Nature or Nurture? An Analysis of Rational Addiction to Mobile Social Applications

Completed Research Papers

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Abstract

Through the lens of rational addiction theory (Becker and Murphy, 1988), this study investigates whether addiction to mobile social apps should be viewed as a rational behavior rather than an uncontrollable, irrational disorder. To derive the analytical model, this study extends the rational addiction framework to include a utility-level network effect as the key factor that regulates the inter-temporal consumption of mobile social apps. Further, to validate empirically the rational addiction model in this context, we gathered and analyzed longitudinal panel data on the weekly app usage of thousands of smartphone users. The findings suggest that consistent with the rational addiction theory, users of mobile social apps are rational and forward-looking. They determine their current consumption based on both past and future consumption and the utility derived from network effects. However, the extent of rational addiction to mobile social apps varies considerably across diverse demographic groups and app categories.

Keywords: Rational addiction, social exchanges, mobile apps, network effects, GMM, panel data

Introduction

The emergence of mobile devices and applications ("apps") as a social catalyst has been a blessing and a curse. Mobile users are empowered to promote their social relationships and solidarity through apps, such as social games and network services (e.g., Facebook), which have become increasingly ingrained into their everyday lives. Because it is very easy to carry and use mobile devices anytime and anywhere, users are never out of touch and they are enabled to maintain a constant sense of camaraderie and kinship with people in their social circles. As a consequence, the new mobile paradigm has reshaped and perhaps enriched our social fabric and conventions.

Notwithstanding these putative benefits, the social fever driven by mobile platforms appears to be quickly turning into social fear. Sociologists and psychologists are increasingly concerned that the portability, convenience, and ubiquitous connectivity furnished by mobile conduits may have adverse ramifications on human behaviors. Heavy or excessive use of social netw zorks and gaming apps available through smartphones foster habit-forming activities, and these behaviors can easily develop into an addiction, similar to consuming alcohol, cigarettes, and drugs. According to Flurry, a U.S.-based global market research firm, the average smartphone user spends 2 hours and 38 minutes every day on his or her device, checking messages and social networks, as well as playing games (Khalaf, 2013). Even more remarkably, a recent academic study found that smartphone users activate their devices more than 80 times a day, which equates to every 12 minutes (Starr, 2014). While having breakfast, attending meetings, crossing the street, or even driving, people compulsively check their mobile devices in a desire not to miss a satisfying "social update." As the mobile era moves towards its zenith, the apparent addictive preoccupation and impaired dependency with mobile platforms have become vexing social challenges.

In academic circles, the "nature versus nurture" controversy surrounding addictive behaviors continues to intrigue scholars and medical professionals. In fact, researchers who support the "nature" perspective have long taken it for granted that addiction is an acute type of irrational behavior and a chronic disease that requires psychological and medical treatment. However, in his seminal article, "Theory of Rational Addiction," the Nobel Laureate economist Gary Becker and his colleague defied conventional knowledge by claiming that addictions to substances (e.g., cigarettes and alcohol) can also be explained by utility-maximizing, rational human behavior that can be "nurtured" (e.g., controlled) by economic factors (e.g., prices). In specific, the essence of rational addiction theory (Becker and Murphy, 1988) is that addicts are rational in that they anticipate the future consequences of their current consumption and act wisely to arrive at a choice with maximum utility. For example, when addicts expect future prices of addictive goods to rise, they reduce their current consumption of these goods, since the higher price will diminish the marginal utility of current and future consumption. This is in stark contrast to the "myopic" theory of habit formation in which one's current assessment of utility depends solely on past and current consumption of addictive goods (Pollak 1970; 1976).

The current study aims to explore the mobile "app-diction" phenomenon (e.g., addictions to mobile social apps) through the lens of rational addiction theory. Building on the theoretical insights offered by Becker and Murphy (1988), this study derives an analytical framework that enriches our understanding of rational addiction to mobile social apps. In addition, to empirically validate whether users of social apps exhibit rational addictive behaviors, we gathered and analyzed one-year panel data on weekly usage of mobile social apps by thousands of smartphone users. Specific research questions we addressed include:

a. Do users exhibit forward-looking and rational addictive behaviors when consuming mobile social apps?

b. How does the degree of rational addiction vary with different app categories (e.g., social networking apps vs. social gaming apps)?

c. To what extent does user heterogeneity—age, education, income, and life style—account for the degree of rational addiction to mobile social apps?

The empirical regularities observed through data analysis suggest that, in accordance with the rational addiction model, users of mobile social apps exhibit rational consumption patterns in which current consumption depends on how they assess both past and future consumption and the extent of network effects (e.g., the number of active users). However, the magnitude of rational addiction to social apps varies substantially across diverse demographic groups. Furthermore, contrary to our expectations, the extent of rational addiction is more pronounced in social network apps than in social game apps. Our findings collectively suggest that there are many reasons to be concerned about addiction to smartphones and mobile apps, but also evidence that effectively addressing these "app-diction" issues is feasible through basic economic principles.

Theoretical Background

Addiction has long been understood as an uncontrollable and irrational behavior motivated by the desire to experience pleasurable and euphoric effects (Pollak 1970, Yaari 1977). For example, medical scientists have treated addiction as a chronic disorder caused by biological or neurological predispositions, while socio-psychologists have attributed it to an uncontrollable responsive behavior that emanates from an interplay of heredity and social environments (Peele 1985). However, the heretofore defining features of addictive behaviors, such as irrationality, compulsion, overindulgence, and loss of control, have been questioned by Becker and Murphy (1988). Using the seminal findings of Stigler and Becker (1977) and Iannaccone (1984) as a prelude to their elegant analytics, Becker and Murphy (1988) proposed the rational addiction model in which addicts are not "myopic" but instead rational. Rational, farsighted addicts anticipate the future consequences of their current behaviors and act prudently in their own best interests (i.e., optimal consumption plans) to maximize discounted utility. The most essential aspect of the theory is that, by weighing the future, addicts, who have full knowledge of addiction's consequences, perform strategic calculations on expected benefits (e.g., utility gains from taking drugs) against costs (e.g., negative impacts on health). They arrive at a rational choice that maximizes utility based on their stable preferences. For example, drug addicts are cognizant that their current drug use will stimulate greater future drug consumption and that drug use results in negative consequences (e.g., health conditions). Nevertheless, addicts appraise the utility gained from taking drugs as outweighing the discounted reduction in utility arising from negative consequences. As a result, Becker and Murphy (1988) construe addiction as rational, utility-maximizing behavior, just like any other economic conduct.

To illustrate further, in previous myopic models of addictive behaviors, addicts neither consider the future consequences of their current consumption nor factor future prices of addictive goods into their current consumption decisions. Instead, they choose current consumption based primarily on past consumption. Therefore, the myopic perspective regards addiction as merely the positive interaction and complementarity between past and current consumption of addictive goods, without reference to future consumption or prices.

As opposed to this backward-looking, myopic model, the rational addiction framework maintains that addicts decide on current consumption with future consumption and future utility in mind to maximize discounted utility. Furthermore, this forward-looking paradigm, which falls under the rubric of the rational choice model (Calvert 1985), centers on the dynamics of current consumption in response to anticipated future prices of addictive goods. For example, rational addicts proactively reduce their current consumption of tobacco when they expect future prices to rise. They recognize that the anticipated price increase will lower the marginal utility of their current and future consumption. In contrast, myopic addicts do not cut their current consumption in response to expected increases in future prices.

In constructing the rational addiction model, Becker and Murphy (1988) assume that an individual's utility depends on three elements: addictive goods C_t, addictive stock A_t, and non-addictive goods Y_t. In addition, these authors explicate the notion of addiction based on its three distinctive aspects, *namely*, withdrawal, reinforcement, and tolerance. Withdrawal illustrates a decline in current utility due to reduced current consumption. Reinforcement arises when high levels of past consumption increase the marginal utility of current consumption and the current consumption itself. Finally, increased tolerance shows that the greater the addictive stock (i.e. a cumulative past addictive consumption), the lower the current utility (Becker and Murphy1988).

The idiosyncrasies that characterize addiction give rise to a behavioral pattern in which past consumption of addictive goods induces current consumption by influencing the marginal utility of both current and future consumption (Becker and Murphy 1988). This inter-temporal, dependent demand structure, often called "adjacent complementarity" (Ryder and Heal 1973), epitomizes the key conceptual building-blocks that underlie the rational addiction model. Consumers become addicted if their past consumption positively affects their current consumption. An addictive behavior is thought to be rational when current consumption is positively dependent on future utility and consumption.

In a subsequent study, Becker et al. (1994) offered a thorough empirical scrutiny of the model of rational addiction by investigating whether lower past and future cigarette prices increase the current consumption of cigarettes. In the empirical framework proposed, they assumed addicts are rational and determine their consumption of both non-addictive and addictive goods within the present value of their lifetime budget. The model further assumes a quadratic utility function in $C_t, A_t,$ and Y_t to elicit the demand function (see Becker et al. (1994, p.398) for derivations). Finally, they identify the resulting demand structure of addictive goods, C(t), which denotes current consumption as a function of both past and future consumption, and the current price of the goods, P_t:

$$C_t = \theta_0 + \theta_1 C_{t-1} + \theta_2 C_{t+1} + \theta_3 P_t \tag{1}$$

where $\theta_1 = -\frac{u_{CA}}{u_{cc}+\frac{u_{AA}}{1+r}} > 0$, $\theta_2 = \frac{\theta_1}{1+r} > 0$, $\theta_3 = \frac{r}{u_{cc}+\frac{u_{AA}}{1+r}} < 0$, and r is a constant discount rate.

A diverse body of work has since leveraged the empirical formality specified in Equation 1, testing the theory of rational addiction by estimating the model parameters: θ_1 and θ_2. The positive effect of past consumption on current consumption (θ_1) signifies addiction, and the addictive behavior is considered rational when the effect of future consumption on current consumption (θ_2) exhibits the same direction as θ_1. Most empirical studies find significant and positive values for θ_1 and θ_2 in diverse habit-forming contexts, including cigarettes (Becker et al. 1994), alcohol (Baltagi and Griffin 2002), cocaine (Grossman and Chaloupka 1998), opium (Liu et al. 1999), caffeine (Olekalns and Bardsley 1996), and gambling (Mobilia. 1993).

Rational Addiction to Mobile Social Apps

This study extends the model of rational addiction (Becker and Murphy, 1988) to investigate whether addiction to social apps (e.g., SNS and social games) follows the patterns of utility-maximizing, rational behaviors. Addiction to social apps can be viewed as one form of technology addiction (Turel et al., 2011). We refine the analytical and empirical components of the frameworks architected by Becker and Murphy (1988) and Becker et al. (1994) in the context of mobile social apps, testing the models on panel data gathered on app consumption behaviors at an individual user level.

Social Exchanges as Economic Actions

Social exchange theory (Homans 1958), which originated from the scientific traditions of neoclassical economics paradigms, offers a conceptual foundation for understanding social relationships through economic principles. According to this canonical theory, social behaviors can be construed as the outcome of negotiated exchange processes, in which rational actors facing social situations select behaviors that maximize their self-interest. If the reward or utility from a social interaction outweighs the punishment or cost, they cultivate the relationship. If the cost is too high, however, they suspend the interpersonal relationships. Regarded as an economic metaphor for social relationships, social exchange theory is underpinned by several key premises. First, individuals engaging in social relationships are rational in that they successfully gauge the costs and benefits woven into social exchanges. The theory further assumes that individuals involved in exchange processes rationally seek to maximize payoffs or rewards to meet their basic social needs. Last, the exchange framework maintains that exchange processes and outcomes alter power and privilege structures in social groups, due to the competitive nature of social systems.

In our model, the act of consuming social apps (e.g., exchanging messages through SNS or playing social games) is viewed as an enacted exchange process in which app users, given time constraints, seek to maximize payoffs through enhancing their social presence and privileges. Users of social apps are forward-looking and rational in that they anticipate the future consequences of their current app consumption and determine their social exchange relationships based upon strategic reward-cost calculations. In keeping with the notion of adjacent complementarity, current consumption of social apps increases the marginal utility of future consumption, and users increase their current app consumption when they expect network effects[1] to increase in the future. As a result, users consuming social apps have a pervasive drive to form and maintain stable social bonds and attachments.

Network Effects and Exchange Dynamics

In Becker and Murphy's (1988) model, the price of addictive substances presumably regulates addicts' inter-temporal consumption preferences. For example, anticipated future prices of addictive commodities influence current consumption through their effect on future stocks and consumption. According to the model, governments can "effortlessly" induce smokers to lower their current cigarette consumption by pre-announcing a cigarette tax increase, since increased future prices negatively affect current consumption through future consumption and utility. Becker et al. (1994) found that a 10% increase in cigarette prices can decrease current consumption by as much as 7.5% in the long run. Moreover, a 10% price increase in one period reduced consumption in the previous period by 0.6% and by 1.5% in the subsequent period. These correlation patterns demonstrate the presence of inter-temporal associations in cigarette demand that result from rational addictive behaviors.

In mobile social apps addiction, users do not directly pay money to consume the apps once they have downloaded and installed them into devices. However, just as price affects the consumption of physical commodities, a utility-level network effect determines how much users consume the social commodities (e.g., social apps) that have limited value in isolation. A user's utility derived from consuming a particular social app escalates exponentially as the number of other people using it increases (Katz and Shapiro 1985). Recently, several studies focusing on online-based social networks (e.g., Susarla et al., 2012, Zeng and Wei 2013) have demonstrated the important role such positive consumption externalities play in disseminating user-generated content across social network platforms (e.g., YouTube and Flickr).

Social app providers have designed several features unique to their platforms, such as Facebook Likes and In-App Currency/Credit Exchanges, in an effort to enhance network effects as these artifacts constantly lubricate social exchanges through shared emotions, thoughts, and gossip. Users consume social apps to form or maintain lasting, positive, and affectively pleasant relationships with other people within or across their usual social boundaries. Furthermore, users often endeavor to enhance their social presence and authority by receiving others' recognition and care. In this way, the more active users involved or the greater the network effect within a platform, the greater the utility derived from the exchanges. As a consequence, a utility-level network effect strongly influences how actively individuals engage in social activities (Fang et al., 2013), affecting their ability to convert their time resources efficiently into forming and maintaining interpersonal relationships. Therefore, rational app addicts will proactively increase their current consumption of app when they expect future network effects to increase. These addicts appraise the utility gained from consuming social apps as outweighing the discounted reduction in utility arising from negative consequences (e.g., escapism, procrastination, preoccupation, and poor time-management).

An Analytical Model

In line with the discussion above, an individual's utility depends on the factors specified in Equation 2.

$$U_{i,t} = u\left[C_{i,t}, Y_{i,t}, A_{i,t}, N_t\right] \tag{2}$$

where $C_{i,t}$ is the amount of social app consumption of individual i at time, t, and $Y_{i,t}$ refers to the time spent on any other activities of i at time t. $A_{i,t}$ indicates the amount of addictive stock of i at time t. Finally, N_t reflects the extent of network effect at time t. W in Equation 3 represents the total amount of time (i.e., 24 hours per day) allowed for each individual for any given day, denoting a time budget constraint. This constraint is similar to the budget constraint in the Becker-Murphy model.

[1] The details on network effects are described in the next section.

$$C_{i,t} + Y_{i,t} = W \tag{3}$$

Because of the time budget constraint, a utility function can be restated as shown in Equation 4. In Equation 5, each individual app user chooses C_t to maximize the sum of lifetime utility discounted at the rate *r* and subject to the time budget constraint in Equation 3.

$$U_{i,t} = u\left(C_{i,t}, A_{i,t}, N_t\right) \tag{4}$$

$$\max_{C} \sum_{t=1}^{\infty} (1 + r)^{-t} u(C_{i,t}, A_{i,t}, N_t) \tag{5}$$

Consistent with the rational addiction model, the addictive stock is assumed equal to the consumption of previous periods (Equation 6) and a quadratic utility function in $C_{i,t}$, $A_{i,t}$, and N_t is employed to derive the empirical demand function (Equation 7).

$$A_{i,t} = C_{i,t-1} \tag{6}$$

$$U_{i,t} = a_1 C_{i,t} + a_2 A_{i,t} + a_3 N_t + \frac{1}{2} u_{cc} C_{i,t}^2 + \frac{1}{2} u_{AA} A_{i,t}^2 + \frac{1}{2} u_{NN} N_t^2 + u_{CA} C_{i,t} A_{i,t} + u_{CN} C_{i,t} N_t + u_{NA} N_t A_{i,t} \tag{7}$$

By substituting Equations 6 and 7 into Equation 5, a utility-maximizing demand function subject to the time constraint can be derived. The resulting demand function of social apps represents current consumption, $C_{i,t}$, as a function of past ($C_{i,t-1}$) and future consumptions ($C_{i,t+1}$), as well as the current extent of network effects, N_t (see Equation 8 and also the Appendix for details):

$$C_{i,t} = \delta_0 + \delta_1 C_{i,t-1} + \delta_2 C_{i,t+1} + \delta_3 N_t \tag{8}$$

where $\delta_1 = -\frac{u_{CA}}{u_{cc} + \frac{u_{AA}}{1+r}} > 0$, $\delta_2 = \frac{b_1}{1+r} > 0$, and $\delta_3 = -\frac{u_{NC}}{u_{cc} + \frac{u_{AA}}{1+r}} > 0$.

Empirical Validation

We provide a brief overview of the empirical background and variables in the data and illustrate our econometric specification models. Furthermore, we discuss how we identified the estimates of the parameters, and present our main and additional results.

Empirical Context and Data Description

We collected a panel dataset consisting of information on app time use for two mobile social apps—a popular social networking app (Facebook) and a social gaming app (Anipang). Facebook is a widely used social networking service, and an important function of its service is building and maintaining relationships. For example, users become Facebook friends and then share their thoughts, opinions, photos, videos, and links to other sites they find interesting. Anipang is a mobile messaging, platform-based social puzzle game. The mobile messaging platform allows a user to find friends who are playing the puzzle game. The basic structure of Anipang is similar to a popular social puzzle game—Candy Crush. Players earn points by matching any three or more animals. After completing a round, players can check their ranking among their friends in a social messaging app for those who play the game. A leader board shows how well players are doing compared to their friends. Each game only lasts for one minute. To continue the game, players need in-app currency—hearts. In addition to waiting several minutes to get more hearts, there are two ways to acquire hearts. First, friends can give each other hearts as gifts and, second, invite friends on the social messaging app list to join the game. These mechanisms encourage users to communicate continuously with other users.

The data is provided by Nielsen KoreanClick, a Korean market research company specializing in online and mobile internet audience measurement. Nielsen KoreanClick maintains a panel of mobile app users, ranging in age from 10 to 70, selected based on stratified sampling in Korea. After individuals agree to be panel members, they download and install a Nielsen Mobile App on their mobile devices. This app collects data on users' consumption of mobile apps for market research purposes. We collected data between October 1, 2012 and October 27, 2013 (56 weeks). The data include 3,983 panel members and incorporate individual-level, weekly information on the users' activities on the aforementioned mobile platform apps throughout the sampling period.

Model Estimation and Identification

To identify the impact that past and future consumption of a particular mobile social app has on the current consumption at an individual user's level, we consider the following econometric model:

$$C_{i,t} = \delta_0 + \delta_1 C_{i,t-1} + \delta_2 C_{i,t+1} + \delta_3 N_t + \mu_i + \lambda_t + u_{it} \quad (9)$$

where the subscript i denotes the i-th user and the subscript t denotes the t-th week. $C_{i,t}$ is the consumption of a mobile social app (measured in seconds) by user i at time t. N_t is the number of active users in the platform during time t. Last, μ_i is a user-specific effect, λ_t is a week-specific effect, and u_{it} is a remainder disturbance.

The rational-addiction model in a mobile social app context poses several endogeneity issues due to the presence of a lead and a lag of the dependent variable, a potential simultaneity between the number of active users and the dependent variable, and a potential serial correlation among the disturbances. In the usual dynamic panel-data models (e.g., Arellano and Bond 1991), only $C_{i,t-1}$ appears and not $C_{i,t+1}$. Hence, we cannot use the usual prescribed instruments by using two period lagged variables—$C_{i,t-2}$. If the $u_{i,t}$s are serially correlated, even higher lagged $C_{i,t}$'s —($C_{i,t-3}$, $C_{i,t-4}$, and so forth)—are not valid instruments for our model. We found that $u_{i,t}$s are not serially correlated in our empirical context, thus we use $C_{i,t-3}$, $C_{i,t-4}$, ..., $C_{i,t-k}$ as instruments. In addition, the Becker and Murphy model suggests that we use both a lagged and a future number of active users—(N_{t-1}, and N_{t+1})—as instruments. However, we found that these instruments are invalid in our empirical context because the number of active users can be correlated with a disturbance, becoming another source of endogeneity. Instead, we used a second period lagged variable—N_{t-2}—as an instrument for their current values for the number of active users. Finally, we propose to add a lagged consumption of active users for a different mobile social app $C'_{i,t-1}$ to the set of instruments in the Becker and Murphy model. The rationale for using these instruments is that the lagged consumption of active users $C'_{i,t-1}$ for another app is likely to be correlated with the lagged consumption $C_{i,t-1}$ for a focal app (i.e., contemporaneous app time use decisions by the same user across multiple apps) but less likely to be correlated with current consumption $C_{i,t}$.

We found that a set of our instruments are valid in our data, and they conform to the requirements necessary for analyzing our panel data. To be specific, we evaluated the Hansen test for over-identification and difference-in-Hansen test of exogeneity of instrument subsets, and found that our instruments are valid at 10% significance level. In addition, we conducted AR tests for autocorrelation of the residuals to ensure that our lagged endogenous variables are appropriate instruments. By construction, the residuals of the differenced Equation (9) should possess serial correlation due to the presence of a lead and a lag of the dependent variable. That is, we should reject Arellano-Bond tests for AR(1) and AR(2). However, if the assumption of serial independence in the original errors is warranted, the differenced residuals should not exhibit significant AR(3) behavior. Our results were consistent with our expectations in that we rejected the Arellano-Bond test for AR(1) and AR(2), respectively, but could not reject it for AR(3) at the 5% significance level. Hence, a set of our instruments are appropriate in our data.

Main Results

Table 1 shows the main model results obtained from the difference generalized method of moments (GMM) estimation. We find that δ_1 and δ_2 are positive and statistically significant in both social apps, indicating that users exhibit rational addictive behaviors when consuming mobile social apps. We find discount rates are also positive and statistically significant in both social apps, demonstrating that, in our context, the reinforcement effect from past consumption is larger than the forward-looking rationality from future consumption. For example, Column 1 shows that the discount rate is positive (0.0823) due to the larger coefficient of past consumption (0.434) than the coefficient of future consumption (0.401).

Similarly, Column 2 shows that the coefficient of past consumption (0.469) is larger in magnitude than the coefficient of future consumption (0.463); thus, the discount rate is positive (0.0130).

We find that δ_3 is positive and statistically significant in both social apps (1.373 and 0.470, respectively), suggesting that as network effects become stronger rational app addicts increase their consumption of social apps. For example, SNS apps allow people to communicate with each other socially: They can exchange messages, and receive automatic notification when their friends update their profiles. Thus, they can regulate their app consumption according to the number of active users on the platform. In another example, leader scoreboards in social game apps help users learn about and predict the usage patterns of their friends more accurately and, subsequently, manage their inter-temporal consumption wisely. Furthermore, players often need to invite their friends to be able to play more. Such incentive structures in social games can also make players regulate their consumption rationally.

Table 1. GMM Estimates of Rational Addiction Model

	C(t)	
	Social Networking Service	Social Game
Variables	*Facebook*	*Anipang*
$C_{i,t-1}$, $\hat{\delta}_1$	0.434***	0.469***
	(0.0267)	(0.00869)
$C_{i,t+1}$, $\hat{\delta}_2$	0.401***	0.463***
	(0.0122)	(0.0198)
N_t, $\hat{\delta}_3$	1.373***	0.470***
	(0.175)	(0.169)
discount rate, r	0.0823	0.0130
Observations	104,975	50,247
Number of users	2,710	1,824

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are in parentheses. For SNS, we use [Ci,t-4,..., Ci,t-41] and [Nt-3,..., Nt-40] and social game app C´i,t-1 as instruments. For social game, we use [Ci,t-4,..., Ci,t-16] and [Nt-3,..., Nt-15] and SNS app C´i,t-1 as instruments.

Additional Analyses Results

We estimated the model using sub-samples to account for the varying degree of rational addiction to mobile social apps by user heterogeneity—age, education, income, and life style. We divide the sample into 2 sub-samples according to age (7-29 and 30-69), 2 sub-samples according to education (high school graduates and university graduates), 2 sub-samples according to income (≤$3,000/month and >$3,000/month), and 4 sub-samples according to life style (conspicuous consumer, rational familist, sociable activist, and trend setter). Conspicuous consumers tend to purchase luxurious products to show off their status (Zukin and Maguire 2004). Rational familists refer to family-oriented consumers who are sensitive to price and quality of a product. Social activists represent consumers who value highly social relationships and care about their own wellbeing. Finally, trend setters establish new trends and exhibit risk-taking behaviors when purchasing products.

Table 2 demonstrates that the results are robust for sub-samples from the SNS and the social game in our data, respectively. Overall, our key coefficient estimates remain qualitatively similar in terms of sign and statistical significance. Panel 1 shows that addictive behavior towards the SNS is more pronounced for younger and more-educated user groups than older and less-educated counterparts. In addition, similar observations were found for higher-income, and conspicuous life style user groups. In terms of the rationality of addictive behaviors, we find that the addictive behaviors towards a SNS are more rational for

Table 2. Sub-Sample Analyses Results

SNS (Panel 1)	Age		Education		Income		Life style			
	7~29	30~69 [a, b]	High School Graduated	University Graduated [a, c]	Below \$3000 [d]	Above \$3000 [a]	Conspicuous Consumer	Rational Familist	Sociable Activist	Trend Setter/ Leader
VARIABLES	C(t)	C(t)	C(t)	C(t)	C(t)	C(t)	C(t)	C(t)	C(t)	C(t)
$C_{i,t-1}$, $\hat{\delta}_1$	0.444***	0.382***	0.357***	0.406***	0.298***	0.359***	0.471***	0.410***	0.385***	0.391***
	(0.0260)	(0.0240)	(0.0321)	(0.0169)	(0.0345)	(0.0271)	(0.0158)	(0.0199)	(0.0548)	(0.0167)
$C_{i,t+1}$, $\hat{\delta}_2$	0.420***	0.328***	0.336***	0.349***	0.269***	0.328***	0.440***	0.391***	0.361***	0.376***
	(0.0113)	(0.0262)	(0.0242)	(0.0181)	(0.0379)	(0.0304)	(0.0142)	(0.0202)	(0.0231)	(0.0204)
N_t, $\hat{\delta}_3$	2.122***	0.384**	1.330***	0.480***	1.079***	0.554**	1.581***	0.866***	2.210***	0.773***
	(0.289)	(0.187)	(0.437)	(0.155)	(0.337)	(0.279)	(0.268)	(0.245)	(0.507)	(0.214)
discount rate, r	0.0571	0.1646	0.0625	0.1633	0.1078	0.0945	0.0705	0.0486	0.0665	0.0399
Observations	50,183	54,792	10,029	61,463	10,500	43,065	23,579	19,621	26,921	28,351
Number of users	1,189	1,521	268	1,649	294	1,206	598	522	701	709

Social Game (Panel 2)	Age		Education		Income		Life style			
	7~29	30~69	High School Graduated	University Graduated	Below \$3000 [e]	Above \$3000	Conspicuous Consumer	Rational Familist	Sociable Activist [f]	Trend Setter/ Leader
VARIABLES	C(t)	C(t)	C(t)	C(t)	C(t)	C(t)	C(t)	C(t)	C(t)	C(t)
$C_{i,t-1}$, $\hat{\delta}_1$	0.447***	0.467***	0.444***	0.458***	0.422***	0.464***	0.417***	0.468***	0.419***	0.442***
	(0.0202)	(0.00916)	(0.0179)	(0.0104)	(0.0224)	(0.00912)	(0.0182)	(0.0143)	(0.0214)	(0.0152)
$C_{i,t+1}$, $\hat{\delta}_2$	0.383***	0.465***	0.437***	0.463***	0.410***	0.466***	0.401***	0.493***	0.442***	0.405***
	(0.0395)	(0.0200)	(0.0183)	(0.0211)	(0.0292)	(0.0207)	(0.0279)	(0.0224)	(0.0227)	(0.0320)
N_t, $\hat{\delta}_3$	0.690***	0.575***	0.922***	0.633***	1.208***	0.673***	1.201***	0.669**	1.244***	1.125***
	(0.254)	(0.202)	(0.336)	(0.216)	(0.315)	(0.235)	(0.305)	(0.331)	(0.364)	(0.414)
discount rate, r	0.1671	0.0043	0.0160	-0.0108	0.0293	-0.0043	0.0399	-0.0507	-0.0520	0.0913
Observations	9,741	40,506	7,609	38,141	9,184	30,721	9,829	13,324	12,154	12,961
Number of users	458	1,366	244	1,343	286	1,059	359	464	454	476

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are in parentheses. Hansen test of over-identification, and difference-in-Hansen tests of exogeneity of the instrument subset test at the 10% level. We reject the Arellano-Bond test for AR(1) and AR(2), but cannot reject it for AR(3) at the 5% significance level. Hence, our set of instruments is appropriate to the data. For SNS, we use [Ci,t-4,…, Ci,t-41] and [Nt-3,…, Nt-40] and social game app C′i,t-1 as instruments. For the social game, we use [Ci,t-4,…, Ci,t-16] and [Nt-3,…, Nt-15] and SNS app C′i,t-1 as instruments.

a Cannot be rejected for AR(3) at the 1% significance level

b Difference-in-Hansen tests of exogeneity of instrument subset test at the 5% level.

c We use [Ci,t-4,…, Ci,t-41] and [Nt-3,…, Nt-40] and the social game app C′i,t-2 as instruments.

d We use [Ci,t-3,…, Ci,t-41] and [Nt-2,…, Nt-40] and the social game app C′i,t-1 as instruments.

e we use [Ci,t-4,…, Ci,t-16] and [Nt-3,…, Nt-15] and SNS app C′i,t-3 as instruments.

f we use [Ci,t-4,…, Ci,t-11] and [Nt-3,…, Nt-10] and SNS app C′i,t-1 as instruments.

younger, higher-income, trend setter/leader life style user groups, respectively, due to their larger coefficients of future consumption than in comparison groups. Further, we find that rational addicts who are in younger, less-educated, and sociable activist life style user groups are more responsive to network effects in the SNS than users in comparison groups.

Panel 2 shows that addictive behaviors towards the social game are more pronounced for older, more-educated, and rational familist life style user groups, respectively. In terms of the rationality of addictive behaviors, we find that addictive behaviors towards the social game are more rational for older, more-educated, higher-income, rational familist life style user groups, respectively. In addition, we find that rational addicts who are in less-educated and social activist life style user groups are more responsive to network effects in the social game. Hence, our sub-sample analysis results demonstrate that the extent of rational addiction to social apps varies considerably across diverse demographic groups and app categories.

Robustness Checks

The test of the myopic model

Because a future consumption term in Equation 9 is derived from the second term of the first-order condition, a significant value for $\hat{\delta}_2$ indicates that each individual carefully considers the impact of current consumption on future utility and future consumption (Becker et al. 1994). However, the myopic model does not incorporate the future utility term in the first-order condition; instead, it only includes past consumption. Therefore, the myopic model is likely to overestimate the impact of past consumption. As expected, Table 3 shows that the myopic model of addiction overestimates the effects of past consumption for both SNS (0.577 > 0.434, *p*-value <0.01) and social games (0.661 > 0.469, *p*-value <0.01).

Table 3. GMM Estimates Using the Myopic Model of Addiction

	C(t)	
	SNS	Social Game
Variables	Facebook	Anipang
$C_{i,t-1}$, $\hat{\delta}_1$	0.577***	0.661***
	(0.0418)	(0.0162)
N_t, $\hat{\delta}_3$	2.259***	1.787***
	(0.322)	(0.224)
Observations	107,737	52,156
Number of users	2,762	1,909

*Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are in parentheses. For SNS, we use [Ci,t-4,..., Ci,t-41] and [Nt-3,..., Nt-40] and the social game app C'i,t-1 as instruments. For the social game, we use [Ci,t-3,..., Ci,t-26] and [Nt-2,..., Nt-25] and SNS app C'i,t-1 as instruments.*

Falsification tests

Auld and Grootendorst (2004) demonstrated that the rational addiction model tends to yield spurious evidence in favor of the rational addiction hypothesis even for non-addictive goods, such as milk, eggs, oranges, and apples, especially when aggregate data are used. Note that we do not use aggregate data, but individual user-level data to estimate the rational addiction model in this study. Nevertheless, to address the issue of the potential spurious relations, we conducted falsification tests. To disprove alternative explanations such as, for example, mobile apps are generally addictive. Specifically, we considered popular smartphone "utility apps" that are regarded as non-socially addictive, such as the camera, photo gallery, and address book. If these apps are not germane to rational addiction theory, our results in favor of the rational addiction hypothesis will be further strengthened. Table 4 shows the results of the falsification tests. No significant impact of future or past consumption is evident at the 95% confidence level. Apps, such as the camera, photo gallery, and address book, are neither addictive, nor rational. Consequently, we can successfully reject the falsification argument and assert the rigor of our rational addiction framework in this context.

Table 4. GMM Estimates of the Rational Addiction Model using Non-addictive Apps

	C(t)		
Variables	Camera	Gallery	Address Book
$C_{i,t-1}$, $\hat{\delta}_1$	0.174*	-0.0314	0.212
	(0.105)	(0.185)	(0.185)
$C_{i,t+1}$, $\hat{\delta}_2$	0.0241	-0.0301	0.0961
	(0.0772)	(0.370)	(0.313)
N_t, $\hat{\delta}_3$	1.676***	-1.243	-0.143
	(0.196)	(0.945)	(0.366)
Observations	9,923	9,620	12,139
Number of users	2,426	2,311	2,704

*Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are in parentheses. We collected data between March 5, 2012 and April 29, 2012 (8 weeks) for the falsification test. For the camera, we use [Ci,t-3,..., Ci,t-8] and [Nt-2,..., Nt-7] and SNS app C′i,t-1 as instruments. For the gallery, we use [Ci,t-4,..., Ci,t-8] and [N,t-3,..., Nt-7] and SNS app C′i,t-1 as instruments. For the address book, we use [Ci,t-3,..., Ci,t-8] and [Nt-2,..., Nt-7] and SNS app C′i,t-1 as instruments.*

Forward-looking behavior tests

Most empirical research on rational addiction relies on the assumption that individuals can forecast future prices accurately. This assumption has been criticized because very few price increases are announced a year in advance (Gruber and Koszegi 2001). To redress this oversight, Gruber and Koszegi (2001) suggested an alternative mechanism for testing forward-looking behaviors using monthly cigarette consumption data. They find that tax increases that are yet to be implemented lead to decreased consumption of cigarettes, which is strong evidence of forward-looking behaviors. In keeping with Gruber and Koszegi's (2001) approach, we test whether users of social apps exhibit forward-looking behaviors. We consider the following model for a specific event for each social app:

$$C_{i,t} = \alpha + \beta * EVENT_t + \gamma * PreAnnounce_t + \delta * I_i + \phi * T_t + \epsilon \quad (10)$$

where $C_{i,t}$ is the amount of social app consumption by individual i at time t; $EVENT_t$ is the dummy variable indicating that the event is actually launched at time t; $PreAnnounce_t$ is the dummy variable indicating that the event is pre-announced at time t; and I_i and T_t are full sets of individual and week dummies, respectively. In this scenario, when an event is pre-announced but not yet implemented, $PreAnnounce_t$ has a value of 1 and $EVENT_t$ has a value of 0. When an event is actually launched, both $EVENT_t$ and $PreAnnounce_t$ have a value of 1. For SNS, we use the launch of "Facebook Home," which provides new features for Facebook app, as an event for Facebook. Similarly, for social game, "Anipang for Sacheonseong," which is the upgrade of Anipang, is considered an external event for Anipang.

Table 5 presents the results of Gruber and Koszegi's (2001) test for forward-looking behavior using these two events. The coefficient of $PreAnnounce_t$ is positive and significant for Facebook. Facebook users were found to increase their weekly consumption substantially (i.e., by as much as 651 seconds) when the dominant SNS company pre-announced the launch of its Facebook Home app. This finding provides strong evidence of forward-looking behaviors, at least for this population. In the case of Anipang, the coefficient of $PreAnnounce_t$ is negative and significant. This shows that Anipang users have already reduced their weekly consumption significantly (i.e., as much as by 12,291 seconds) when the top social game provider pre-announced its future launch of a new replacing version. One plausible explanation is that Anipang users forecast that the network effect of Anipang would decrease when the new version was launched. These results confirm the forward-looking behavior of social app users, which is further strong evidence in favor of the rational addiction model.

Table 5. Effect of Pre-announcement on App Consumption – Fixed Effects Model

	C(t)	
	SNS[a]	Social Game
VARIABLES	Facebook	Anipang
$EVENT_t, \hat{\beta}$	2,717***	-605.4
	-167.4	-429.1
$PreAnnounce_t, \hat{\gamma}$	651.0***	-12,291***
	-159.6	-299.9
Observations	113,532	56,338
Number of users	2,986	2,182

*Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are in parentheses. A complete set of time dummy variables is included to account for fixed time effects. Facebook Home was launched on 17 April 2013 and pre-announced on 5 April 2013 in Korea. Anipang for Sacheonseong was launched on 19 February 2013 and pre-announced on 10 January 2013.*

Implications

Implications for Research

The rational addiction framework has been applied extensively to investigate addictive behaviors in diverse contexts. Nevertheless, the corpus of its empirical validation has been largely limited to physical commodities, such as alcohol, cigarettes, and drugs, which cost money to consume. The current study, on the other hand, examined whether this theory can serve as a powerful theoretical framework to better understand addictions to interpersonal exchanges and social commodities (e.g., SNS and social games).

To apply the rational addiction model into this context, we have amended and refined the model in several ways. Based on social exchange theory (Homans 1958), which offers a solid conceptual foundation for analyzing the linkage between social and economic actions, our model construes interpersonal dynamics as a form of economic exchange based on a strategic, rational and cost-reward calculations. Social platforms, such as Facebook, can be thought of as social markets where users constantly "trade" by making or breaking relationships, arriving at relational choices that maximize utility. Furthermore, just as price regulates the inter-temporal consumption of physical commodities, a utility-level network effect (e.g., the number of active users available for social relationships) governs how users consume social apps across different time periods. The amount of utility derived from consuming these apps is significantly dependent on the extent of network effects. For example, the degree of utility gained from posting a photo on Facebook varies depending on how many people in social circles actually view and make comments on it in replies, Facebook Likes or other personal correspondence. Users who voluntarily join and patronize open platforms are likely to desire strongly to maintain social bonds and attachment in their quests to amplify their social presence and visibility. As a consequence, their actions on platforms (e.g., consuming apps) are greatly influenced by how strong network effects become. These theoretical alterations and enrichments can offer fresh vantage points from which to study addictive behaviors involving non-physical, monetary-free commodities.

This study provides a finer level of granularity on the emerging phenomenon of rational addiction to social apps through a nuanced, empirical scrutiny of how individual user's characteristics (e.g., age and life styles) and education and income levels influence these addictive behaviors. While previous studies into patterns of rational addiction have offered holistic insights based on analyzing aggregated consumption data with no reference to individual characteristics, our individualized level and comprehensive panel data enabled us to observe notable differences across diverse user groups. Data on app consumption was available in precise, accurate formats (i.e., seconds) and over relatively long time horizons (i.e., one year), which were suitable for detecting inter-temporal demand structures. In fact, while most studies on internet addiction rely on small-scale survey instruments –prone to subjective biases– to gauge consumption intensity, the present study reflects actual consumption measured down to its smallest details.

Furthermore, a rigorous methodology was employed to identify inter-temporal consumption patterns precisely. As an empirical strategy, we chose difference GMM, which is often considered a more rigorous and complete instrument than regular multi-stage regressions (e.g., 2SLS) adopted by Becker et al. (1994) because of its conservative assumptions on data distribution and additional orthogonality conditions.

Implications for Practice and Policy-Making

Regulatory agencies and lawmakers have become increasingly concerned with the addictive qualities of SNS and platform games, treating it as a growing social pandemic affecting many lives, especially young, "vulnerable" people. In fact, these social apps may have already become pastimes for adolescents with narcissistic tendencies who, many experts believe, are likely to fall prey to adverse consequences, including mental escapism, procrastination, preoccupation, poor time-management, or even suicide (Kuss and Griffiths, 2011).

To address this issue, government agencies have taken preventative steps, but only in a regulatory and coercive way. For example, since 2010, Korea's Ministry of Culture, Sports, and Tourism has implemented a new controversial law, dubbed the "Cinderella Law," that forbids game providers from offering services to teenagers under 16, between midnight and 6 a.m. Similarly, the Vietnamese government has adopted curfews that automatically block access to online games at night and early in the morning. China's Ministry of Culture has issued a mandate forcing online game producers to exclude addictive features in online games, such as gambling and pornography. In addition, underage players are not allowed to use online game currencies created by game developers. In Europe and the United States, all online games must be strictly rated by regulatory boards (e.g., PEGI in Europe and ESRB in the US.). These rating schemes are obviously intended to regulate addictions to pervasive game content, especially among adolescents. Apart from regulation, concerned parents use punishments or often resort to clinics or specialized experts to cure their teenagers' addiction to SNS or games.

Although only temporarily successful, in a limited form, in curbing addiction, the effectiveness of these legal and policy measures has been extensively questioned, due to many obvious legal loopholes and dodges inherent in these supervisory directives and guidelines. In fact, the U.S. Supreme Court has recently overturned California state law banning the sale of certain video game products to minors because the rule at stake violates free-speech rights.[2] In Korea, the "Cinderella Law" of 2011 has been found ineffective since teenagers use their parents' logins to play games during the lockdown period.[3]

Our findings suggest that individuals' internal self-regulation, based on rationality may be the best form of regulation to effectively cope with "app-dictions." According to the data analyzed, although variations exist across diverse demographic groups, users of social apps embedded in smartphones are indeed "smart" and rational in that they manage their current consumption to maximize their utility. Network effects play an important role in the distribution of users' app consumption across temporal spaces. To further enhance the rationality of smartphone consumers and prevent them from crossing the lines into uncontrollable addiction, developers of social apps should design additional usability features that aid users to easily identify the extent of network effects. Currently, financial markets offer investors the current state of market activity on a real-time basis (e.g., number of trades), which helps them to project ahead of time their optimal trade timing and strategies. Users of social apps may benefit from similar signaling add-ons to plan the distribution of their consumption of social apps and to manage this usage wisely to maximize utility. For example, some social games, such as Anipang in Korea, currently publish a

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[2] http://www.washingtonpost.com/politics/supreme-court-strikes-calif-law-banning-sale-of-violent-video-games-to-minors/2011/06/26/AGwtxenH_story.html

[3] http://www.techspot.com/news/46867-korea-bans-kids-from-late-night-gaming-they-dont-listen.html

leader scoreboard, which lists who has the highest points among a user's circle of friends connected through a platform. To promote more competition and social exchanges, the scoreboard is constantly updated for a player's SNS contacts. In addition to scoreboards, developers should also disseminate usage metrics in the open, which inform players how intensively their contacts are participating. Users of social apps exhibit different consumption patterns when new rules are enacted (Claussen et al., 2013). With usage information posts, users can learn about and predict the consumption patterns of their friends more accurately and, subsequently, manage their own inter-temporal consumption wisely to gain optimal utility.

Just as pre-announcements of future price increases reduce current cigarette smoking, announcements of significant version upgrades or feature enhancements far ahead of time may induce users of social apps to be forward-looking and distribute their time resources efficiently, arriving at rational consumption choices. Upon a pre-announcement, rational app users pursue strategic cost-reward calculations to determine the discounted utility of the new features. Taken together, user rationality, visible signals of user flow, and pre-announcements of app enhancements can directly help users keep their social-app impulses under full control.

Limitations and Future Research

Several limitations of this study along with directions for future research need to be noted. Our findings are derived based primarily on an analysis of the two most representative social apps, and, therefore, we make no attempts to generalize our results to other social apps. Furthermore, major SNS sites, such as Facebook, Twitter, and Linkedin, differ substantially in terms of value propositions, business scope, and target customers, as well as available socialization features and functionalities. These structural heterogeneities inherent to diverse SNS sites may influence users' future orientation and app consumption patterns. Future research should be directed toward determining if these differences influence the findings reported in this study.

Another caveat is related to the model specification. Consistent with Becker et al. (1994), our model focused on parsimony and substantive importance at the expense of predictive power. In consequence, we may have omitted several control variables in our specification. For example, in addition to network effects, other factors (e.g., platform type, price, reward systems) may affect social apps consumption. Although our model competently explains a large portion of variances in observed consumption regularities, we acknowledge the model's parsimony as a limitation. Future studies could expand the menu of variables to enhance the model's richness and comprehensiveness.

Finally, the mobile paradigm is rapidly altering the dynamics of users' socialization process and communication protocols. Although the empirical scrutiny of one-year long, weekly panel data may suffice to understand users' behaviors, the unprecedented pace of the mobile revolution and the perpetual flux in the demand structures for technology suggest that nothing is stable and permanent, including the way we rationalize and justify our online behaviors. Therefore, a more nuanced and systematical inquiry is clearly needed into the continuous interplay between human rationality and technology evolution.

Conclusion

The pervasive penetration of mobile devices has made it harder than ever to resist social exchanges through apps. On the one hand, mobile platforms and apps have been touted as a boon for social connectivity within or across one's interpersonal boundaries. On the other hand, the excessive use of and compulsive addiction to social apps has become a major social problem. The benefits from social apps appear to be overshadowed by addiction challenges.

This study extended the rational addiction framework of Becker and Murphy (1988) to investigate whether the fundamental economic principle of utility-maximization and rational behaviors directs the consumption patterns of highly addictive social apps, such as SNS and social games. The findings based on massive panel data on weekly app consumption reveal full support for the rational addiction paradigm. To maximize the discount utility of social apps, users of these apps are sensitive to network effects when they build their inter-temporal consumption structures. Users of these apps are rational in that they wisely manage their time resources and effectively adjust consumption over time horizons to derive optimal utility. The principle of "invisible hand," which lets individuals seek out their own best interest, appears to be an effective long-term therapy for addiction to social exchanges through mobile devices.

Nevertheless, our results cannot be interpreted as evidence that users' "app-diction" problems are unimportant or easy to endure. In addition, we cannot claim that rationality explains all salient behaviors related to "app-dictions." Following Becker and Murphy's (1988) lead, we note that the rational addiction perspective offers a unique prism through which to understand human behaviors. Researchers must be mindful about the dynamic interplay between technological innovation and human behaviors since technology seems to advance beyond our rational capability.

Appendix

Assume a representative individual *i* with the instantaneous utility function (Equation (2)):

$$U_{I,t} = u[C_{I,t}, A_{I,t}, Y_{I,t}, N_t] \tag{A1}$$

where $C_{i,t}$ is the amount of social app consumption of individual i at time t, and $Y_{i,t}$ refers to the time spent on any other activities of i at time t. $A_{i,t}$ indicates the amount of addictive stock of i at time t. Finally, N_t reflects the extent of network effects at time t. Further, we assume that the utility function is concave with negative second derivatives, and consumption of addictive goods does not affect the marginal utility of non-addictive good consumption.

$$U_{CC}, U_{AA}, U_{YY} < 0, U_{CY}, U_{AY} = 0 \tag{A2}$$

As pointed out earlier, there are three characteristics of addictive consumptions—withdrawal, tolerance, and reinforcement— that are represented in mathematical forms below.

$$U_C > 0, U_A < 0, U_{CA} > 0 \tag{A3}$$

In addition, we assume that network effects L_t positively affect the marginal utility of app consumption, and addictive stock doesn't affect the marginal effect of network effects on utility.

$$U_{NC} > 0, U_{NA} = 0 \tag{A4}$$

Because time is finite, each individual should be allotted his (her) time for playing an addictive application within his (her) time budget W (which we call *time constraint* in the text).

$$C_{i,t} + Y_{i,t} = W \tag{A5}$$

where W is the length of time period t. Due to this time constraint, $Y_{i,t}$ can be expressed as a function of $C_{i,t}$. As a result, we can rewrite the utility function as a function of $C_{i,t}$, $A_{i,t}$, and N_t (Equation (4)).

$$U_{i,t} = u[C_{i,t}, A_{i,t}, N_t] \tag{A6}$$

Then, the individual i's problem is to choose $C_{i,t}$ to maximize the sum of lifetime utility discounted at the rate r.

$$\max_C \sum_{t=1}^{\infty} (1+r)^{-t} u[C_{i,t}, A_{i,t}, N_t] \tag{A7}$$

where r is a constant discount rate. In addition, following prior work on rational addiction (Becker et al. 1994), we assume that addictive stock is equal to the consumption of previous period (Equation (6)) and a quadratic functional form for the utility function in $C_{i,t}$, $A_{i,t}$, and N_t (Equation (7)) to obtain the following empirical demand function.

$$A_{i,t} = C_{i,t-1} \tag{A8}$$

$$\begin{gathered} U_{i,t} = a_1 C_{i,t} + a_2 A_{i,t} + a_3 N_t + \frac{1}{2} u_{cc} C_{i,t}^2 + \frac{1}{2} u_{AA} A_{i,t}^2 + \frac{1}{2} u_{NN} N_t \\ + u_{CA} C_{i,t} A_{i,t} + u_{CN} C_{i,t} N_t + u_{NA} N_t A_{i,t} \end{gathered} \tag{A9}$$

Finally, substitute these equations into Equation (A7), then maximize Equation (A7) to obtain the empirical demand function of an addictive application $C_{i,t}$:

$$C_{i,t} = b_0 + b_1 C_{i,t-1} + b_2 C_{i,t+1} + b_3 N_t \tag{A10}$$

where $b_0 = -\frac{a_1 + \frac{a_2}{1+r}}{u_{CC} + \frac{u_{AA}}{1+r}}$, $b_1 = -\frac{u_{CA}}{u_{cc} + \frac{u_{AA}}{1+r}} > 0$, $b_2 = \frac{\delta_1}{1+r} > 0$, and $b_3 = -\frac{u_{NC}}{u_{cc} + \frac{u_{AA}}{1+r}} > 0$.

Based on Equations (A2) and (A3), positive value of b_1 indicates that a good is addictive, and positive value of b_2 indicates that an addiction is a result of rational forward-looking behavior.

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