the beginning. However, Goswami and Urminsky (2017) argue that reduction in post-goal engagement does not indicate a decrease in intrinsic motivation. Instead, these authors explain that people simply need rest from goal-related behavior after they obtain a goal since they have not maintained the balance between goal-relevant activities and other activities while being engaged with goal-relevant behavior to obtain the goal. These authors also demonstrated that goals influence people to exert greater effort on goal-relevant tasks, and individuals do not have a balance between goal-related tasks and other activities if the goal is activated. However, once the goals or incentives end, people spend more time on other activities rather than goal-related tasks. Similarly, the author expects that game users will exert more effort on goal-related tasks as they move closer to a goal in the game, whereas they will reduce their effort on goal-irrelevant activities. However, once the user achieves a goal in the game, they will adjust their balance of efforts between goal-relevant and goal-irrelevant activities. Thus, once game users reach the goal, they will pay more attention on goal-irrelevant activities, and less on goal-relevant tasks.

4.2.4 The Impact of Pre-goal Experience on Post-goal Reset

The effects of achieving a goal may be moderated by personal or situational factors (e.g., Klein et al. 1999; Wright 1992; Renn 1998; Ke and Zhang 2009). Prior literature has demonstrated that people can be engaged with goal-related activities to achieve a goal. However, in this current research, the author examines how the experience of achieving a goal affects game user behavior after they have achieved the goal (post-goal behavior). A moderating effect of task or goal difficulty on goal commitment or performance to achieve a goal has been examined in prior literature (e.g., Wright 1992; Klein et al. 1999; Presslee et al. 2013). In these studies, it has been demonstrated that people are either more or less likely to be engaged with a task depending on the level of task or goal difficulty. In the current study, the author is interested in how experiencing difficult tasks to obtain a goal affects user post-goal resetting behavior. However, if people are more engaged with goal-related behavior before achieving a goal, they are more likely to adjust their behavior between goal-related versus irrelevant behavior after achieving the goal. Therefore, post-goal resetting is greater once people have experienced difficulty obtaining a goal.

Zhang et al. (2017) examined the role of friends in goal attainment and claimed that friends can inspire people to persistently invest effort into goal-related behavior. Similarly, Klein et al. (1999) investigated the positive relationship between social influence and goal commitment. Thus, once people have more friends working in the same fields, the presence of these friends can help people consistently exert effort on goal-related behavior, even after they obtain a goal and are far from the next goal. Once a person works with many co-workers with different goals and relative distances to a goal, that individual must exert effort on goal-related behavior even after reaching the goal. This occurs because the user’s co-workers have different statuses and they also need to achieve personal goals. This case can be considered as multiple goal setting, meaning that a person has their goal but must also consider other co-workers' goals as a goal. Thus, the author expects that having more co-workers or friends in a network mitigates post-goal resets.

4.3 Field Setting and Data

4.3.1 Field Setting

The setting of video games is suitable for examining goal-gradient effects since many features in games are considered as goals for users and these features can increase user motivation to play games and achieve goals in the game. For example, earning badges, levels, or rankings can encourage game users to engage in gaming by increasing their internal and external motivations. The size of the game market is estimated to be $138 billion in 2018, and with the maturing of the Internet and mobile technology, it is expected to reach more than $180 billion within three years (Takahashi 2018). In addition, many game-design elements are also popular in non-game contexts, referred to as gamification, to improve user engagement, job performance, or education efficiency. Thus, understanding the role of game features is important to provide business implications for practitioners in gaming as well as other fields.

The genre of the game investigated in this research is a role-playing game (RPG) in which game users select the roles of their characters in a fantasy setting and develop these over time. Most RPGs have a game design to quantify characters' progression during the game, which is referred to as "levels". By accomplishing missions or beating monsters, a game user is rewarded with "experience points" and their character reaches the next level once a certain amount of experience points is achieved. This increase in level is named *leveling up* or *level-up*. At the first level (i.e., level 1), game users are generally easily granted an additional level in a brief period (e.g., a few seconds to few minutes). However, leveling up at higher levels requires more substantial time investment (e.g., a few days to several weeks) since a higher level requires many experience points for another level-up and users must complete more difficult missions in these levels.

Among all elements in the game's design, the author focuses on level-based progression. In a game, users can gain experience points once they complete a mission. In the current setting, the mission is mainly related to beating virtual monsters in the game. Then, if the user accumulates a sufficient amount of experience points, they progress to the next level. Thus, "level" or "level-up" refers to gaining sufficient experience points to reach the next level. By achieving a new level, a user's or character's abilities or stats increase. That is, the virtual character has more powers and abilities, and can then undertake more difficult missions. Thus, achieving a new level can be considered as a new goal for game users.

In addition, games have multiple levels. In the current game setting, the total number of levels is 80; a user starts the game at level one, advances to levels two, three, and so on. In this context, the author can observe users' behavior after they have achieved a new goal (i.e., level), and not only test goal-gradient effects, but also postgoal reset. Moreover, in the freemium setting, a game user can play the game without any charge, but must purchase virtual items with real cash. In the game, there are two types of virtual items—goal-related items (i.e., functional items), which improve game users' gaming performance, and goal-irrelevant items (i.e., decorative items), which are used to decorate the virtual avatar's appearance. Thus, the author can test the goal-gradient effect on time spending versus and money spending. In addition, money spending can be categorized into spending on goal-relevant items versus goal-irreverent items.

The author investigates the research questions using data from an online role-playing game in South Korea. Role-playing games constitute a genre in which a user develops their virtual avatar over time by progressing in the virtual world. Progression is a typical game design helps keep players engaged with gaming content. Also, game players earn experience points—the unit of measurement of character progression in many role-playing games—by completing missions or defeating enemies (e.g., monsters) to progress through various levels. Game players can also lose points if they do not play well, i.e., if they are beaten by monsters. As a gamer gains a certain amount of experience points, their virtual character "levels up" and progress to a new level, which comes with benefits such as new abilities and improved statistics. This, in turn, allows the gamer's character to become stronger and enables the gamer to participate in more difficult tasks, such as fighting stronger monsters or completing more difficult missions. While a player completes the missions, gains points, and reaches the next levels during lower levels relatively easily, it must be much more difficult and take a longer time to reach the next levels in the higher levels. While gamers can play most online games for free, online game companies earn revenue when gamers spend real currency to buy virtual products (i.e., freemium strategy). In the game setting for this study, there are two types of virtual products a user can purchase with real cash. First, functional products, which help gamers more easily defeat monsters and play better (e.g., health drinks, safety cards). Thus, these functional items are related to progression in the game. Second, decorative products, which gamers can use to ornament their avatars (e.g., jewelry, clothes). Thus, the decorative items are goal-irrelevant products not directly related to level progression.

4.3.2 Data

The author investigates, using a unique online game dataset provided by a major game company in South Korea, individual users' in-game behavior before and after reaching certain levels. This dataset includes all individual gamers' gaming activities and purchase behaviors in the gaming community of interest. To construct the analysis sample, the author selected game users who have reached at least level 20 from all users who played the game during the given five-month period of the dataset. In the analysis sample, user behavior at levels between 20 and 59 are examined.[24] After sampling, the final analysis dataset contained 31,403 game users and the author analyzed their behaviors from level 20 to 59. The author aggregated the dataset based on the users' progression. The author notes that a user gains a certain amount of experience points, which are obtained once the user defeats monsters or completes missions, to "level-up". As such, a user's progression in one level can be expressed as a percentage. For example, a user must obtain 1,000 experience points to level-up from level 20 to 21, and thus, 50 experience points is equal to a 5% progression within level 20 to move to level 21. Once the game user reaches level 21, the required amount of experience points is higher than for level 20. Thus, analysis dataset is aggregated by each 5% increment of progress within a level. Within a level, the analysis dataset has 20 observations for a game user (e.g., 0-5%, 5-10%, 10-15%). Some users played the game until level 59—the last level used in the analysis, and some users left the game before reaching this level. Thus, the individual-percentage level panel is an unbalanced dataset. The author primarily focuses on two behaviors: 1) content engagement, which captures how quickly a user progressed from X% to X+5% and was measured as the amount of time spent on making a 5% progress; and 2) amount of money spent on purchasing virtual items while making a 5% progress.

4.3.3 Dependent Variables

The individual user and their 5% intervals of progress is the unit of analysis used in this study. The focus of the analysis is understanding the impact of achieving a new level on a focal users' game playing and purchasing behaviors. $Min\_Elapsed_{ilt}$ measures the amount of time, in

[24] Since achieving a new level is easy and fast when a player is in a lower level, the author cannot observe an enough number of observations. For example, a user just needs to defeat one monster to become level 1 to 2. Only a few portions of users exceeded the level 60.

minutes, that a user *i* spent in the virtual community to make a *t*-th 5% progress within level *l*.[25] This includes not only the time a user has spent beating monsters, but also just staying in the virtual community without performing any action. Thus, this variable captures how a user was engaged when making progress. $Func\_Spending_{ilt}$ measures the amount of money (in Korean Won)[26] that a user *i* spent on purchasing functional items (i.e., goal-relevant items) within a *t*-th 5% interval in level *l*. The author notes that users can access basic game content without paying. This variable exhibited positive skewness, and to alleviate this issue, the author uses a log transformation of the spending variable.[27] $Deco\_Spending_{ilt}$ measures the total amount of money (in Korean Won) that a user *i* spent on purchasing decorative products (i.e., goal-irrelevant items) within a *t*-th 5% interval in a level *l*. Similar to $Func\_Spending_{ilt}$, the author uses a log-transformation of $Deco\_Spending_{ilt}$.

4.3.4 Independent Variables

$Before\_Goal_{ilt}$ is a binary dummy variable equal to 1 if a user *i*'s progression status at time *t* in level *l* indicates the progress between 95% and 100%, but is 0 otherwise. Thus, this variable captures the status of a user right before that user achieves a new level. $After\_Goal_{ilt}$ is another binary dummy which equals to 1 if a user *i*'s progression at time *t* in level *l* belongs to a percentage between 0% and 5%. This variable indicates that a user has just achieved a new level. $HealthPts_{ilt}$ measures the number of health points a user lost while the user *i* made a *t*-th 5% progress in level *l*. When a user completes missions or defeats monsters, the virtual character's health points are

[25] Each level *l* could have up to 20 times (i.e., *t*) since the author observes users' behaviors within each 5% progress interval and there are 20 observations within a level.
[26] 1 U.S. Dollar is equal to 1,082 Korean Won (as of May 17, 2018).
[27] There are a lot of observations which have zero

deducted if their avatar is attacked by the monsters.[28] Thus, a larger change in health points could capture the difficulty of game as the user makes a 5% progress. The author uses a lagged value of change in health points. $Coworks_{ilt}$ measures the total number of times that a user *i* collaborates with other users to complete missions or defeats monsters within the *t*-th 5% interval in level *l*. In this game, there is collaboration system that a user can find virtual friend(s) to participate in a mission or defeat monsters together. Similar to $HealthPts_{ilt}$, the author uses lagged value of $Coworks_{ilt}$. In addition to the variables described above, the author includes level fixed effects to accounts for factors that may affect game playing and purchase behaviors at a given level.

In Table 14, operationalization and summary statistics of all the variables are presented.

Variable	Operationalizations	Mean	StdDev	Min	Max
Min_Elapsed	Amount of time (in minutes) took to make a progress 5%.	15.63	33.13	5	11,165
Func_Spend	Amount of Korean Won spent on purchasing functional products	30.21	1,198	0	554,400
Deco_Spend	Amount of Korean Won spent on purchasing decorative products	14.76	434	0	100,700
Before_Goal	Binary variable which equals to one if a user's progress is between 95% and 100%	.049	.21	0	1
After_Goal	Binary variable which equals to one if a user's progress is between 0% and 5%	.053	.22	0	1
HealthPts	Health points that a user spent to make a progress from X% to X+5%.	3,830	6,819	0	677,972
Coworks	Number of missions that a user complete mission with other players between X% to X+5%.	2.52	9.34	0	6,641
Level	Level	32.19	9.83	20	59
Engage_Time	Percentage of time that a user spent on progress related behaviors	.284	.180	0	1
Note: Number of observation is 5,493,757.					

Table 14. Operationalizations and Summary Statistics

[28] If all health points are deducted, the user gets some penalties and cannot play the game for the next 1 minute.

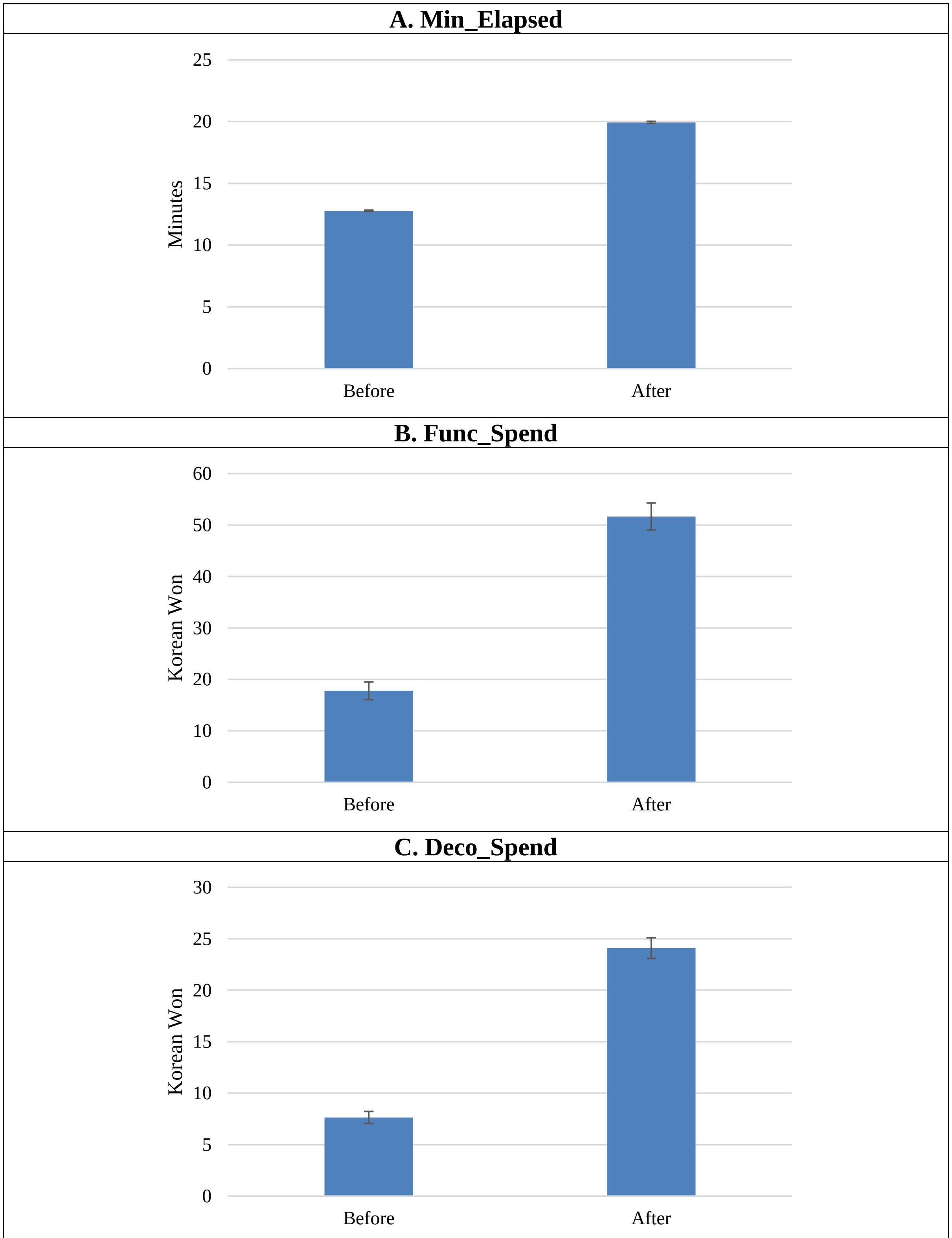
4.4 Results

4.4.1 Preliminary Evidence

The primary objective of this paper is to investigate the effects of achieving a new level on users' in-game playing and spending behaviors. To provide insight into the potential effects of achieving a new level, the author first presents the patterns of time and money spending around the point when a user levels up. Note that the author aggregates players' behaviors at each 5% progress interval. Thus, *before* achieving a level indicates progress between 95% and 100% at level l and *after* achieving a level denotes the progress status between 0% and 5% at level $l + 1$.

In Figure 7, the model-free evidence illustrates users' game engagement (i.e., *Min_Elapsed*) and purchase behavior (i.e., *Func_Spend* and *Deco_Spend*) within each 5% interval before and after achieving a new level. Panel A shows the time spent in the virtual communities to earn each 5% progress before and after achieving a new level (i.e., from 95% to 100% in a level, and from 0% to 5% in the next level). The Y-axis indicates average time spent (in minutes) (i.e., *Min_Elapsed*). The author finds that, on average, game users spent less time on a 5% progress immediately before achieving a new level compared to time spent on a 5% progress immediately after achieving a new level. Panels B and C depict the players' average spending[29] (in Korean Won) on purchasing functional and decorative items in each 5% interval before and after achieving a new level (i.e., *Func_Spend* and *Deco_Spend*). Notably, game players' spending on both types of virtual items right before achieving a new level is lower than after achieving a level.

[29] Precisely, it is calculated based on time that a player actually consumes the virtual item.



Notes: Standard errors are shown in the bars.

Figure 7. Model Free Evidence: Before and After Achieving a New Level

This preliminary evidence reveals that game players are highly engaged in making progress or gaming content immediately before achieving a new level. However, this high engagement does not indicate an increase in consumption of both goal-relevant and goal-irrelevant products. Rather, game users spend more money right after achieving a new level.

4.4.2 Empirical Model

In the analysis, the author models three player behaviors: 1) time spent on making a 5% progress (denoted by *Min_Elapsed*); 2) money spent on purchasing functional items (denoted by *Func_Spend*); and 3) money spent on purchasing decorative items (denoted by *Deco_Spend*). The author also demonstrates how users behave before and after achieving levels. As shown in the model-free evidence, relative distance to a new level affects game players' behaviors. However, game player behavior can also be explained by other confounding factors. Thus, in the main analysis, the author controls for other potential factors, insofar as the data were available. First, depending on the user's level, that user's playing behaviors can vary since each level has its own unobservable characteristics. Then, the author uses level fixed effects to control heterogeneity across levels. Similarly, the author also controls individual heterogeneity with individual players fixed effect.

The author also analyzes the three types of behavior around a new level in each 5% progress interval. In the empirical model, the dependent variable (denoted by y_{ilt}) indicates individual user i's behavior at a 5% interval t in a level l.

The basic model is as follows:

$$
\begin{aligned}
y_{ilt} = {} & \beta_0 + \beta_1 Before\_Goal_{ilt} + \beta_2 After\_Goal_{ilt} \\
& + \beta_3 After\_Goal_{ilt} \times \log(HealthPts_{ilt-1}) + \beta_4 After\_Goal_{ilt} \times \log(Coworks_{ilt-1}) \\
& + \beta_5 \log(HealthPts_{ilt-1}) + \beta_6 \log(Coworks_{ilt-1}) \\
& + \varphi_i + \zeta_l + \varepsilon_{ilt}
\end{aligned} \tag{4.1}
$$

where i indicates an individual player, l is a level, and t is an index of a 5% progress. φ_i is the individual player fixed effects, ζ_l is a level fixed effect, and ε_{ilt} is an error term.

The author measures three dependent variables and the error terms in three dependent variables could also be correlated. Thus, the author jointly estimates three equations:

$$
\begin{pmatrix} \varepsilon_{ilt}^1 \\ \varepsilon_{ilt}^2 \\ \varepsilon_{ilt}^3 \end{pmatrix} \sim IIDN\left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} , \begin{bmatrix} \sigma_{\varepsilon^1}^2 & \rho_{12} & \rho_{13} \\ \rho_{21} & \sigma_{\varepsilon^2}^2 & \rho_{23} \\ \rho_{31} & \rho_{32} & \sigma_{\varepsilon^3}^2 \end{bmatrix} \right) \tag{4.2}
$$

where ε_{ilt}^1, ε_{ilt}^2, and ε_{ilt}^3 indicate error terms in Equation 4.1 of the three dependent variables, respectively, ρ_{nm} is the correlation coefficient between the variances of the error terms between models of two dependent variables ($\sigma_{\varepsilon^n}^2$ and $\sigma_{\varepsilon^m}^2$ respectively). For the identification purpose, the author sets $\sigma_{\varepsilon^1}^2$, $\sigma_{\varepsilon^2}^2$, and $\sigma_{\varepsilon^3}^2$ equal to 1.

4.4.3 Results

The author presents the parameter estimates of model with a main effect only and a full model for the three dependent variables in Table 15. Note that three outcome variables are jointly estimated. In the full model, the author uses mean centering for moderating variables.

4.4.3.1 Min_Elapsed

The author finds that game users spend less time right before achieving a new level (coef = -.0652), but in contrast, they spend more time right after achieving a new level (coef = .1117). Thus, users appear to want to quickly achieve a new level once they are close to the next level, whereas they are not motivated to work hard if they have just achieved a new goal or the next goal is too far away from their current status. Next, the moderating effect of health point deduction was positive and significant (coef = .0167), indicating that users are not motivated to work harder or highly engaged in making another progress after achieving a new level if they had difficulty playing the game just before achieving a new level. Finally, the moderating effect of the number of coworks was negative and significant. It indicates that a game user cannot relax, even after they achieve a new level, if they have been working more with others.

DV	A. Log(Min_Elapsed)		B. Log(Func_Spend)		D. Log(Deco_Spend)	
	Main	w/ Moderators	Main	w/ Moderators	Main	w/ Moderators
Before_Goal	-.0653*** (.0011)	-.0652*** (.0011)	-.0076*** (.0010)	-.0076*** (.0010)	-.0075*** (.0008)	-.0075*** (.0008)
After_Goal	.1138*** (.0010)	.1117*** (.0010)	.0172*** (.0009)	.0168*** (.0009)	.0115*** (.0008)	.0113*** (.0008)
Lag_HealthPts	.0061*** (.0001)	.0053*** (.0001)	.0010*** (.0001)	.0008*** (.0001)	.0002** (.0001)	.0001 (.0001)
Lag_Coworks	.0767*** (.0003)	.0773*** (.0003)	.0038*** (.0002)	.0038*** (.0003)	.0035*** (.0002)	.0036*** (.0002)
After_Goal x Lag_HealthPts	-	.0167*** (.0006)	-	.0040*** (.0005)	-	.0019*** (.0004)
After_Goal x Lag_ Coworks	-	-.0132*** (.0012)	-	-.0006 (.0010)	-	-.0019** (.0008)
Number of observations = 5,493,757 (Number of individuals = 31,403) p-values: * < 0.05 ** < 0.01 *** < 0.001						

Table 15. Parameter Estimates: Goal Gradient Effects

4.4.3.2 Func_Spend

Before achieving a new level, users are less likely to spend money on purchasing functional items (coef = .0076), whereas they spend more on functional items right after achieving a new level (coef = .0168). Considering the moderating effects, recent health point loss had a positive moderating effect on function item purchase (coef = .0040), whereas the number of coworks did not have a significant moderating effect. Thus, if a user has just experienced difficulty playing the game before achieving a new level, they are more likely to purchase functional items after reaching the next level.

4.4.3.3 Deco_Spend

Similar to functional product purchase, people are less likely to purchase decorative products right before reaching a new level (coef = -.0075). However, users are more likely to purchase decorative products immediately after achieving a new level (coef = .0113). The author also finds a positive and significant moderating effect of change in health points (coef = .0019) and a negative and significant moderating effect of number of coworks (coef = -.0019).

4.5 Robustness Checks

The author checks for the robustness of the core results regarding the effect of goal achievement by using: 1) alternative dependent variables, 2) alternative measures of independent variables, and 3) alternative model specifications.

4.5.1 Alternative Dependent Variables

In the main models, the author uses three dependent variables, i.e., *Min_Elapsed*, *Func_Spend*, and *Deco_Spend*. All three variables captured the total amount of time or spend within a 5% progress interval. Instead of using total amount, the author uses average time or spend within a given period (i.e., a five-minute interval). Thus, instead of using *Min_Elapsed*, the author first uses the percentage of time that a user actually spent on beating monsters or completing missions, which is directly related to making progress (denoted by *Pct_EngageTime*). For the spending variables, the author considers the average amount a user spent in a five-minute interval (denoted by *Avg_Func_Spend* and *Avg_Deco_Spend*, respectively). The results of models with these alternative measures are presented in Table 16. The author finds that game users spent more time beating monsters and completing missions before achieving a new level, whereas they were less likely to spend time more on these behaviors after achieving a new level. These findings are consistent with the results of the main analysis. In terms of spending behaviors, the author also finds that the effects of achieving a new level were consistent with the results in the main analysis.

DV	**A. Log(Avg_Battle)**		**B. Log(Avg_Func)**		**D. Log(Avg_Deco)**	
	Main	w/ Moderators	Main	w/ Moderators	Main	w/ Moderators
Before_Goal	$.1254^{***}$ (.0021)	$.1253^{***}$ (.0021)	$-.0053^{***}$ (.0006)	$-.0051^{***}$ (.0007)	$-.0051^{***}$ (.0007)	$-.0053^{***}$ (.0006)
After_Goal	$-.1368^{***}$ (.0021)	$.0720^{***}$ (.0091)	$.0079^{***}$ (.0006)	$-.0173^{***}$ (.0032)	$.0115^{***}$ (.0007)	-.0036 (.0025)
Lag_HealthPts	$.1417^{***}$ (.0003)	$.1432^{***}$ (.0003)	$.0002^{**}$ (.0001)	$.0007^{***}$ (.0001)	$.0009^{***}$ (.0001)	.0001 (.0001)
Lag_Coworks	$-.0684^{***}$ (.0005)	$-.0693^{***}$ (.0005)	$.0034^{***}$ (.0001)	$.0024^{***}$ (.0002)	$.0023^{***}$ (.0002)	$.0035^{***}$ (.0001)
After_Goal x Lag_HealthPts	-	$-.0314^{***}$ (.0013)	-	$.0042^{***}$ (.0005)	-	$.0018^{***}$ (.0003)
After_Goal x Lag_ Coworks	-	$.0173^{***}$ (.0024)	-	-.0012 (.0008)	-	$-.0017^{***}$ (.0006)
Number of observations = 5,493,757 (Number of individuals = 31,403) p-values: * < 0.05 ** < 0.01 *** < 0.001						

Table 16. Alternative Dependent Variables

4.5.2 Alternative Percentage Criteria

Instead of using a 5% progression to construct the *Before_Goal* and *After_Goal* variables, the author uses 10%. Thus, in this robustness check, *Before_Goal* and *After_Goal* indicate binary variables which equal to 1 if a user's progress is in the interval of 90% to 100% and 0% to 10%, respectively. The results of models with alternative measures of a before and after goal are presented in Table 17. The author finds that the core results remained valid even after the alternative measures were used.

DV	A. Log(Min_Elapsed)		B. Log(Func_Spend)		D. Log(Deco_Spend)	
	Main	w/ Moderators	Main	w/ Moderators	Main	w/ Moderators
Before_Goal	-.0490*** (.0008)	-.0489*** (.0008)	-.0063*** (.0007)	-.0063*** (.0007)	-.0061*** (.0006)	-.0061*** (.0006)
After_Goal	-.0746*** (.0008)	-.0282*** (.0034)	.0107*** (.0007)	-.0129*** (.0003)	.0085*** (.0006)	-.0026 (.0024)
Lag_HealthPts	.0151*** (.0002)	.0136*** (.0002)	.0013*** (.0001)	.0009*** (.0001)	.0003*** (.0001)	.0002 (.0001)
Lag_Coworks	.0863*** (.0003)	.0877*** (.0003)	.0040*** (.0002)	.0036*** (.0004)	.0052*** (.0002)	.0053*** (.0002)
After_Goal x Lag_HealthPts	-	.0159*** (.0005)	-	.0042*** (.0002)	-	.0017*** (.0003)
After_Goal x Lag_ Coworks	-	-.0135*** (.0008)	-	-.0020*** (.0007)	-	-.0007 (.0006)
Number of observations = 5,493,757 (Number of individuals = 31,403) p-values: * < 0.05 ** < 0.01 *** < 0.001						

Table 17. 10% Progress Interval

4.6 Discussion and Conclusion

Freemium—a product or service is provided for free while premium features are charged—has become a popular business strategy or pricing approach in digital settings, e.g., online games, mobile apps, Dropbox, LinkedIn. In the context of the game industry, this strategy is called “free-to-play”. Since most game companies provide free products or services in digital environments where they can easily enter digital markets compared to physical markets, companies in this market face tough competition. Thus, to appeal to consumers and sustain user interest, game developers must design engaging game contents. In the game industry, to improve user engagement, game companies have used various types of game designs that can leverage basic human instinct related to, for example, competition, socializing, achievement, self-expression. Among various designs, the author focuses on levels that a user obtains once that user accumulates a sufficient amount of experience points by completing missions or beating monsters in the game. Thus, findings from this research can provide business implications related to how game design affects user engagement and purchase behaviors. This research can also provide insights for theories in the fields of goal-setting and goal-gradient effects.

While there is a long history of studies in goal-related literature related to identifying the effects of having a goal, the current study provides implications for theories related to goal-setting and the goal-gradient hypothesis with three aspects. First, a limited number of studies has demonstrated postgoal effects. Most literature related to goal-setting theory and the goal-gradient hypothesis have studied either the effect of having a goal on job performance or increases in effort as people move closer to their goal. However, only few studies demonstrate the postgoal resetting when there are recurring goals. In addition, there is no study which shows postgoal resetting between goal-relevant and goal-irrelevant behaviors. However, Jhang and Lynch (2015) have investigated how goal-relevant and goal-irrelevant efforts are different with proximity to a goal; as a goal becomes closer, efforts related to the goal increase whereas efforts not related to the goal decreases. In addition to the goal-gradient effects on goal-relevant versus goal-irrelevant behaviors, the current study reveals differences of postgoal resetting between goal-relevant and goal-irrelevant behaviors. Finally, the current study provides evidence that goal-related behavior does not increase with the proximity to the goal if there is additional cost on that behavior. Also, purchasing functional items does not increase as a goal is closer. The pattern of purchasing functional items present like behaviors not related to the goal.

This study also provides practical implications related to game design, user engagement, and freemium pricing. First, the findings reveal that having a goal-related feature in the game increases the user's engagement, as has also been found in prior literature. Thus, game developers or other manages in a digital setting can use goal-related features to increase user or customer engagement. Second, the findings also provide evidence that time spending and money spending before and after achieving a level have different patterns. That is, users are highly engaged before achieving a new level and consequently, exert more efforts. However, users spend more money once they achieve the next game level. Distance from or to goals have time difference between two behaviors. Thus, game managers should understand and leverage the distance or timing from the goals to improve user efforts and spending. Finally, the effects of achieving a goal on time and money spending vary depending on a user's recent experience and collaborate network in the game.

5. CONCLUSION

This dissertation makes important and valuable contributions both towards theory and practice. The author explores the effects of three factors—i.e., social connection (Essay 1), demarketing (Essay 2), and game design (Essay 3)—on game users' behaviors. Three essays provide implications for theory, along with practical implications for game developers and policy makers from multiple angles—i.e., individual level, network level, and industry level. First, from a theoretical perspective, this dissertation develops and empirically examines an integrated framework that includes various factors which affect game users' behaviors. Second, from a managerial perspective, this dissertation provides implications that allow game developers to design better gaming contents and social structure which can engage and motivate users to make in-game purchases. Finally, this research also helps policy makers and game companies to protect game users from negative consequences from playing games.

The results suggest that game users' engagement and purchase behaviors can be significantly affected by game contents, social interaction in the online communities, and policy changes. Then, the results of three essays have implications for both theory and practice, and help provide insights on how managers can monetize game contents and social networks, use these for greater engagement in games and online communities, and protect users from negative outcomes of playing games.

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