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An Empirical Analysis of User Content Generation and Usage Behavior on the Mobile Internet

Anindya Ghose, Sang Pil Han
Stern School of Business, New York University, New York, New York 10012
{aghose@stern.nyu.edu, shan2@stern.nyu.edu}

We quantify how user mobile Internet usage relates to unique characteristics of the mobile Internet. In particular, we focus on examining how the mobile-phone-based content generation behavior of users relates to content usage behavior. The key objective is to analyze whether there is a positive or negative interdependence between the two activities. We use a unique panel data set that consists of individual-level mobile Internet usage data that encompass individual multimedia content generation and usage behavior. We combine this knowledge with data on user calling patterns, such as duration, frequency, and locations from where calls are placed, to construct their social network and to compute their geographical mobility. We build an individual-level simultaneous equation panel data model that controls for the different sources of endogeneity of the social network. We find that there is a negative and statistically significant temporal interdependence between content generation and usage. This finding implies that an increase in content usage in the previous period has a negative impact on content generation in the current period and vice versa. The marginal effect of this interdependence is stronger on content usage (up to 8.7%) than on content generation (up to 4.3%). The extent of geographical mobility of users has a positive effect on their mobile Internet activities. Users more frequently engage in content usage compared to content generation when they are traveling. In addition, the variance of user mobility has a stronger impact on their mobile Internet activities than does the mean. We also find that the social network has a strong positive effect on user behavior in the mobile Internet. These analyses unpack the mechanisms that stimulate user behavior on the mobile Internet. Implications for shaping user mobile Internet usage behavior are discussed.

Key words: mobile Internet; social networks; content generation; content usage; interdependence; geographical mobility; identification
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1. Introduction

Rapid advances in mobile Internet technologies now allow consumers to interact, create, and share content based on physical location. Such ubiquitous access to the mobile Internet also provides companies with new marketing opportunities. Newer marketing strategies need to be implemented in such an environment. This change requires a deeper understanding of user behavior on the mobile Internet. However, little is known as yet about how user mobile Internet usage relates to certain unique characteristics of the mobile Internet space. We examine that topic in this paper.

There are a few aspects of mobile Internet that distinguish it from other types of Internet access via devices like personal computers (PCs) or laptops. First, in many countries, users incur explicit expenses (for example, by paying usage-based data transmission charges) during their mobile Internet usage. These are based on the number of bytes uploaded or downloaded.[1] This feature is in contrast to using PCs where the Internet can be accessed using a fixed connection or a WiFi connection without incurring any monetary costs based on usage. Second, users can access the Internet via mobile devices anytime and anywhere, subject to signal reception. In contrast, PCs render stricter limitations on geographical mobility and access, typically constraining it to office or home or locations where there is access in place. Third, screen sizes are smaller on mobile devices compared to PCs, thereby rendering higher search costs for mobile devices.

Usage-based data pricing and ubiquitous access can lead to a situation where a diverse set of factors, such as resource constraints (time or money), geographical mobility, and social networks will influence

[1] The fee structure in our empirical context is usage-based pricing. Subscribers are charged on a per-byte basis for data traffic they generate through content uploading and/or downloading.

user mobile Internet behavior. Advanced mobile technologies, such as third-generation (3G) services, allow people to build and maintain their social relationships through cocreation and joint usage of content. Hence, people must decide how much content to generate and how much content to use. For example, in a given week, the higher the amount of time or money spent by a user to use content (e.g., downloading music, games, productivity apps, etc.), the lower the amount of time or money left for that user to generate content (e.g., uploading photos, reviews, videos, etc.).[2] In contrast to this scenario, higher levels of content consumption by users can motivate higher levels of content contribution. This can occur when users begin to feel they are an integral part of the communities established on these sites and hence engage in reciprocal behavior.

Either way, content generation and usage may not be independent decision-making processes at all. Whether the former negative interdependence is stronger than the latter positive one is an empirical question we aim to examine here. Keeping these issues in mind then, in this paper we focus on examining how user content generation behavior relates to user content usage behavior over time. Is there a positive or negative interdependence between these two activities? What other factors, if any, affect user content generation and usage activities on the mobile Internet?

We examine these questions by applying a unique data set that consists of mobile data across a panel of users, encompassing both their content generation and usage behavior. That data set consists of 2.34 million individual-level mobile data records across 180,000 users. We also use data on voice calls made by the same users, which allows us to draw their social networks. We include detailed user demographics (age and gender) and geographical data, including the location from where a call is placed. This location information helps us impute the extent of user geographical mobility by mapping the different places they visit. We then construct two different measures of mobility to map both the mean and the variance of user travel patterns at both local and national levels, thereby giving us four different mobility metrics. Our analysis utilizes simultaneous equation models as well as generalized method of moments (GMM)-based dynamic panel models and several other models (both linear and nonlinear) for robustness checks.

There are three key sets of results. First, we find that there exists a negative temporal interdependence between content generation and usage behavior on the mobile Internet. This finding implies that the resource constraint (e.g., time and money constraint) is binding at least for some users. The effect is asymmetric, such that the negative impact of previous period content generation on current period content usage is much higher than the opposite. Second, the extent of geographical mobility of users positively affects their mobile Internet activities. Users more frequently engage in content downloading compared to content uploading when they are traveling. In addition, variance of user travel patterns has a stronger impact on mobile Internet activities than does the mean. Third, mobile Internet usage behavior of social network neighbors positively influences an individual user's mobile Internet usage behavior.

Our paper aims to makes a few key contributions to the literature. We are the first to simultaneously model and estimate the drivers of user content generation and usage behavior in the mobile Internet space and the nature of the interdependence between these processes. We build and estimate an individual-level simultaneous equation panel data model using three-stage least-squares (3SLS) estimation. We further demonstrate the robustness of this analysis by conducting GMM-based dynamic panel data analyses and other analyses that include models with a random coefficient for a constant term, count data models, content share models, content size models, and models using different specifications of social network variables. Our paper is among the first in the emerging literature to research the dual role (content creation and consumption) played by users in social media settings. Second, the unique nature of our data allows us to map how the mean and the variance of user geographical mobility at both local and national levels actually drive their content generation and usage behavior. We are the first to provide novel insights into how location plays a role in user behavior on the mobile Internet. This paper can thus serve as the foundation for future research on both the economic and the social impact of the mobile Internet. Third, our model unpacks the causal mechanisms that stimulate user behavior on the mobile Internet in the presence of social networks. Mobile-phone-based data generate unique kinds of social networks because of the inherent dynamics present in communication and travel patterns of users; these patterns make these social networks distinct from various other kinds of social networks already studied in the existing literature. Our model distinguishes and controls for the different sources of endogeneity in this mobile setting, such as endogenous group formation, correlated unobservables, and simultaneity. Hence, another key contribution of this paper is to provide a precise empirical framework for resolving identification issues in social networks now and in the future.

[2] We use the terms "content generation" and "content uploading" interchangeably in this paper. Similarly, we use the terms "content usage" and "content downloading" interchangeably as well.

2. Literature Review

Our paper is related to a small group of literature that discusses the interplay between user Internet usages, mobility, and social networks.

First, we relate the dynamic interdependence between user content generation and usage behaviors to two relevant streams of literature—economic behavior under resource constraints and reciprocity stemming from social exchange theory. Researchers have long recognized that time acts as a constraint (Becker 1965, Jacoby et al. 1976). In online settings, users need to allocate their resources between content generation and content usage activities because users can take on the dual role of creators as well as consumers (Ghose and Han 2009, Trusov et al. 2010, Albuquerque et al. 2010, Ghose et al. 2011). On the mobile Internet, not only do users need to invest time, but also incur explicit transmission charges to generate and use content in certain countries. This suggests that there is a negative temporal interdependence between content generation and content usage activities over time. In contrast, the prior work in the online content sharing literature (Xia et al. 2011) draws on reciprocity stemming from social exchange theory (Homans 1958) and suggests that the more a user benefits from the contributions of other users, the more that user is willing to create and share content (Xia et al. 2011). This behavior suggests that there is a positive temporal interdependence between content generation and content usage activities over time. Because the extent of reciprocal interactions in the mobile Internet setting is largely unknown, the overall extent and directional interdependence of the temporal effect between content generation and usage remains still an intriguing empirical question.

Second, we examine the impact of the extent of the geographical mobility of a user on the mobile Internet activity of that same user. There are two possible scenarios. The first is that the more a user travels, the more travel-related discretionary time the user is likely to have. Shim et al. (2008) analyze mobile usage patterns where people view television programs on their phone screens. They find that the highest usage occurs between 6 A.M. and 9 A.M. in the morning and between 6 P.M. and 8 P.M. in the evening, which is consistent with the notion that most users view content using mobile phones while commuting from home to work and back. O'Hara et al. (2007) find that people use mobile video content to pass time, manage solitude, and disengage from others. In contrast, it is possible that mobile Internet usage can occur at geographically fixed places as well. Hence, the overall extent of the impact of a user's geographical mobility on that same user's propensity to engage in mobile Internet activity remains still an empirical question of interest.

Third, users can be influenced by others with whom they communicate. There is some evidence of this influence in the business world, such as adoption of new services and products (Hill et al. 2006, Tucker 2008, Aral et al. 2009, Nair et al. 2010, Nam et al. 2010, Iyengar et al. 2011, Oestricher-Singer and Sundararajan 2010), switching from an existing service provider (Dasgupta et al. 2008), and diffusion of user-generated content in online space (Susarla et al. 2011). Therefore, a user's mobile Internet activities can be influenced by the mobile Internet activity of their peers.

3. Data Description and Basic Patterns

In this section, we provide a short overview of the mobile Internet service found in our data, describe the data that we obtained from a large telecommunications service company in South Korea, and finally provide the basic patterns seen in those data that motivated our subsequent model development.

3.1. Data Source

Our sample consists of 2.34 million mobile data records from 180,000 3G mobile users who used the services of a particular company between March 15, 2008, and June 15, 2008. The South Korea 3G mobile market had over 10 million subscribers in June 2008. 3G mobile services enable users to upload and download their content faster than conventional mobile services. These services are more commonly available on larger-screen handsets (i.e., smart phones).

There are two broad categories of websites that users can access through their mobile phones as demonstrated in our data. The first category is regular social networking and community websites. Examples of such websites in our data include Cyworld and Facebook. The second category of websites includes portal sites specifically created by mobile phone service carriers. Examples include Nate Portal and KTF Portal, the Asian equivalents of U.S. sites like Vodafone live and T-Mobile's Web "n" Walk. Content on these sites can be accessed via a mobile phone by users who subscribe to the services of their mobile operator. Like social networking sites, these mobile portals are community-oriented sites that allow users to download and upload (to share with others) multimedia content like photos, music, videos, apps, etc. The transmission charges are the same in our data, irrespective of whether users upload or download content and whether users access social networking community sites or mobile portal sites. We measure the level of user mobile Internet activities based on the frequency of content generation and usage.[3]

[3] In our robustness checks, we also use the amount of bytes transmitted via user content uploading and downloading as an alternative measure for the level of user mobile Internet activity.

Table 1 Summary Statistics

Variable	Observations	Mean	Std. dev.
Weekly, user-specific content activity data			
Number of Mobile Internet Session Activation	2,340,000	4.0	41.38
Number of Uploading	610,809	0.27	3.54
Number of Downloading	610,809	22.57	86.80
Weekly, user-specific call data			
Number of Calls Made	900,000	11.88	16.32
Call Duration (hours)	900,000	2.61	5.68
Weekly, user-specific geographical data			
Mean Local Mobility	900,000	14.04	13.18
Mean National Mobility	900,000	5.91	2.88
Local Mobility Dispersion	900,000	2.85	3.83
National Mobility Dispersion	900,000	0.70	0.80
User characteristics			
Age	180,000	30.13	5.91
Sex (1 = male, 0 = female)	180,000	0.53	0.50
Handset Age (months)	180,000	9.63	3.97

Note. We observe content generation and usage data only when a user starts mobile Internet sessions; thus the number of uploading and the number of downloading are lower than the number of sessions.

3.2. Variable Description

Our mobile Internet data include individual-level information on user content generation and usage activities over time. The temporal unit in our analysis is a "week." Technically, a unique mobile Internet session starts when a user pushes a button on a keypad or clicks an icon on a touchpad, and it ends when the user deactivates that mobile Internet session. Only when a user initiates a mobile Internet session can the user either download content or upload content, or do both. An activity involving more than zero bytes of data transmission is an event. One mobile Internet session usually consists of multiple events. As shown in Table 1, a user content usage occurs far more frequently than user content generation.

We construct four metrics with respect to user geographical mobility: (1) mean local mobility, (2) mean national mobility, (3) local mobility dispersion, and (4) national mobility dispersion. The first two metrics capture the *mean* of user travel patterns, and the last two metrics capture the *variance* of their travel patterns. Users often engage in mobile content activities when they are outdoors and when they are traveling. In such circumstances, the geographical locations from where their call is placed will change over time. We refer to the number of unique locations from where calls are placed by a user as a measure of their *mean mobility*. In a sense, this variable captures the *mean* travel pattern of a user. There are two different levels of granularity regarding the extent of mobility of each user, namely, local and national. Both variables measure the number of distinct locations from where a user makes calls at the zip code level and the province/state level, respectively. Because the total number of unique zip codes is much higher than the number of provinces or states gathered in our data (i.e., 30,116 versus 16), the number of distinct zip-code-level locations thus corresponds to a user's *mean local mobility*, whereas the number of distinct province-level locations corresponds to a user's *mean national mobility*.

The concept of *mobility dispersion* measures the extent of geographical deviation from one's commonly visited places (i.e., home and office), and in that sense, the term captures the *variance* of a user's travel patterns. A user's mobility dispersion refers to a fraction of uncommonly visited places compared to the total number of places visited during a given week.[4] The notion behind the use of this variable is that deviations from routine patterns of travel might indicate a trip to a location that is different from a user's regular travel. Such unique travel occasions could lead to a higher propensity (compared to the mean) to upload and download to share travel experiences (i.e., sharing photos taken at tourist attractions). As before, we have both local and national levels of granularity to apply for the mobility dispersion metric.

We also gather data on voice calls made by the same users, which enables us to draw their social networks. Voice call records contain a caller's telephone number and the receiver's telephone number, call duration, and frequency. Our voice call data can help us identify an exogenously defined network of social neighbors because we do not use mobile Internet activity data per se to construct the network.

[4] We define *commonly* visited places as those places where a user visits at least once every week. Hence, we define an *uncommonly* visited place as one a user does not visit every week.

Social network variables in our sample correspond to the level of content activity (i.e., frequencies of content uploads and downloads) of network neighbors for each user in the sample.

We use social network data to capture a source of learning based on word of mouth as identified in prior work (for example, Ghose and Han 2009). Mobile-phone-based data generate unique kinds of social networks because of the inherent dynamics of communication and mobility patterns, which make them distinct from other kinds of social networks studied in the existing literature. There are four possible types of user behavior that can accrue from the interplay of mobility and calling patterns—(a) low mobility and infrequent calls to people at travel destinations, (b) high mobility and infrequent calls to people at travel destinations, (c) low mobility and frequent calls to people at travel destinations, and (d) high mobility and frequent calls to people at travel destinations. The inclusion of social network and mobility variables in the model helps us capture more precisely all four types of user behavior.

Finally, we have data on demographics like age, gender, and product characteristics such as handset age. The summary statistics of these key variables used are provided in Table 1.

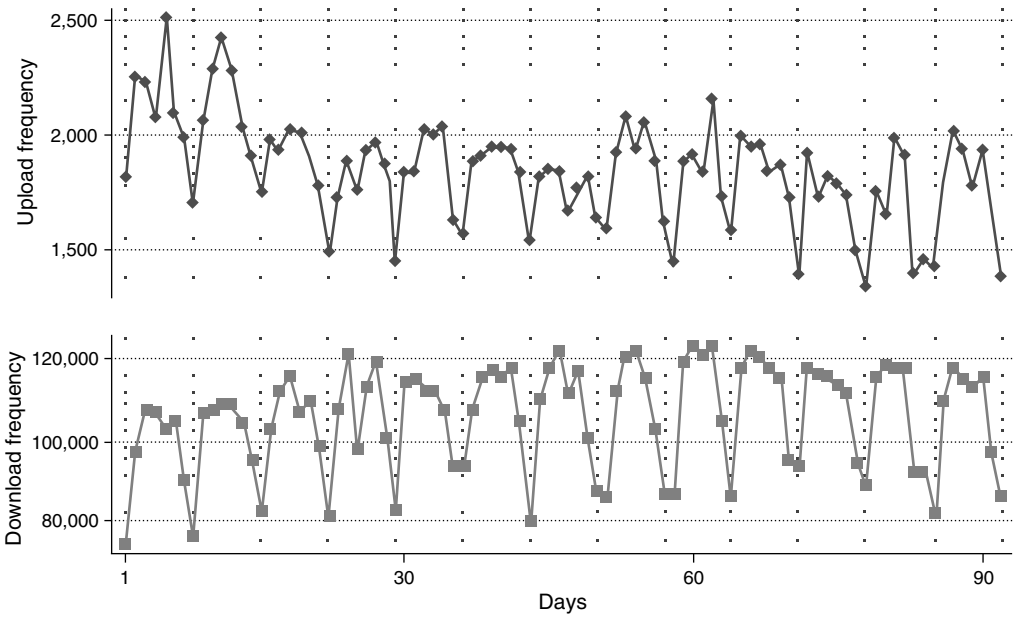
3.3. Basic Patterns in the Data

We now discuss stylized patterns found in the data that motivate our subsequent econometric model development. First, we describe the interdependence in content generation and content usage at both the aggregate level and the individual level, which are linked to the key objective of this paper. Second, we describe the relationship between mobile Internet session initiation and content downloading and uploading activities. We also discuss specific evidence supporting the need for incorporating various econometric issues that we address in our model.

3.3.1. Interdependence Between Content Generation and Content Usage. To have a better sense for how content generation and usage patterns are associated with each other, we plot the total number of content uploads and content downloads in our sample over 13 weeks (i.e., 91 days). Figure 1 shows a strong weekly cycle for both content uploads and downloads; that is, mobile Internet activity during weekdays is generally higher than during weekends except on national holidays. This finding is consistent with prior work that shows that consumers surf on the Internet more during weekdays and regular working hours than they do during weekends and off-peak hours (Baye et al. 2009). The plotting of content activities also demonstrates similar patterns between the dual time series, implying that content generation and usage are indeed associated at the aggregate level.

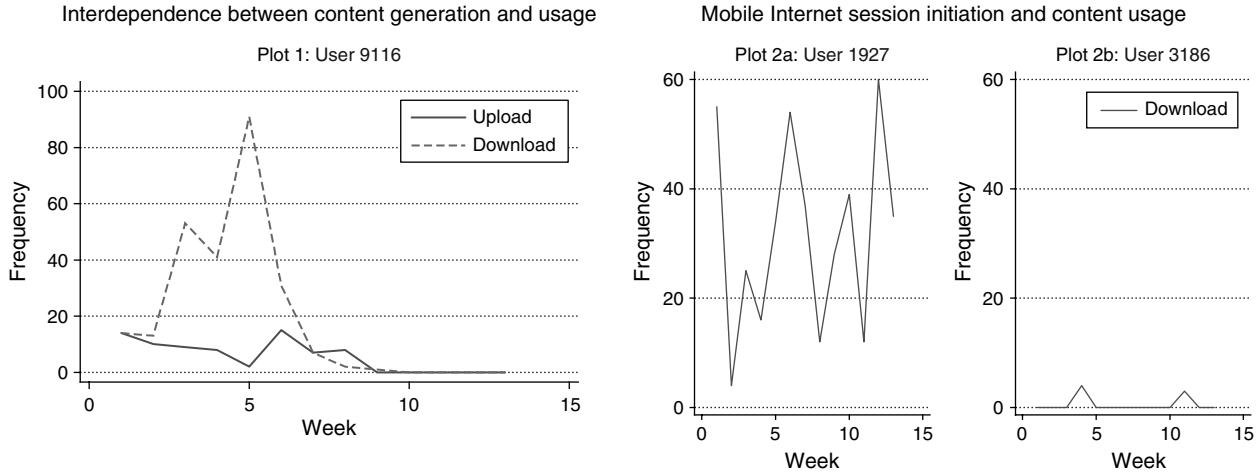
Furthermore, we plot individual-level mobile Internet use patterns of some of the users in our data. Plot 1 in Figure 2 shows the weekly frequency patterns of the content generation and usage of User 9116 and then provides evidence that suggests the need to incorporate "simultaneity" into our model. This plot shows that uploading frequency highly correlates

Figure 1 Aggregate-Level Mobile Internet Activity Frequency Series Plot



Notes. Vertical dotted lines represent Sundays. Mobile Internet activity during weekdays is generally higher than that during weekends except the national holidays (e.g., Day 50, Children's Day; Day 57, Buddha's birthday; Day 83, Memorial Day).

Figure 2 Individual-Level Mobile Internet Activity Frequency Series Plots



with downloading frequency for this particular user. This kind of correlated behavior can be driven by several factors—observed user heterogeneity (i.e., young users like both content generation and usage), correlated unobservables (i.e., users who like to upload also like to download, and vice versa), etc. Although a single-equation panel data model can accommodate observed user heterogeneity (e.g., by including such variables as age and gender in the random effects (RE) specification and by differencing out user-specific, time-invariant characteristics), it cannot address the correlated unobservables mentioned above. This feature suggests the need for the use of a "simultaneous equation model" for content generation and usage equations. Furthermore, Plot 1 suggests evidence of negative interdependence between content generation and usage, especially during the first nine weeks.

3.3.2. Mobile Internet Session Initiation and Content Activities. Plot 2a and Plot 2b in Figure 2 show the weekly frequency patterns of content generation and usage of User 1927 and User 3186, respectively. Although these two users have the same demographic characteristics (i.e., age and gender), they are very different in terms of their propensity to initiate mobile Internet sessions as well as in terms of the number of their content uploads and downloads. Note that User 1927 in Plot 2a, having a higher frequency of mobile Internet session initiation (13 times), has engaged more frequently in content usage when compared to User 3186 in Plot 2b, who has a lower propensity for initiating a mobile Internet session (2 times). In other words, even after controlling for observed demographics like age and gender, some unobserved user characteristics like inherent interest in initiating a mobile Internet session do explain behavioral differences, such as the content usage between users. This feature motivates the need to incorporate a "selection constraint" in our model to control for the nonrandomness in the user mobile Internet session initiation stage.

Descriptive statistics from our data suggest that young, male users tend more frequently to engage in mobile content generation and usage than other groups. Thus, there could be a disproportionately higher number of young, male users in this sample for mobile session-initiating users (i.e., the selected sample) compared to the total sample. Indeed, results from a random effect dynamic probit model for the user session initiation equation support this argument (see Appendix B). Furthermore, if we were to group those users who have initiated mobile Internet sessions by the amount of their content activities (both uploads and downloads) and divide the entire group into heavy users versus light users, we would see a disproportionately higher number of young, male users in the heavy-user sample compared to the light-user sample.

Last, Plots 1, 2a, and 2b indicate that the frequencies of generation and usage in week 1 vary by user. For example, User 1927 (Plot 2a) has 56 instances of downloading, whereas User 9116 (Plot 1) has about 18 instances of downloading. This implies that users could be different in terms of prior experiences with respect to content generation and usage at the beginning of the sample (i.e., week 1). We thus model this "initial condition" issue by specifying selection equations for week 1 and for weeks 2–13, separately.

4. The Econometric Model

To analyze the underlying process of user content generation and content usage, we build and estimate an individual-level simultaneous equations panel data model using 3SLS estimation. We further demonstrate the robustness of this analysis by conducting GMM-based dynamic panel data analyses. We also present and discuss other robustness check

analyses that include models with a random coefficient in a constant term, count data models, content share models, content size models, and models using network variables based on different specifications.

In the mobile Internet space where users generate and use content with their phones, users face a two-step decision-making process. In Step 1, they decide whether to initiate a mobile Internet session by clicking a button on the mobile phone. In Step 2, once they have initiated a mobile Internet session, they determine how much to upload (if any) and how much to download (if any). They can engage in both uploading and downloading activities multiple times during a given mobile Internet session. Hence, there are three related user decisions—(a) mobile Internet session initiation, (b) content generation, and (c) content usage. Conditional on doing (a), the user could decide to do (b), (c), or both.

There are five econometric issues to address here: (i) sample selection bias, (ii) social network endogeneity, (iii) initial conditions problem, (iv) unobserved user heterogeneity, and (v) simultaneity.

First, recall that we (researchers) can observe the content generation and usage frequency of users only if these users initiate their mobile Internet sessions. Sample selection can arise in this setting because those people who more frequently initiate their mobile Internet sessions can also be more prone to content generation (or usage) than those who less frequently initiate their mobile Internet sessions. If uncorrected, the estimates in the main equations become biased and inconsistent, leading to a misleading inference (Heckman 1979). Furthermore, it could undermine the external validity of estimates in that the estimates are only relevant for the selected sample (i.e., people who actually initiated mobile Internet sessions), thereby limiting the generalizability of any results. In other words, the main source of the selection bias here is the user decision to initiate a mobile Internet session based on their discretion and intrinsic preferences as opposed to being randomly chosen. We control for this sample selection bias by including a selection correction term in our main equations (i.e., content generation and usage frequencies).

Second, the mobile Internet behavior of a user and his social network can seem to be correlated, regardless of whether it occurred because of causal influence or not. To identify the social network effect, we control for three other factors that can lead to spurious correlated behaviors: endogenous group formation, correlated unobservables, and simultaneity. Endogenous group formation can arise in our setting if users communicate with other users with similar tastes for content generation and usage. Correlated unobservables can arise in our setting if marketing activities and promotions exist that are targeted to a user and that user's network neighbors. Simultaneity can arise in our setting if network neighbors affect the user and the user also affects them simultaneously. We explain these aspects in detail in §4.3.2.

Third, we account for the well-known initial conditions problem in our model as follows: (1) for each user, the first observation in our sample may not be the true initial outcome of his mobile content generation and usage process, and (2) the frequencies of generation and usage in week 1 vary greatly by user. Fourth, users are, in general, different in terms of their propensities and preferences toward content generation and usage. Whereas some consumers tend to be users of content created by others, others contribute by creating and uploading content to web portals and social networking sites. We account for this phenomenon by incorporating both observed and unobserved user heterogeneity in our model. Finally, as several plots of usage have shown before, there could be simultaneity between content generation and usage, and we need to account for that as well. We address each of five econometric issues above in the following §§4.1 and 4.2. We discuss the identification issues involved in the model in §4.3.

4.1. Selection Equations: Mobile Internet Session Initiation

To address the sample selection bias statistically, we explicitly specify our econometric model by extending Verbeek and Nijman's (1996) two-step method.[5] In Step 1, related to the user's decision in Step 1, we run an RE dynamic probit model for the user's binary decision for whether to initiate a mobile Internet session or not initiate one during a given week. Estimates from Step 1 are used to obtain a Heckman's (1979) selection correction term. In Step 2, we insert the correction term into content generation and content usage equations, respectively, and estimate the two equations simultaneously, using a 3SLS method.

To account for social network effects, we use a lagged social network variable. To control for observed user heterogeneity, we include time-invariant user-specific variables like age and sex. In addition, to account for the initial condition problem, we specify two separate equations for a user's mobile Internet session initiation decision: one for the first time period

[5] A single-shot estimation model cannot address all econometric issues involved in our context. This has been documented in prior work. For example, Verbeek and Nijman (1996) and Stewart (2006) point out that a single-shot estimation is not able to control for simultaneity. Similarly, Biørn (2004) points out that a single-shot estimation is unable to handle the selection issue. Furthermore, a single-shot estimation is also computationally very intensive, given the size of our group of data (2.3 million observations). Hence, we utilize the computationally less stringent two-step estimator for our model while explicitly incorporating all economic issues involved in our context.

only and the second for the remaining time periods. We also include a lagged dependent variable. This variable also allows us to control for state dependence.

There are two forms of dynamics in consumer decisions that can be modeled in a reduced form model like ours—(i) habit persistence due to switching costs and (ii) variety-seeking behavior that has been identified in prior work (Osborne 2007). In our setting, although many users may have prior experience with PC-based Internet browsing, they may be relatively new to mobile-phone-based Internet browsing. Therefore, some users may have switching costs. Furthermore, some consumers may be variety seeking. Our data confirm that users with higher levels of mobility tend to engage more in mobile Internet activities. Hence, we can expect this kind of switching behavior across users in mobile Internet settings. Therefore, by including a lagged dependent variable in the selection equation, we can examine whether there are switching costs (whether the sign of the lagged dependent variable is positive and statistically significant) and any variety-seeking behavior (whether the sign of the lagged dependent variable is negative and statistically significant).

An orthogonality problem may arise in our model. Because our selection equation is based on an RE model, the estimator will be inconsistent if the unobserved, user-specific, time-invariant factor is correlated with the regressors therein. Hence, we follow the Mundlak (1978) and Zabel (1992) approaches and add the mean values of time-varying regressors (in our case, the mean value of session initiation by social network) to the selection equation. Notations and variable descriptions are provided in Table A.1 (see Appendix A).

Specifically, we specify that user i decides whether to initiate mobile Internet sessions using an indicator function (i.e., 1 = yes and 0 = no). We specify a model for the initial period ($t = 1$) as follows:

$$\begin{aligned} Session^*_{i,1} &= \pi_0 + \pi_1 Age_i + \pi_2 Age_i^2 + \pi_3 Sex_i \\ &\quad + \pi_4 Handset\ Age_i + \pi_5 tz_{-i,t} + u_i \qquad (1) \\ Session_{i,1} &= 1(Session^*_{i,1} > 0). \end{aligned}$$

For the remaining periods ($t \geq 2$), we specify a model as follows:

$$\begin{aligned} &Session^*_{i,t} \\ &= \alpha_0 + \alpha_1 Session_{i,t-1} + \alpha_2 Social\ Network\ Session_{i,t-1} \\ &\quad + \alpha_3 Age_i + \alpha_4 Age_i^2 + \alpha_5 Sex_i \\ &\quad + \alpha_6 \overline{Social\ Network\ Session_i} + \delta_i + \lambda_t \qquad (2) \\ &\quad + \alpha_7 z_{-i,t} + \eta_{i,t}, \\ &\qquad Session_{i,t} = 1(Session^*_{i,t} > 0), \end{aligned}$$

where δ_i is a user-specific random coefficient, λ_t is a time-period dummy, $z_{-i,t}$ is a mean mobile Internet session initiation of all other users in user i's billing zip code, and $\eta_{i,t}$ is an error term.

If the initial conditions correlate with the unobserved, user-specific, time-invariant factor, as would be expected in most situations, our estimators will be inconsistent. Because the u_i in Equation (1) does correlate with δ_i in Equation (2), but does not correlate with $\eta_{i,t}$ for $t = 2, 3, \ldots, T$, we specify u_i as follows:[6]

$$u_i = \theta\delta_i + \eta_{i,1}, \qquad (3)$$

where θ is an initial condition parameter. We then estimate the RE dynamic probit model, using maximum likelihood estimation methods based on Stewart (2006, 2007).[7]

4.2. The Main Equations: Content Generation and Content Usage Frequencies

We specify a fixed effect (FE) model for content generation and usage equations.[8] To account for sample selection bias, we insert a selection correction term into the content generation and content usage equations. To incorporate temporal interdependence, we include a lagged content download frequency variable in a content upload equation and a lagged content upload frequency variable in a content download equation. We include each one of four mobility metrics in our main equations in separate estimations to demonstrate robustness to both the mean and the variance of the mobility metric, at both local and national levels. To account for the individual-level social network effect, as before, we include *lagged* social network variables to alleviate the endogeneity bias that can arise when using the social network variable.[9] We include the number of voice calls as a control variable in the content generation and usage equations to control for user inherent propensity to

[6] We check serial autocorrelation in the error term and find the estimate for serial autocorrelation is not statistically significant (p-value is 0.627).

[7] Given that there are several user-specific, time-invariant variables that may affect a user's mobile Internet session initiation, we use an RE dynamic probit model for the selection equation.

[8] Verbeek and Nijman (1996) demonstrate that a fixed effect estimator in the main equations in their two-step approach is more robust to selection biases than a random effects estimator. Moreover, they also show that the conditions for the consistency of a fixed effect estimator are weaker than those for a consistent random effects estimator.

[9] We also specify an alternative model, allowing for contemporaneous social network effects by using an instrumental variable approach for each equation, similar to Iyengar et al. (2011). The result indicates that the contemporaneous social network effect is positive and statistically significant, whereas other estimates qualitatively remain the same. Hence, we find no evidence of misspecification bias from using a lagged social network variable.

make calls. Furthermore, we include control variables, including user-specific dummies, time-period dummies, and time-period- and location-specific fixed effects at the user level, to control for endogeneity from using a social network variable as a regressor.

We take the logarithm on variables to control for their right-skewed nature (i.e., there are some heavy uploaders and heavy downloaders as seen in Table 1). We implement a 3SLS estimation on the first-differenced equations of log-transformed content generation and content usage frequencies. The simultaneous estimation method allows for efficiency gain compared to single-equation estimation methods by taking into account the cross-equation error correlation.[10] Specifically, content generation frequency and usage frequency equations are specified as follows for $t=2,3,\ldots,T$:[11]

$$\begin{aligned}&\log(Upload_{i,t})\\&=\beta_0+\beta_1(Download_{i,t-1})+\beta_2\log(Mobility_{i,t})\\&\quad+\beta_3\log(Social\ Network\ Upload_{i,t-1})\\&\quad+\beta_4\log(Voice_{i,t})+\beta_5 Selection_{i,t}+\beta_6\log(g_{-i,t})\\&\quad+\beta_7\log(\overline{Social\ Network\ Upload_i})+\kappa_i+\varphi_t+v_{i,t},\end{aligned}\quad(4)$$

$$\begin{aligned}&\log(Download_{i,t})\\&=\gamma_0+\gamma_1\log(Upload_{i,t-1})+\gamma_2\log(Mobility_{i,t})\\&\quad+\gamma_3\log(Social\ Network\ Download_{i,t-1})\\&\quad+\gamma_4\log(Voice_{i,t})+\gamma_5 Selection_{i,t}+\gamma_6\log(h_{-i,t})\\&\quad+\gamma_7\log(\overline{Social\ Network\ Download_i})+\psi_i+\tau_t+\varepsilon_{i,t},\end{aligned}\quad(5)$$

where $Social\ Network\ Activity_{i,t-1}=\sum_{m\in n_{t-1}(i)}(w_{i,m,t-1}\cdot Activity_{m,t-1})$; $w_{i,m,t-1}$ is the normalized number of calls user i made to user m in week $t-1$; *Activity* is either *Upload* or *Download*; and $g_{-i,t}$ and $h_{-i,t}$ are mean uploading and downloading frequencies of all other users in user i's billing zip code, respectively. In addition, κ_i and ψ_i are user-specific dummies, φ_t and τ_t are time-period dummies, and $v_{i,t}$ and $\varepsilon_{i,t}$ are user- and time-specific error terms.

Furthermore, recall that we specified an FE model for equations of content generation and usage frequencies. It is well known that estimation of an FE model with a lagged endogenous variable is subject to potential finite-sample bias (Nerlove 1967, Nickell 1981). Our analysis may suffer from this bias because the number of observations per user is 13 for the entire sample but only 5 for the subsample. Hence, we take a first-differencing transformation on each variable in the model to alleviate the potential bias from the fixed effect model (Wooldridge 2002) and difference out both observed and unobserved user-specific, time-invariant variables (e.g., age, gender, job characteristics, prior Internet experience, etc.).[12] Although we find there exists no serial correlation in the error term from the selection equation and in the error term from each of the main equations separately, we control for the potential serial correlation in the main simultaneous equations of content generation and usage by using the robust variance matrix (Wooldridge 2002).[13] The robust variance matrix estimator (Arellano 1987) is valid in the presence of serial correlation in error terms in Equations (4) and (5) (Wooldridge 2002).

To be specific, the first-differenced content generation frequency and usage frequency equations that we estimate are specified as follows, for $t=2,3,\ldots,T$:

$$\begin{aligned}&\Delta\log(Upload_{i,t})\\&=\beta_1\Delta\log(Download_{i,t-1})+\beta_2\Delta\log(Mobility_{i,t})\\&\quad+\beta_3\Delta\log(Social\ Network\ Upload_{i,t-1})\\&\quad+\beta_4\Delta\log(Voice_{i,t})+\beta_5\Delta Selection_{i,t}+\beta_6\Delta\log(g_{-i,t})\\&\quad+\Delta\varphi_t+\Delta v_{i,t},\end{aligned}\quad(6)$$

$$\begin{aligned}&\Delta\log(Download_{i,t})\\&=+\gamma_1\Delta\log(Upload_{i,t-1})+\gamma_2\Delta\log(Mobility_{i,t})\\&\quad+\gamma_3\Delta\log(Social\ Network\ Download_{i,t-1})\\&\quad+\gamma_4\Delta\log(Voice_{i,t})+\Delta\gamma_5 Selection_{i,t}+\gamma_6\Delta\log(h_{-i,t})\\&\quad+\Delta\tau_t+\Delta\varepsilon_{i,t}.\end{aligned}\quad(7)$$

[10] When the disturbance covariance matrix is not known, generalized least squares is inefficient compared to full information maximum likelihood and three-stage least-squares estimation (Lahiri and Schmidt 1978).

[11] Note that we cannot include a lagged dependent variable as a regressor in Equations (4) and (5) because the lagged dependent variable in each equation correlate with the disturbance term after first-differencing transformation, leading to inconsistency in the estimates. In addition, a series of control variables helps us capture the impact of any potential omitted variable (i.e., lagged dependent variable). These control variables include (i) time-period fixed effects, (ii) time and location-specific mean content activity variables at the user level, and (iii) mean content activity by social network neighbors at the user level, which can mitigate this bias. That said, our main results are robust even when we include a lagged dependent variable and estimate that variable using GMM-based dynamic panel data models (see Appendix C).

[12] This approach is similar to Verbeek's (1990), where Verbeek takes the within transformation to eliminate the incidental parameters and maximizes the likelihood of the transformed data. He also shows that the corresponding estimator is consistent, even when only a few time series observations are available.

[13] We include the time-based control variables to control for underlying time trends that help eliminate serial correlation in our data. That said, we estimate our main equations separately, using the generalized estimating equations method and find that the estimated AR(1) coefficients in the upload equation and the download equations are 0.006 and 0.007, respectively. Obviously, with such small AR(1) values, the other estimates qualitatively remain the same as in the result for our main model.

4.3. Identification

We discuss two issues in the identification of our model: (1) identifying the selection equations and the main equations of content generation and usage frequencies, and (2) identifying the social network effect.

4.3.1. Identification of the Selection Equations and the Main Equations. Our identification strategy for the selection equations and the main equations includes normalization of parameters for binary decision variables, exclusion restrictions, and the use of instrument variables as part of our estimation process.

In the selection equations, because a user's mobile Internet session initiation is a binary choice, we need location and scale normalization on the latent dependent variable, $Session^*_{i,t}$, for identification. For location normalization, we set the user i's utility of not engaging in any mobile Internet sessions in week t as $Session^*_{i,t}=0$. For scale normalization, we set the variance of the unobserved, user-specific, time-specific effect, σ^2_η, to 1. In addition, sample selection issues require our explicitly estimating the selection equation, using both time invariant and time varying regressors (i.e., age, sex, mobile Internet session initiation by social network). We call these variables Z. Because a selection correction term is a nonlinear function of the variables included in the selection equations, our main equations of content generation and usage frequencies with regressors X are identified due to this nonlinearity, even if $Z=X$. However, this nonlinearity arises from the assumption of normality in the probit model. Thus, we check an exclusion restriction by including variables in Z that are not included in X, which makes the identification cleaner (Puhani 2000). The exclusion restriction is satisfied because we include some time-invariant variables (e.g., age and gender) as well as a time-varying variable (e.g., mobile Internet session initiation by social network) only in the selection equation, but exclude these variables in the main equations.

In the main equations, in the absence of better data, we use time-series-based instruments for identification. Content upload and download frequency variables in a given week are taken to be endogenous to the system of equations, whereas all other variables in the system are treated as exogenous to the system or predetermined. For example, in the content upload frequency equation, variables like lagged download frequency, geographical mobility, and lagged social network (see §4.3.2) are exogenous or predetermined. This is true for the following reasons.

First, geographical mobility is exogenous because it is very unlikely that one's mobility is determined by one's propensity to generate and use content. Instead, it is far more likely that a user's propensity to generate and use content is driven by the extent of their geographical mobility. Second, we assume that only past content usage level affects the current content generation level of a user and similarly only past content generation usage level affects the current content usage level of a user. Hence, the download frequency variable at time $t-1$ is predetermined because it cannot be determined at time t. This is true because the error term at time t in Equation (4) is uncorrelated with current and lagged values of the predetermined variable (i.e., $E[\log(Downlaod_{i,t-1})v_{i,t}]=0$) but may be correlated with future values (i.e., $E[\log(Downlaod_{i,t})v_{i,t}]\neq 0$). This claim holds true because we found no serial autocorrelation in the error terms after controlling for time trends (see §4.3.2). For the same reason, log upload at $t-1$ in the Equation (5) is a predetermined variable. This alleviates the concern of endogeneity from simultaneity and thus focuses on the dynamics in the interdependence between content generation and usage of a user. Third, the lagged social network variable is predetermined at time t, because we control for other sources for endogeneity from using a social network variable as a regressor (see §4.3.2). These are valid instruments for the endogenous variable because they are uncorrelated with the unobservable error term. A similar set of arguments applies to the content download frequency equation.

As a robustness check, we also include a nontime-series-based variable as an instrument. In particular, we include the *handset age* variable as an additional instrument in the content generation equation, excluding it from the content usage equation. The key assumption behind this argument is that the age of the handset is more likely to impede users from uploading multimedia content than downloading content. Users can download multimedia content, irrespective of how advanced their handset features are, such as the number of pixels in their mobile camera, the technical sophistication of the software, and applications installed in the handset—the kinds of features that are required to experience multimedia content downloaded from the Web. In contrast, the lack of handset functionality and advanced features is more likely to prevent users from creating and uploading content because older phones are not equipped with advanced digital cameras and audio/video/photo editing applications—the kinds of features users need to upload content on the Internet. The qualitative nature of all these results remains the same, however, with the inclusion of this variable as an instrument.

Furthermore, we examine whether both the necessary order condition and sufficient rank condition are satisfied for our main equations of content generation and usage frequencies. The order condition is met because each equation excludes exogenous or predetermined variables (i.e., a mobility variable, a lagged social network variable, a lagged temporal interdependent variable, mean mobile Internet activity of

all other users in user i's billing zip code area, etc.), although it has no right-hand-side endogenous variable. Furthermore, we check the rank condition using Baum's (2007) Stata code to find that the rank condition for each main equation is satisfied.

4.3.2. Identification of the Social Network Effect. To address the endogeneity issue of the social network variable, we adopt the identification strategy and modeling approach in accordance with the prior work that has studied the impact of the social network effect on user behavior (Manski 1993, Hartman et al. 2008, Nair et al. 2010). We distinguish causality from correlation by separating causal effects from each of three sources of correlation: (1) endogenous group formation, (2) correlated unobservables, and (3) simultaneity. In doing so, we incorporate several additional variables. We explain these in detail below.

First, regarding the endogenous group formation, the observed correlation in the behavior of an individual and other individuals in the social network could arise from omitted individual characteristics that correlate within the group. For example, users can choose to call users with similar tastes in multimedia content generation and usage. They might virtually meet at social networking sites or physically meet in the same office/home neighborhood, and such meetings can lead to the formation of groups endogenously. This will produce an upward bias in the social network effects. Consistent with the literature, we include a user-specific random effect in the selection equation (i.e., Equation (3)) and a user-specific fixed effect in the main equations (i.e., Equations (4) and (5)) to account for this issue.

Second, regarding the correlated unobservables, some unobservables could drive the behavior of an individual and other individuals in one's social network. For example, marketing promotions targeted to users or exogenous incidents, such as celebrity sightings and festive events, can drive individuals in a given social network to upload and download photos/videos to social networking sites. If uncorrected, this effect could be mistaken for a social network effect. In other words, any spatially correlated, location-specific shocks to users in the same group can lead to such a bias, and we need to account for it.

In addition to adding the user-specific effect, there are three additional controls for correlated unobservables. The first is to include time-period fixed effects. These can control for common factors or shocks to all individuals at a given time. Examples include the mobile carrier's nationwide mobile marketing campaigns or promotions, such as free trial downloads of content. The second is location fixed effects (i.e., zip code dummies). These can control for time-invariant, spatially correlated unobservables. For example, users in urban areas may be more tech savvy and more prone to engaging in mobile Internet activities compared to users in rural areas. The third is to include time and location effects to control for unobservables that correlate at the level of zip code *and* time. We apply both billing-zip-code-based and calling-zip-code-based content activities variables.[14] For example, celebrity sightings, concerts, family weddings, social events, festivals, unusual street incidents, etc., may give people the opportunities to capture and share such moments with friends and families via their mobile devices. Hence, we include the time- and location-specific mean session initiation frequency of all other users in the same zip code area of user i, denoted by $\overline{Session}_{-i,t}$, in the selection equation and the time- and location-specific mean content upload and download frequencies of all other users in the zip code area of user i, denoted by $g_{-i,t}$ and $h_{-i,t}$ in the main equations, respectively.

Our econometric specification is able to address all three issues required to distinguish causality from correlation in the social network effect—endogenous group formation, correlated unobservables, and simultaneity. Hence, our empirical estimates do demonstrate a causal effect of the social network on user content generation and usage on the mobile Internet. However, we would like to be cautious in our interpretation. In the absence of controlled variation using natural or field experiments during our sampling period, we interpret the relationship between social network behavior and user behavior in our paper as being one that establishes an upper bound on the causal effect of the social network.

5. Results

In this section, we discuss our results and briefly summarize the key findings from the selection equation. They show that positive state dependence exists, suggesting that some users incur switching costs in our context and also that there is a positive social network

[14] Each user's billing-zip-code-based content activity variables capture the demand changes around that user only in the fixed location over time. To account for spatial change in demand, we included three additional location-varying and time-varying average content activity variables based on user i's top three places at which he placed calls (i.e., calling-zip-code-based content activity variables). The rationale for the inclusion of these variables is that user i and his network neighbors might travel to the same zip code area in a given week, and hence they could be influenced by an exogenous demand shock arising from that location. Examples include celebrity appearances, concerts, some unusual street incidents, etc. Our results confirm that with the inclusion of an additional three (location- and time-varying content activity) control variables, the lagged network variable estimates remain qualitatively the same as before. Therefore, these results suggest that the impact of correlated unobservables from colocation of users on the social network variable is not a major issue.

effect in initiating mobile Internet sessions. Furthermore, user mobile Internet initiation behavior greatly varies by age, implying an inverted U-shaped relationship between age and mobile media usage with a peak at around approximately 21 years old. These estimates appear in Appendix B.

In §5.1, we present the 3SLS estimation results of content generation and usage equations using a 13-week sample. These results shed light on temporal interdependence and to some extent on the social network effect.[15] In §5.2, we present the estimation results using a 5-week sample that contains data on the communication strength between social network neighbors and data on the geographical mobility of users.[16] In §5.3, we look at the cohort analysis results to gain additional insights of results through subsample analyses. In §5.4, we discuss a series of robustness checks that demonstrate the robustness of our main results. In §5.5, we discuss the economic implications of our results.

5.1. Results Using the Total Sample

Recall that we can observe the content upload and download frequency of users *only* if they initiate their mobile Internet sessions. Results show that our estimates for a selection correction term are indeed positive and statistically significant in content generation and usage equations (the coefficient estimates are 0.0216 and 0.7267, respectively). This suggests that people who more frequently initiate mobile Internet sessions are more likely to engage in uploading and downloading content as opposed to those who less frequently initiate mobile Internet sessions. Moreover, results from the selection equations (see Appendix B for details) show that males and younger users who are prone to uploading or downloading content through their mobile phones more frequently initiate mobile Internet sessions. These results confirm that controlling for sample selection bias is crucial in our setting.

The main results from the simultaneous equations of content upload and download using the full sample are given in Table 2. We find that there is a negative and statistically significant temporal interdependence between content generation and usage. This finding implies that an increase in content usage in a previous period does associate with a decrease in content generation in the current period and vice versa (the coefficient estimates are −0.0091 and −0.0178, respectively). This finding provides evidence that the resource constraint (e.g., time and money constraint) binds at least for some people.

Table 2 3SLS Estimation Results on Content Frequency (Total Sample)

Dependent variable	Explanatory variable	Coefficient
Log *Upload Frequency* (t)	Log *Download Frequency* ($t-1$)	−0.0091 (0.0005)***
	Log *Upload Frequency by NN* ($t-1$)	0.0115 (0.0042)***
	Selection (t)	0.0216 (0.0007)***
Log *Download Frequency* (t)	Log *Upload Frequency* ($t-1$)	−0.0178 (0.0073)***
	Log *Download Frequency by NN* ($t-1$)	0.0143 (0.0047)***
	Selection (t)	0.7267 (0.0026)***

Notes. NN refers to network neighbors. Estimates for time-period fixed effects and mean uploading and downloading frequency of all other users in user i's billing zip code effects are not reported for brevity.
***Significant at 0.01.

We find positive and statistically significant social network effects in content generation and usage equations (the coefficient estimates are 0.0115 and 0.0143, respectively). We also find statistically significant estimates for our control variables like time-period dummies, mean uploading and downloading frequencies of all other users in user i's billing zip code variables, etc.

We discuss the impact of each effect using their marginal effects.[17] For example, a one-standard-deviation increase in the frequency of content downloading in the previous period decreases the frequency of content uploading in the current period by 3.6% when evaluated at the mean. Similarly, a one-standard-deviation increase in the frequency of content uploading in the previous period decreases the frequency of content downloading in the current period by 5.1%. Thus, the marginal effect of temporal interdependence is asymmetric and stronger in content usage than it is in content generation.

In addition, the marginal effect of social network effect is larger in content usage than in content generation (11.0% and 1.5%, respectively). Recall that this result of lagged social network effect does not incorporate the communication strength between users

[15] Recall that we do not observe voice call records during the entire 13-week period, but observe them only over a 5-week period. Thus, to measure the amount of content generation and content usage of network neighbors of a given user at a given time period, we define user i's network neighbors based on 5-week voice call records and treat them as fixed throughout the 13-week period; that is, the group of network neighbors of user i is denoted as $n(i)$ in the 13-week sample, rather than $n_t(i)$.

[16] We implemented all models here without the social network variable to alleviate any remaining concerns about endogeneity, even from the use of a lagged social network variable. We find qualitatively the same result between with and without the lagged network variable. Details are available upon request.

[17] Given the log–log specification in Equations (4) and (5), the coefficients represent elasticities. In addition to these elasticities, we interpret the coefficients using marginal effects as well as economic implications (see §5.5).

when imputing the structure of the social network for a given user. When we incorporate this information, we can obtain a more accurate measure of the social network effect on user behavior. This finding is discussed below in §5.2.

5.2. Results Using the Communication Strength and Geographical Mobility Subsample

It is possible that a user's content generation propensity more strongly associates with that of his family, close friends, or colleagues (whom the user calls more frequently or speaks to for a longer duration), rather than that of acquaintances (whom the user calls less frequently or speaks to for a shorter duration). To incorporate the dynamic, weighted social network effect on user behavior, we next present results from a 3SLS estimation using a 5-week sample that has time-varying data on the extent of communication strength between users and their network neighbors. In addition, the 5-week sample includes the four different mobility metrics of users described earlier in §3.

We conduct our analyses on both frequency-based and duration-based models in which we incorporate call frequencies and call durations, respectively, to determine the magnitude of the communication strength. Our results are robust for the use of either factor (call frequencies and call duration) as a weight for computing the strength of social network effect. Our results are also robust for the exclusion of the number of voice calls as a control.

The main results are given in Table 3. As before, the estimates for selection correction terms are positive and statistically significant in both equations, reassuring that controlling for sample selection bias is crucial in our setting. Our results show that there exists a negative and statistically significant interdependence between content usage in the current period and content generation in the previous period. As an example, the coefficient estimates are -0.0098 and -0.0239, respectively, in a model with a mean local mobility variable. This result is consistent, irrespective of the use of different mobility variables. As before, this finding lends support to the claim that the resource constraint (e.g., time and money constraint) binds at least for some. These effects are also asymmetric. The marginal effect of temporal interdependence is stronger in content downloading than in content uploading (-6.8% and -4.3%, respectively, in a model with a mean local mobility variable)—namely, the negative impact of a previous period's content uploading on the current period's content downloading propensity is higher than the opposite.

We find that our mobility metrics positively associate with content generation and usage activities of users. For example, mean local mobility of a user positively associates with content generation and usage (the coefficient estimates are 0.0087 and 0.0193, respectively). We find that the marginal effect of mean local mobility on content downloading is higher than on content uploading (1.2% and 0.5%, respectively) when evaluated at the mean, whereas the marginal effect of mean national mobility on content downloading and content uploading is similar (0.5% and 0.3%, respectively). In addition, local mobility dispersion positively associates with content generation and usage (the coefficient estimates are 0.0057 and 0.0328, respectively). We also find that the marginal effect on content downloading is much higher than it is on content uploading (3.3% and 0.6%, respectively). Similarly, the marginal effect of national mobility dispersion on content downloading is higher than the effect on content uploading (1.0% and 0.3%, respectively). These results suggest that users more frequently engage in content downloading than content uploading when traveling. Furthermore, in general, the variance of user travel patterns (mobility dispersion) has a stronger impact on their mobile Internet activities than on the mean (mean mobility).

The relationship between content generation and usage behavior of users and their social networks is positive and statistically significant (for example, the coefficient estimates are 0.0162 and 0.0348, respectively, in the model applying the mean local mobility variable). This result is consistent, irrespective of the use of different mobility variables. We find that the marginal effect of the social network on content downloading is much higher than it is on content uploading (26.8% and 1.4%, respectively). In addition, we find statistically significant estimates for our control variables like time-period dummies and mean uploading and downloading frequencies of all other users.

5.3. Cohort Analysis Results

We implement four sets of cohort analyses. First, a useful test for the central notion of economic behavior under resource constraints espoused in this paper is to examine whether users who appear closer to a binding constraint on resources show a stronger (negative) temporal interdependence between content generation and usage. Toward this end, we divide the sample based on the age of the user into two cohorts: "younger" users (below the age of 22) and "older" users (above the age of 22). Results are robust with respect to this age cutoff point. The assumption is that younger users are more likely to face monetary constraints compared to older ones because of a lower amount of discretionary income. Hence, we would expect a greater level of negative temporal interdependence between content generation and usage behavior for such users. 3SLS estimation results show that this assumption holds true. For example, the marginal effect of temporal interdependence in

Table 3 3SLS Estimation Results on Content Frequency

Dependent variable	Explanatory variable	Coefficient			
Log *Upload Frequency* (t)	Log *Download Freq.* ($t-1$)	−0.0098 (0.0005)***	−0.0098 (0.0005)***	−0.0097 (0.0005)***	−0.0097 (0.0005)***
	Log *Mean Local Mobility* (t)	0.0087 (0.0014)***			
	Log *Mean National Mobility* (t)		0.0163 (0.0025)***		
	Log *Local Mobility Dispersion* (t)			0.0057 (0.0016)***	
	Log *National Mobility Dispersion* (t)				0.0057 (0.0012)***
	Log *Number of Voice Calls* (t)	0.0010 (0.0007)	0.0013 (0.0007)*	0.0018 (0.0007)***	0.0010 (0.0007)
	Log *Upload Freq. by NN* ($t-1$)	0.0162 (0.0054)***	0.0163 (0.0054)***	0.0163 (0.0054)***	0.0163 (0.0054)***
	Selection (t)	0.0118 (0.0004)***	0.0116 (0.0004)***	0.0126 (0.0004)***	0.0130 (0.0004)***
Log *Download Frequency* (t)	Log *Upload Freq.* ($t-1$)	−0.0239 (0.0092)***	−0.0238 (0.0092)***	−0.0234 (0.0091)***	−0.0234 (0.0091)***
	Log *Mean Local Mobility* (t)	0.0193 (0.0057)***			
	Log *Mean National Mobility* (t)		0.0218 (0.0098)**		
	Log *Local Mobility Dispersion* (t)			0.0328 (0.0065)***	
	Log *National Mobility Dispersion* (t)				0.0218 (0.0047)***
	Log *Number of Voice Calls* (t)	0.0385 (0.0027)***	0.0401 (0.0026)***	0.0377 (0.0026)***	0.0356 (0.0028)***
	Log *Download Freq. by NN* ($t-1$)	0.0348 (0.0057)***	0.0348 (0.0057)***	0.0348 (0.0057)***	0.0348 (0.0057)***
	Selection (t)	0.3633 (0.0014)***	0.3635 (0.0014)***	0.3658 (0.0014)***	0.3666 (0.0014)***

Notes. We included each one of the two mean mobility metrics and the two mobility dispersion metrics in our main equations at both the local and national levels. NN refers to network neighbors. Estimates for time-period fixed effects and mean uploading and downloading frequency of all other users in user i's billing zip code effects are not reported for brevity.

*Significant at 0.1; **significant at 0.05; ***significant at 0.01.

content downloading (content uploading) is −8.7% (−4.1%) for the younger user cohort, whereas it is −2.7% (−2.0%) for the older user cohort. This finding implies that the resource constraint binds more tightly on younger users than on older users.

Second, we divide the sample based on the location of the user into two cohorts: "urban" users (who live in six major cities in South Korea) and "suburban" users (who live in other areas in South Korea). The premise is that urban users are more likely to have better 3G broadband coverage as well as travel-related discretionary time via public transportation (i.e., subways or buses) compared to suburban users. Hence, we would expect a higher impact of mean mobility on urban user content generation and usage behavior. The 3SLS estimation results show that this assumption also holds true. For example, the marginal effect of mean local mobility on content downloading (content uploading) is 2.2% (1.8%) in the urban user cohort, whereas it is 1.8% (0.3%) in the suburban user cohort.

Third, we implement a subsample analysis by excluding users who either upload or download disproportionately to alleviate potential bias from including these outliers (i.e., user-generated-content junkies or free riders). The subsample consists of those users whose upload frequency is in a similar range to their download frequency. To be specific, we include a user into our subsample if the absolute difference between download frequency and upload frequency for the same user is less than a given cutoff value (e.g., 3, 5, or 10). We thus find qualitatively the same result as for the main result.

Last, we run analyses on a subsample consisting of only those users who engage in both generation and usage activities in the same week at least once in the sample to mitigate the potential bias from including users who either upload or download but do not engage in both activities. This subsample constitutes 15.7% of the total sample. We find support for the negative temporal interdependence between content uploading and downloading behavior. The results for the geographical mobility effect and the social network effect are qualitatively the same as in our main results.

5.4. Robustness Checks

We did implement a series of robustness checks. Because of the evidence of positive state dependence from the selection equation results, we conduct tests to check the robustness of the results by estimating the main equations separately with a lagged dependent variable to control for the state dependence, using *GMM-based* dynamic *panel data model*. We find that the results are qualitatively the same as our main results (for details, see Table C.1 in Appendix C).

To capture unobserved heterogeneity among the users, we also estimate *a mixed effect model* where we include a random coefficient for a constant term (i.e., β_0 in Equation (4) and γ_0 in Equation (5)). Furthermore, strictly speaking, user content upload and download variables in our sample take on nonnegative integer values. We thus use various types of *linear* models (i.e., 3SLS and GMM dynamic panel data models). However, for count data, linear models do have shortcomings. Hence, one could argue that we should examine our questions using *count data models*. However, count data models with fixed effects are known to suffer from the "incidental parameters problem," except for the Poisson model. Therefore, we did implement a Poisson fixed effect model in which the incidental parameter problem is not a problem (Lancaster 2000, Greene 2007). We find that the results are qualitatively the same as our main results from 3SLS estimation (for details, see Table C.2 in Appendix C).

Because the total amount of money and time resources of a user can potentially vary every week, an alternative model would be to model the user's share of content uploads with respect to the user's total amount of content uploads and downloads (*content share model*). Besides the frequency of content uploads and downloads, costs that users will incur also depend on how many bytes a user uploads and downloads. Toward this end, we use the amount of bytes uploaded and downloaded for each user instead of frequency of uploading and downloading (*content size model*). We find that these results remain the same as for the 3SLS estimation result for our main model (for details, see Tables C.3 and C.4 in Appendix C).[18]

5.5. Economic Implications

We can see clearly that elasticity estimates for interdependence parameters are small. To understand their economic importance in the context of this industry, it is not that useful to study the impact of a small percentage change in the variables. In particular, such is the case because the mean of several variables is small, whereas the standard deviation is proportionately much higher. Instead, it is more meaningful to evaluate the impact of different percentile changes in content generation and usage frequency variables for different sizes of the user base and impute their monetary value.

To this end, we look at the economic impact on the top 25th percentile user group based on this group's overall content upload and download frequencies.[19] This user group represents 2,500,000 users of the company contained in our data (the company has about 10 million users). We assume that an exogenous shock shifts the content upload and download activity level at time 0 from the top 25th to the top 10th percentile.[20] In this setting, users are charged by the amount of traffic transmitted during their content generation, and usage activities are charged at \$1.5 per one megabyte of data transmission. Based on the top 25th percentile of the user group data (2,500,000 users), a one-time content upload leads to an average of 0.14 megabytes of data transmission, and a user uploads about 0.49 times on average during a week. As noted above, the elasticity of current content upload frequency with respect to the lagged content download frequency is -0.0098. Suppose there is an increase in the usage frequency of this group such that that usage takes the group from the top 25th percentile (48.8 times/week) to the top 10th percentile (82 times/week) in week 0.

The "immediate" impact from an increase in the download frequency in week 1 is then as follows: *elasticity* × *change rate in usage* × *average number of bytes uploaded per instance* × *price per byte* × *number of users* × *average number of times downloaded per week*. This produces an amount of $-$\$170,814. One week's revenue gain will be equal to the following week's loss because a higher frequency of downloads in week t will lead to a lower frequency of uploads in week $t+1$ and vice versa.

To account for this dynamic effect, we analyze "long-term" effects by using the impulse response function of a shock. The impulse response function is widely used to trace the impact of a shock on a single endogenous variable being introduced into the coupled system (Dekimpe and Hanssens 1995,

[18] We also tried alternative specifications for social network effects—a lagged cumulative effect and lagged binary indicator. Neither led to any change in the qualitative nature of the results. Details are available upon request.

[19] We also look at the economic impact on other user groups—top 1st percentile user group and top 10th percentile user group. Details are available upon request.

[20] We examine the economic impact from other percentile changes in mobile Internet content generation and usage frequencies as well based on the following amounts: (1) from the top 90th to the top 10th percentile; (2) from the top 75th to the top 25th percentile; and (3) from the top 50th to the top 25th percentile. The main implications remain consistent, irrespective of the percentiles. Details are available upon request. Furthermore, we assume that the shock is exogenous and does not alter the parameter estimates of the model.

Vanhonacker et al. 2000). In a similar way, using the corresponding values for the variables in the above equation, we compute the impact in weeks 2, 3, and so on. This leads to an annualized long-term effect of −$6,761,035. This finding implies that the company can incur a loss of approximately $6.76 million in traffic revenues a year from the top 25th percentile user group because of the negative interdependence between content generation and usage. This $6.76 million constitutes more than 2.6% of the company's gross annual revenue accrued from the top 25th percentile user group.[21]

Our discussion of "long-term" effect is based on shocks that do not incur any monetary expenses by the company. For example, shocks such as celebrity appearances, concerts, family weddings, social events, festivals, unusual street incidents, etc., may provide people with opportunities to capture and share such moments with friends and families using their handheld mobile devices. Other shocks explicitly generated by the firm may involve that mobile carrier's marketing actions and policy changes, which can also stimulate changes in user behavior. Examples include discounted rate plans on Internet usage, discounts on handsets conditional on certain usage levels, targeted coupons promoting Internet usage, etc. However, we do not have data on these. Hence, the monetary effect of a shock that is based on the parameter estimates by the current model would provide only an upper bound of the effect.

6. Discussion and Implications

Mobile-Internet-based content services constitute one of the fastest-growing applications on the Web today. However, very little is known about the interdependence between content generation and content usage behavior of users. Nor do we know much about the other factors that can drive user behavior on the mobile Internet. To examine these factors, we present a generalized empirical framework of user behavior in the mobile Internet space. We analyze that framework using an unprecedented user-level data set that contains rich data on user demographics, calling patterns, calling locations, and social networks.

Our data come from a setting where users enroll in usage-based data pricing. Recently media reports have pointed out that the major wireless carriers in the United States, namely, AT&T and Verizon Wireless, are getting ready to implement a usage-based data pricing scheme for data/Internet usage (Rethink Wireless 2010). These mobile carriers have profited from low fixed-fee penetration pricing. However, these carriers have seen enormous growth in data traffic, which often outpaces the capacity of their networks. For example, AT&T has experienced 5,000% growth in data traffic over the past three years, but 40% of that traffic is consumed by just 3% of its smartphone users (Rethink Wireless 2010). A global survey of mobile telecom executives across 50 countries and six continents conducted by *The Economist* (2010) revealed that 60% of respondents believe usage-based data pricing is the way of the future in mobile data and content services. Our results based on this usage-based data pricing scheme can provide useful managerial insights for companies' contemplating such pricing schemes.

The insights from this study also have managerial implications. First, the asymmetric, negative temporal interdependence between content generation and usage provides mobile phone companies with insights on how to stimulate content generation and usage. Our results imply that content generation requires disproportionately more effort and resources than does content usage. This could stem from technical complexity in using content generation and uploading functionalities on their phones, lack of prior experience in uploading content through mobile devices, reduced uploading speed due to bandwidth congestion, etc. There is some evidence of technical difficulties' occurring in user content generation in an online setting (Stoeckl et al. 2007). Hence, companies could provide easy-to-use content preprocessing tools and less complicated content uploading procedures for the mobile Web. This asymmetric interdependence could provide mobile phone companies with new ideas regarding differential pricing strategies for data uploading versus data downloading and increase user engagement with mobile media.

Furthermore, the provision of monetary incentives might be effective in triggering user content generation behavior. In many ways, content diffusion in a mobile Internet environment is similar to that in peer-to-peer networks because free riders can create supply-side constraints. Hence, firms that engage in mobile content provision and advertising could consider offering distribution referrals as monetary payments to users who generate and distribute content. Implementation could be delivered through discounts in data transmission charges given to such users.

Second, the asymmetric association of the extent of user geographical mobility with their content usage compared to content generation behavior can provide mobile phone companies with additional insights on targeted mobile advertisements. Previous research on location-based mobile advertising shows that users find ads distressful when they receive them in home and work locations (Banerjee and Dholakia 2008). Our results suggest that users more frequently engage in content usage compared to content generation when they are traveling. In addition, the variance of user

[21] Because we use high-frequency data, same-period effects may be minimal in our setting.

travel patterns has a stronger impact on mobile Internet activities than the mean of user travel patterns. Using this precise mobility information, firms could engage in dynamically personalized mobile advertisements that would be less annoying to users.

Third, our results on the positive effect of the social network on user behavior can provide insights into how companies can target the right set of users and influence users in mobile Internet space. Hence, mechanisms designed to update a user instantly on the frequency with which his network neighbors have downloaded or uploaded a certain type of content can affect the incentives of that user to do the same.

Our paper does have limitations. These limitations arise mainly from the lack of data. For example, we do not have information about the specific type of content uploaded or downloaded (e.g., photo, audio, text, etc.) and the destination websites (e.g., social networking sites, mobile portal sites, etc.). Future work could examine this information. Another area for future research is to study how content generated via mobile phones diffuses through different kinds of social networks, such as text-messaging-based networks, multimedia content-based networks, and offline location-based spatial networks. We hope that this study will generate further interest in and engagement with the emerging literature on the economics of user-generated mobile content and, more broadly, in the growth in mobile commerce and the mobile Internet.

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Appendix A

Table A.1 Notations and Variable Descriptions

$Session_{i,t}$	Whether user i started mobile Internet sessions in week t (1 = yes, 0 = no)
$Social\ Network\ Session_{i,t-1}$	Weighted average number of mobile Internet session initiations by network neighbors of user i at time $t-1$; that is, $\sum_{m \in n_{t-1(i)}} (w_{i,m,t-1} \cdot Session_{m,t-1})$
$n_{t-1}(i)$	User i's social network neighbors based on voice call records (i.e., users called by user i) in week $t-1$
$Session_{m,t-1}$	Whether user i's social network neighbor m started his/her mobile Internet sessions in week $t-1$ (1 = yes, 0 = no)
$w_{i,m,t-1}$	Normalized number of calls user i made to user m in week $t-1$, that is, $w_{i,m,t}$ is a fraction of voice calls from user i to user m in week $t-1$ with respect to the total voice calls originated from user i in week $t-1$
Age_i	User i's age
Sex_i	User i's sex (1 = male, 0 = female)
$Handset\ Age_i$	Months elapsed since user i's handset was launched in the market
$\overline{Social\ Network\ Session}_i$	Time mean mobile Internet session initiation by social network neighbors of user i
δ_i	Unobservable, user-specific, time-invariant effect ($\delta_i \sim \text{IIN}(0, \sigma_\delta^2)$), where IIN is independent identical normal
λ_t	Time-period fixed effects
$Z_{-i,t}$	Mean mobile Internet session initiation of all other users in user i's billing zip code
$\eta_{i,t}$	Unobservable, individual-specific, time-specific effect ($\eta_{i,t} \sim \text{IIN}(0, \sigma_\eta^2)$); η_n^2 is set to 1 for normalization, and δ_i are independent of $\eta_{i,t}$
θ	Initial conditions parameter
$Upload_{i,t}$	Number of times user i uploaded content in week t
$Upload_{m,t-1}$	Number of times user i's network neighbor m uploaded content in week $t-1$
$Download_{i,t}$	Number of times user i downloaded content in week t
$Download_{m,t-1}$	Number of times user i's network neighbor m downloaded content in week $t-1$
$Mean\ Mobility_{i,t}$	Any one of the following two mean mobility metrics: (1) number of unique zip-code-level locations from where user i placed calls in week t; (2) number of unique province-level/state-level locations from where user i placed calls in week t
$Mobility\ Dispersion_{i,t}$	Any one of the following two mobility dispersion metrics: (1) fraction of geographical deviation from one's commonly visited places at zip code level for a user in week t; (2) fraction of geographical deviation from one's commonly visited places at province/state level for a user in week t
$Selection_{i,t}$	Selection correction term for user i at time t
$g_{-i,t}$, $h_{-i,t}$	Mean uploading and downloading frequencies of all other users in user i's billing zip code area, respectively
β_0, γ_0	Intercepts
κ_i, ψ_i	User-specific dummies
φ_t, τ_t	Time-period dummies
$\eta_{i,t}$, $v_{i,t}$, $\varepsilon_{i,t}$	Unobservable, user-specific, time-specific effect; $\eta_{i,t} \sim \text{IIN}(0, \sigma_\eta^2)$, $v_{i,t} \sim \text{IIN}(0, \sigma_n^2)$, and $\varepsilon_{i,t} \sim \text{IIN}(0, \sigma_\varepsilon^2)$

Appendix B. Selection Equation Results

Table B.1 shows the results from the RE dynamic probit model. In the second week and thereafter (i.e., $t \geq 2$), we find the estimate for *Session* $(t-1)$ is positive (0.4602) and statistically significant, suggesting a positive state dependence in initiating mobile Internet sessions. The estimate for *Session by NN* $(t-1)$ is positive (0.0020) and statistically significant, suggesting a positive impact of lagged social network. An interesting aspect is that user behavior greatly varies by age, given that the coefficient of *Age* is positive (0.0960) and statistically significant, and the coefficient of Age^2 is negative (−0.0023) and statistically significant, implying an inverted U-shaped relationship between age and mobile media usage with a peak around approximately 21 years old. Results also show that male users are more likely to engage in mobile Internet content activities than female users. For the first week of observation window (i.e., $t=1$), we observe similar results regarding age and gender as above. In addition, the estimate for *Handset Age* is negative (−0.0007) and statistically significant. This implies that the oldness of a 3G mobile handset is negatively associated with user propensity to engage in mobile content activities. Furthermore, note that the significant estimate for θ suggests that the exogeneity of initial conditions is strongly rejected (refer to Equation (3) for θ). Finally, based on these selection equation estimates, we compute a selection correction term, which is later inserted into content generation and usage equations.

Table B.1 Selection Equation Results

Equation	Explanatory variable	Coefficient
Session $(t \geq 2)$	*Session* $(t-1)$ (1 = yes, 0 = no)	0.4602 (0.0232)***
	Social Network Session $(t-1)$ (1 = yes, 0 = no)	0.0020 (0.0008)**
	Age	0.0960 (0.0217)***
	Age^2	−0.0023 (0.0004)***
	Sex (1 = male, 0 = female)	0.1442 (0.0379)***
		0.0001 (0.0002)
	Constant	−1.6300 (0.2898)***
Session $(t=1)$	*Age*	0.0548 (0.0219)**
	Age^2	−0.0014 (0.0006)**
	Sex (1 = male, 0 = female)	0.1754 (0.0642)***
	Handset Age (months)	−0.0007 (0.0003)***
	Constant	−0.9163 (0.3206)***
	θ	0.8176 (0.0339)***
	σ_δ^2	0.2499 (0.0098)***

Notes. $\overline{\textit{Social Network Session}}$ is the time of mean mobile Internet initiation by social network neighbors. Estimates for time-period fixed effects and effects of mean mobile Internet session initiation of all other users in user *i*'s billing zip code are not reported for brevity.

**Significant at 0.05; ***significant at 0.01.

Appendix C. Robustness Check Results

Table C.1 GMM-Based Dynamic Panel Data Model Results on Content Frequency

Dependent variable	Explanatory variable	Coefficient			
Log *Upload Frequency* (t)	Log *Upload Freq.* $(t-1)$	0.0744 (0.0054)***	0.0748 (0.0057)***	0.0735 (0.0051)***	0.0735 (0.0051)***
	Log *Download Freq.* $(t-1)$	−0.0234 (0.0011)***	−0.0234 (0.0011)***	−0.0234 (0.0011)***	−0.0234 (0.0011)***
	Log *Mean Local Mobility* (t)	0.0127 (0.0038)***			
	Log *Mean National Mobility* (t)		0.0190 (0.0076)***		
	Log *Local Mobility Dispersion* (t)			0.0068 (0.0040)*	
	Log *National Mobility Dispersion* (t)				0.0037 (0.0019)*
	Log *Number of Voice Calls* (t)	0.0040 (0.0019)**	0.0030 (0.0015)**	0.0055 (0.0026)**	0.0045 (0.0016)***
	Log *Upload Freq. by NN* $(t-1)$	0.0300 (0.0098)***	0.0298 (0.0099)***	0.0301 (0.0098)***	0.0302 (0.0098)***
Log *Download Frequency* (t)	Log *Download Freq.* $(t-1)$	0.1093 (0.0054)***	0.1109 (0.0055)***	0.1051 (0.0054)***	0.1054 (0.0057)***
	Log *Upload Freq.* $(t-1)$	−0.1840 (0.0157)***	−0.1842 (0.0156)***	−0.1820 (0.0156)***	−0.1823 (0.0156)***
	Log *Mean Local Mobility* (t)	0.0149 (0.0018)***			
	Log *Mean National Mobility* (t)		0.0314 (0.0034)***		
	Log *Local Mobility Dispersion* (t)			0.0231 (0.0039)***	
	Log *National Mobility Dispersion* (t)				0.0112 (0.0030)***
	Log *Number of Voice Calls* (t)	0.0175 (0.0063)***	0.0209 (0.0061)***	0.0357 (0.0077)***	0.0271 (0.0085)***
	Log *Download Freq. by NN* $(t-1)$	0.0432 (0.0105)***	0.0438 (0.0107)***	0.0428 (0.0106)***	0.0432 (0.0110)***

Notes. We included each one of the two mean mobility metrics and the two mobility dispersion metrics in our main equations at both the local and national levels. NN refers to network neighbors. Estimates for time-period fixed effects and effects of mean uploading and downloading frequency of all other users in user *i*'s billing zip code are not reported for brevity.

*Significant at 0.1; **significant at 0.05; ***significant at 0.01.

Table C.2 Alternative Model Results on Content Frequency (Mixed Effect Model and Poisson Fixed Effect Model)

		Coefficient							
Dependent variable	Explanatory variable	Mixed effect model (with random coefficients on constant terms)				Poisson fixed effect model			
Log *Upload Frequency* (t)	Log *Upload Freq.* ($t-1$)	0.6512 (0.0022)***	0.6517 (0.0022)***	0.6527 (0.0022)***	0.6517 (0.0022)***	0.0011 (0.0001)***	0.0011 (0.0001)***	0.0011 (0.0001)***	0.0010 (0.0001)***
	Log *Download Freq.* ($t-1$)	−0.0069 (0.0007)***	−0.0068 (0.0007)***	−0.0068 (0.0007)***	−0.0068 (0.0007)***	−3.6e−4 (6.0e−5)***	−3.7e−4 (6.0e−5)***	−3.5e−4 (6.0e−5)***	−3.6e−4 (6.0e−5)***
	Log *Mean Local Mobility* (t)	0.0064 (0.0017)***				0.0313 (0.0044)***			
	Log *Mean National Mobility* (t)		0.0083 (0.0038)**				0.2621 (0.0210)***		
	Log *Local Mobility Dispersion* (t)			0.0002 (0.0018)				0.0124 (0.0028)***	
	Log *National Mobility Dispersion* (t)				0.0012 (0.0012)				0.0678 (0.0091)***
	Log *Number of Voice Calls* (t)	−0.00011 (0.00015)	−0.00006 (0.00005)	−0.00003 (0.00004)	−0.00006 (0.00005)	0.0073 (0.0006)***	0.0073 (0.0006)***	0.0066 (0.0008)***	0.0075 (0.0006)***
	Log *Upload Freq. by NN* ($t-1$)	0.0405 (0.0061)***	0.0408 (0.0061)***	0.0409 (0.0061)***	0.0408 (0.0061)***	0.0052 (0.0015)***	0.0052 (0.0015)***	0.0046 (0.0015)***	0.0047 (0.0015)***
Log *Download Frequency* (t)	Log *Download Freq.* ($t-1$)	0.6671 (0.0021)***	0.6673 (0.0021)***	0.6672 (0.0021)***	0.6673 (0.0021)***	5.4e−6 (7.7e−7)***	5.7e−6 (7.7e−7)***	5.3e−6 (7.7e−7)***	5.2e−6 (7.7e−7)***
	Log *Upload Freq.* ($t-1$)	−0.0281 (0.0108)***	−0.0279 (0.0108)**	−0.0277 (0.0108)***	−0.0276 (0.0108)***	−0.0011 (0.0003)***	−0.0011 (0.0003)***	−0.0012 (0.0003)***	−0.0012 (0.0003)***
	Log *Mean Local Mobility*	0.0326 (0.0067)***				0.0057 (0.0006)***			
	Log *Mean National Mobility* (t)		0.0439 (0.0144)***				0.0432 (0.0020)***		
	Log *Local Mobility Dispersion* (t)			0.0092 (0.0069)				0.0007 (0.0002)***	
	Log *National Mobility Dispersion* (t)				0.0104 (0.0045)***				0.0120 (0.0009)***
	Log *Number of Voice Calls* (t)	0.0009 (0.0002)***	0.0011 (0.0002)***	0.0013 (0.0002)***	0.0010 (0.0002)***	0.0010 (0.0001)***	0.0010 (0.0001)***	0.0011 (0.0001)***	0.0011 (0.0001)***
	Log *Download Freq. by NN* ($t-1$)	0.0275 (0.0037)***	0.0283 (0.0037)***	0.0285 (0.0037)***	0.0278 (0.0037)***	7.0e−5 (2.7e−5)***	7.0e−5 (2.7e−5)***	7.0e−5 (2.7e−5)***	7.0e−5 (2.7e−5)***

Notes. We included each one of the two mean mobility metrics and the two mobility dispersion metrics in our main equations at both the local and national levels. NN refers to network neighbors. Estimates for time-period fixed effects and effects of mean uploading and downloading frequency of all other users in user i's billing zip code are not reported for brevity.

**Significant at 0.05; ***significant at 0.01.

Table C.3 GMM-Based Dynamic Panel Data Model Results on Content Share

Dependent variable	Explanatory variable	Coefficient			
Upload Share (t)	*Download Share* ($t-1$)	−0.1190 (0.0120)***	−0.1199 (0.0120)***	−0.1199 (0.0120)***	−0.1191 (0.0120)***
	Mean Local Mobility (t)	0.0006 (0.0002)***			
	Mean National Mobility (t)		0.0033 (0.0009)***		
	Local Mobility Dispersion (t)			0.0002 (0.0001)**	
	National Mobility Dispersion (t)				0.0004 (0.0002)**
	Number of Voice Calls (t)	8.0e−5 (2.0e−5)***	6.0e−5 (2.0e−5)***	7.0e−5 (2.0e−5)***	4.0e−5 (1.0e−5)***
	Upload Share by NN ($t-1$)	0.0797 (0.0047)***	0.0798 (0.0047)***	0.0801 (0.0047)***	0.0800 (0.0047)***

Notes. We included each one of the two mean mobility metrics and the two mobility dispersion metrics in our main equations at both the local and national levels. NN refers to network neighbors. Estimates for time-period fixed effects are not reported for brevity.

***Significant at 0.01.

Table C.4 3SLS Estimation Results on Content Size

Dependent variable	Explanatory variable	Coefficient
Log *Upload Size* (t)	Log *Download Size* ($t-1$)	−0.0166 (0.0010)***
	Log *Upload Size by NN* ($t-1$)	0.0027 (0.0039)
	Selection (t)	0.0159 (0.0023)***
Log *Download Size* (t)	Log *Upload Size* ($t-1$)	−0.0477 (0.0033)***
	Log *Download Size by NN* ($t-1$)	0.0034 (0.0072)
	Selection (t)	0.0534 (0.0041)**

Notes. We used 13-week sample. NN refers to network neighbors. Estimates for time-period fixed effects are not reported for brevity.
**Significant at 0.05; ***significant at 0.01.

References

Albuquerque, P., P. Pavlidis, U. Chatow, K. Chen, Z. Jamal, K. Koh. 2010. Evaluating promotional activities in an online two-sided market for user-generated content. Working paper, University of Rochester, Rochester, NY.

Aral, S., L. Muchnik, A. Sundararajan. 2009. Distinguishing influence-based contagion from homophily-driven diffusion in dynamic networks. *Proc. National Acad. Sci. USA* **106**(51) 21544–21549.

Arellano, M. 1987. Computing robust standard errors for within-groups estimators. *Oxford Bull. Econom. Statist.* **49**(4) 431–434.

Banerjee, S., R. R. Dholakia. 2008. Does location based advertising work? *Internat. J. Mobile Marketing* **3**(2) 68–74.

Baum, C. F. 2007. CHECKREG3: Stata module to check identification status of simultaneous equations system. Statistical Software Components, Department of Economics, Boston College, Boston. http://econpapers.repec.org/software/bocbocode/s456877.htm.

Baye, M., J. Rupert, J. Gatti, P. Kattuman, J. Morgan. 2009. Clicks, discontinuities, and firm demand online. *J. Econom. Management Strategy* **18**(4) 935–975.

Becker, G. S. 1965. A theory of the allocation of time. *Econom. J.* **75**(299) 493–517.

Biørn, E. 2004. Regression systems for unbalanced panel data: A stepwise maximum likelihood procedure. *J. Econom.* **122**(2) 281–291.

Dasgupta, K., R. Singh, B. Viswanathan, D. Chakraborty, S. Mukherjea, A. Nanavati, A. Joshi. 2008. Social ties and their relevance to churn in mobile telecom networks. *EDBT'08 Proc. 11th Internat. Conf. Extending Database Tech.*, ACM, New York, 668–677.

Dekimpe, M. G., D. M. Hanssens. 1995. The persistence of marketing effects on sales. *Marketing Sci.* **14**(1) 1–21.

Economist, The. 2010. The mobile data challenge: A report from the Economist Intelligence Unit. http://graphics.eiu.com/upload/eb/Innopath_MobileData_WEB.pdf.

Ghose, A., S. P. Han. 2009. A dynamic structural model of user learning on the mobile Internet. Working paper, New York University, New York. http://ssrn.com/abstract=1485049.

Ghose, A., A. Goldfarb, S. Han. 2011. How is the mobile Internet different? Search costs and local activities. Working paper, New York University, New York. http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1732759.

Greene, W. 2007. Fixed and random effects models for count data. Working Paper NYU EC-07-16, Stern School of Business, New York University, New York.

Hartmann, W. R., P. Manchanda, H. Nair, M. Bothner, P. Dodds, D. Godes, K. Hosanagar, C. Tucker. 2008. Modeling social interactions: Identification, empirical methods and policy implications. *Marketing Lett.* **19**(3) 287–304.

Heckman, J. J. 1979. Sample selection bias a specification error. *Econometrica* **47**(1) 153–161.

Hill, S., F. Provost, C. Volinsky. 2006. Network-based marketing: Identifying likely adopters via consumer networks. *Statist. Sci.* **21**(2) 256–276.

Homans, G. C. 1958. Social behavior as exchange. *Amer. J. Sociol.* **63**(6) 597–606.

Iyengar, R., C. Van den Bulte, T. W. Valente. 2011. Opinion leadership and social contagion in new product diffusion. *Marketing Sci.* **30**(2) 195–212.

Jacoby, J., G. J. Szybillo, C. K. Berning. 1976. Time and consumer behavior: An interdisciplinary overview. *J. Consumer Res.* **2**(1) 320–339.

Lahiri, K., P. Schmidt. 1978. On the estimation of triangular structural systems. *Econometrica* **46**(5) 1217–1221.

Lancaster, T. 2000. The incidental parameters problem since 1948. *J. Econometrics* **95**(2) 391–414.

Manski, C. 1993. Identification of endogenous social effects. *Rev. Econom. Stud.* **60**(3) 531–542.

Mundlak, Y. 1978. On the pooling of time series and cross section data. *Econometrica* **46**(1) 69–85.

Nair, H. S., P. Manchanda, T. Bhatia 2010. Asymmetric social interactions in physician prescription behavior: The role of opinion leaders. *J. Marketing Res.* **47**(5) 883–895.

Nam, S., P. Manchanda, P. K. Chintagunta. 2010. The effect of signal quality and contiguous word of mouth on customer acquisition for a video-on-demand service. *Marketing Sci.* **29**(4) 690–700.

Nerlove, M. 1967. Experimental evidence on the estimation of dynamic economic relations from a time series of cross sections. *Econom. Stud. Quart.* **18**(3) 42–74.

Nickell, S. 1981. Biases in dynamic models with fixed effects. *Econometrica* **49**(6) 1417–1426.

Oestreicher-Singer, G., A. Sundararajan. 2010. The visible hand? Demand effects of recommendation networks in electronic markets. Working paper, Tel Aviv University, Tel Aviv, Israel.

O'Hara, K., A. Mitchell, A. Vorbau. 2007. Consuming video on mobile devices. *Proc. SIGCHI Conf. Human Factors Comput. Systems,* ACM, New York, 857–866.

Osborne, M. 2007. Consumer learning, switching costs, and heterogeneity: A structural examination. EAG Discussions paper 200710, Antitrust Division, Department of Justice, Washington, DC.

Puhani, P. 2000. The heckman correction for sample selection and its critique. *J. Econom. Surveys* **14**(1) 53–68.

Rethink Wireless. 2010. AT&T will use new device formats to introduce usage-based pricing. Accessed November 1, http://www.rethink-wireless.com/article.asp?article_id=2722.

Shim, J. P., S. Park, J. M. Shim. 2008. Mobile TV phone: current usage, issues, and strategic implications. *Indust. Management and Data Systems* **108**(9) 1269–1282.

Stewart, M. B. 2006. Maximum simulated likelihood estimation of random—Effects dynamic probit models with autocorrelated errors. *Stata J.* **6**(2) 256–272.

Stewart, M. B. 2007. The interrelated dynamics of unemployment and low-wage employment. *J. Appl. Econometrics* **22**(3) 511–531.

Stoeckl, R., P. Rohrmeier, T. Hess. 2007. Motivations to produce user generated content: Differences between webloggers and

video bloggers. *BLED 2007 Proc.*, Paper 30, http://aisel.aisnet.org/bled2007/30.

Susarla, A., J.-H. Oh, Y. Tan. 2011. Social networks and the diffusion of user-generated content: Evidence from YouTube. *Inform. Systems Res.*, ePub ahead of print April 8, http://is.journal.informs.org/cgi/content/abstract/isre.1100.0339v1.

Trusov, M., A. V. Bodapati, R. E. Bucklin. 2010. Determining influential users in Internet social networks. *J. Marketing Res.* **47**(4) 643–658.

Tucker, C. 2008. Identifying formal and informal influence in technology adoption with network externalities. *Management Sci.* **54**(12) 2024–2038.

Vanhonacker, W. R., V. Mahajan, B. J. Bronnenberg. 2000. The emergence of market structure in new repeat-purchase categories: The interplay of market share and retailer distribution. *J. Marketing Res.* **37**(1) 16–31.

Verbeek, M. 1990. On the estimation of a fixed effects model with selectivity bias. *Econom. Lett.* **34**(3) 267–270.

Verbeek, M., T. Nijman. 1996. Incomplete panels and selection bias. L. Mátyás, P. Sevestre, eds. *The Econometrics of Panel Data: A Handbook of the Theory with Applications*. Kluwer Academic Publishers, Dordrecht, The Netherlands, 449–490.

Wooldridge, J. M. 2002. *Econometric Analysis of Cross Section and Panel Data*. MIT Press, Cambridge, MA.

Xia, M., Y. Huang, W. Duan, A. B. Whinston. 2011. To continue sharing or not to continue sharing? An empirical analysis of user decision in peer-to-peer sharing networks. *Inform. Systems Res.*, ePub ahead of print April 8, http://isr.journal.informs.org/cgi/content/abstract/isre.1100.0344v1.

Zabel, J. E. 1992. Estimating fixed and random effects models with selectivity. *Econom. Lett.* **40**(3) 269–272.