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# An Empirical Analysis of User Content Generation and Usage Behavior in Mobile Digital Media

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# AN EMPIRICAL ANALYSIS OF USER CONTENT GENERATION AND USAGE BEHAVIOR IN MOBILE DIGITAL MEDIA

*Completed Research Paper*

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## Abstract

*Different kinds of user-generated content are becoming available in mobile digital and web media settings as well spurred by the rapid advances in the cellular telephony market. We use a unique dataset of individual-level mobile records to study the nature of interdependencies between users' content generation and content usage behavior. While theories of resource constraints from economics posit the existence of a negative interdependency between content generation and usage, theories of social exchange from sociology posit the existence of a positive interdependency between these two activities. Hence, the final directional nature of this interdependency is an empirical question. We find that there exist negative inter-temporal interdependencies between the content generation and usage behavior. The effect is also asymmetric such that the negative impact of previous period's content generation on current period's content usage is higher than vice-versa. Managerial implications for discounting in data transmission prices are discussed.*

**Keywords:** mobile digital media, user-generated content, social networks, Internet, econometrics

## Introduction

Taking cues from electronic commerce, different kinds of user-generated content (hereinafter UGC) are becoming available in mobile media environments, spurred by rapid technological advances in the cellular telephony market. Besides regular content in social networking sites that are being accessed and created through mobile phones, other examples of content created and used in mobile digital media settings include photos, graphics, screensavers, ring tones, videos, mobile games, podcasts, wall papers and various other kinds of multi-media content. Mobile content services has been growing at a CAGR of 23.6 percent (2008-2013), and revenues are expected to reach US$75.6 billion by 2013 (Frost and Sullivan 2009). In fact, the same study finds that by 2012 revenues from mobile content services could outstrip messaging revenues.

A unique aspect of the process of creating content in mobile media settings is that users need to explicitly incur expenses (for example, by paying data transmission charges) during their mobile content generation and usage endeavors based on the number of bytes uploaded or downloaded. This is in contrast to UGC in electronic commerce where content generation on blogs and opinion forums through a PC using a fixed Internet connection can generally be done without incurring any additional direct monetary costs. These explicit expenses lead to a situation where monetary constrain can influence user behavior with respect to how much they invest in content creation and content usage over time.

As mobile phones become an increasingly popular device for browsing the Internet, newer marketing strategies may need to be implemented in this environment, in lieu of or in addition to, traditional Internet marketing methods. This requires a deeper knowledge of users' content creation and usage behavior in mobile media settings as well as the potential for monetizing such content. However, little is known about how content creation by users is related to their usage of such content, or vice-versa, and how these processes are associated with users' personal characteristics, social network characteristics and extent of discretionary time resources.

In this paper, we examine users' content generation and content usage behavior by quantifying the extent of inter-temporal inter-dependencies (between generation or usage activities). While some consumers tend to be users of content created by others, some others contribute by creating and uploading content to portals and social networking sites. For a given user, content generation and usage may not be independent decision-making processes. Rather, they are likely to be inter-related processes. Hence, users in the mobile media setting may switch between their content creation and usage modes due to both time and monetary constraints. For example, in a given day higher the amount of discretionary time spent by a user in consuming content on social media sites (e.g., Facebook, YouTube, Epinions, etc), lower the amount of discretionary time left for that user to generate content (e.g., uploading photos, reviews, videos, and so on). On the other hand, a competing viewpoint from the sociology literature is that higher levels of content usage by users in previous periods may motivate them to contribute higher levels of content in subsequent periods as they begin to feel an integral part of the community established on these sites. Whether the former negative interdependency is stronger than the latter positive one, is an empirical question that we aim to examine in this paper.

Towards examining these issues, we develop an empirical model and test it using a unique dataset consisting of mobile data across a panel of users encompassing their content uploading and downloading behavior. The dataset consists of more than 2.34 million mobile data transaction records across 180,000 users. We also have data on voice calls made by the same users that enables to draw the social networks. We have detailed user-related demographic data. We implement an individual-level simultaneous equations panel data model.

The individual-level analysis using 3SLS (three-stage least squares) based simultaneous equation models enables us to not only quantify the dynamic interdependencies between an individual user's content creation and usage behavior, but also examine the social network. Our results also show that there exist negative inter-temporal interdependencies between content generation in the current period and content usage in the immediate previous period. This is consistent with the theory of users' being subject to resource constraints like time, money or both. The effect is asymmetric such that the negative impact of previous period's content generation on current period's content usage is much higher than vice-versa. The results on the extent of social influence on a user's content creation and usage behavior are positive but not significant.

Implications from this paper can provide mobile content service providers with insights into how to monetize such UGC as well as help mobile advertisers gain an understanding of the interdependency between users' content creation and usage that can be used for mobile phone-based advertising marketing. Furthermore, this research will significantly contribute to the emerging literature on economic value and monetization of UGC by adding to the literature that has examined these issues in electronic commerce.

The rest of this paper is organized as follows. In Section 2, we provide prior literature relevant to our paper to build the theoretical framework. Section 3 describes the data that we employ. We describe the individual-level econometric models in Section 4. Section 5 presents estimation results, and Section 6 discusses implications of the result and concludes.

## Theory and Literature Review

Our paper draws from multiple streams of literatures. Extant research on user-generated content (UGC) focuses on the various factors that motivate users to generate content, especially in the digital media environment. Nov (2007) surveys Wikipedians and finds that fun and ideology are the major motives for UGC in a collaborative environment. Kim et al. (2007) also conduct a survey study and show that three factors that affect user participation in generating video content are extrinsic and intrinsic motivations of the users (e.g., reputation and altruism), the ease of video content generation processes, and trust-based relationships with service providers. Bughin (2007) finds that a desire for fame and a feeling of identification within the community are motives for user collaboration and participation in online video-sharing sites. In a related context, Roberts et al. (2006) study open source software communities and categorize developer motivations into intrinsic (e.g., fun and joy in solving challenges), and extrinsic factors (e.g., reputation, social identity, etc.).

An emerging stream of relevant work in IS and Marketing has formally investigated the economic impact of online UGC. Studies have used the numeric review ratings (e.g., the number of stars) and the volume of reviews in their empirical analyses (Godes and Mayzlin 2004, Chevalier and Mayzlin 2006, Dellarocas et al. 2007, Forman et al. 2008, Duan et al. 2008). An emerging stream of work has examined whether the textual information embedded in online UGC can have an economic impact in the context of reputation systems (Ghose et al. 2005, Pavlou and Dimoka 2006, Ghose 2009), online reviews (Ghose and Ipeirotis 2007, Archak et al. 2008) and stock market discussion forums (Das and Chen 2007) by using automated text mining techniques. All these papers use aggregate-level data.

Our paper is distinct from all the above literature in that we have individual-level data which enable us to consider the content generation and content usage behavior of users as a dynamically interdependent process. Our paper draws from several streams of literatures discussed below.

Users' resource (time and money) allocation decisions across different activities are inter-dependent under resource constraints. Economic theories suggest that when resources are limited, a decision maker efficiently allocates them across available alternatives to maximize utility. Besides money, researchers have long recognized that time also acts as a constraint (Becker 1965, Jacoby et al. 1976) such that users have limited discretionary time. In traditional media settings, users seek to maximize utility through effectively allocating scarce resources (e.g., money and time) across different activities. For example, Hornik and Schlinger (1981) examine media usage patterns and find that people allocate their time to viewing, listening, and reading in order to receive certain gratifications and that different media are used to meet different personal needs. Specifically, Hornik and Schlinger (1981) show that mass media (e.g., television, radio, magazines, and newspapers) do not serve as substitutes for one another in terms of media time use. That is, spending time in one medium does not necessarily reduce the time spent in the others.

In online settings, users allocate resources between content generation and content usage activities (e.g., creating one's own blog vs. viewing someone else's blog, or uploading photos vs. downloading photos posted by others). This has also been documented in various industry studies (see for example, Forrester Research 2009). Unlike traditional media such as TV or magazines where consumers typically only consume content, in online settings people can take on the dual role of creators as well as consumers (Trusov et al. 2006). Nevertheless, there are users who tend to free-ride by only consuming content without creating any in return. This is because the creation and provision of content can often incur a cost to providers (Feldman et al. 2003). In mobile media settings not only do users need to invest time and effort but they also incur explicit transmission charges to generate (i.e., upload) and use (i.e., download) content. Hence, time and monetary resource constraints are important in this setting. Changes in resource constraints may lead the user to reallocate time and money between content generation and content usage activities over time. For example, if a user has spent most of her discretionary time and money in consuming content on mobile portal or social media sites, the user would be left with less time and money to generate content on these sites. Thus, we can posit that there will be a negative inter-temporal interdependency between content creation and content usage.

In contrast to the above argument, some work in the online sharing literature (Asvanund et al. 2004; Xia et al. 2007) draw on the social exchange theory (Homans 1958) and suggest the presence of a positive inter-temporal interdependence between content generation and usage. They predict that the more a user benefits from the contribution of other users, the more the user is willing to create content that could be of use to other participants. This stems from a community-like structure in these forums. Xia et al. (2007) study factors that affect a user's choice to share in an online music sharing community, and find that users are more likely to share if they receive more benefit directly from the community.

Since the extent of reciprocal interactions with each other in the mobile setting is unknown, the overall extent of the inter-temporal effect between content generation and usage still remains an empirical question. Even though we can theorize about the existence of a relationship, the directional nature of this relationship is not unambiguous ex-ante. This is the main objective of this paper.

## Data Description

In this section, we describe the data that we collected from a large telecommunications service company in South Korea. Our sample is drawn from 3G mobile users who used the services of the company between March 15, 2008 and June 15, 2008. 3G mobile services enable users to upload and download their content faster than conventional mobile service. Further, these services are more commonly available on the larger screen handsets that facilitate relatively more user-friendly content generation and usage. The dataset consists of more than 2.34 million mobile data transaction records across 180,000 users encompassing their content uploading and downloading behaviors. We also have data on voice calls made by the same users that enables to draw social networks. For example, voice call records contain both callers' telephone numbers from the initial 180,000 users and call receivers' telephone numbers, and their call duration.

**Table 1: Summary Statistics**

| Variable | Observations | Mean | Std. dev. | Min | Max |
|---|---|---|---|---|---|
| Weekly, User-Specific Mobile Data | | | | | |
| Num. of Sessions | 2,340,000 | 4.00 | 41.38 | 0 | 19061 |
| Num. of Uploading | 610,809 | 0.27 | 3.54 | 0 | 879 |
| Num of Downloading | 610,809 | 22.57 | 86.80 | 0 | 19069 |
| Weekly, User-Specific Call Records and Geographical Data | | | | | |
| Num. of Calls Made | 900,000 | 11.88 | 16.32 | 0 | 515 |
| Call Duration (Hours) | 900,000 | 2.61 | 5.68 | 0 | 186.65 |
| By User Characteristics | | | | | |
| Age | 180,000 | 30.13 | 5.91 | 9 | 38 |
| Gender (1 = Male, 0 = Female) | 180,000 | 0.53 | 0.50 | 0 | 1 |
| Handset Age (Months) | 180,000 | 9.63 | 3.97 | 0 | 22.33 |

***Notes:*** *The total number of users in the sample is 180,000. Note that we observe content generation and usage data only when a user starts mobile sessions, thus the number of uploading and the number of downloading are lower than the number of sessions.*

Our mobile data records include individual-level information on users' content generation and usage activities on a weekly basis. Technically, a unique mobile session initiates when a user pushes a button in a keypad on his or her handset or by clicking an icon on a touchpad, and it ends when the user deactivates the mobile session. Only when a user initiates a mobile session can the user either download content or upload content, or both. Such an activity involving more than zero bytes of data transmission is considered as an event. One mobile session usually consists of multiple events. As shown in Table 1, the mean of number of downloads can exceed the mean of number of sessions (i.e., 22.57 >4.00). Also we observe that a user's content generation occurs far less frequently than content usage (i.e., 0.27 < 22.57). We have precise transmission data and time stamp information for all sessions and for all events. The time period in our analyses is 'week'. This is because the daily frequency of content generation per user is extremely low (i.e., 0.04 times a day). Finally, we also have data on demographics like age, gender and product characteristics such as handset age. The summary statistics of the key variables used is provided in Table 1.

# Econometric Models

To analyze the underlying relationship between users' content generation and content usage behavior in the presence of resource constraints, we implement an individual-level simultaneous equations panel data model using three-stage least-square (3SLS) analysis. It characterizes the interdependent relationship between content generation and usage behavior for a given user.

To formally characterize the econometric model, we model the underlying consumer decision process for mobile phone-based content generation and usage in the following way. There are three related decisions – (i) mobile data session initiation, (ii) content generation (i.e., uploading), and (iii) content usage (i.e., downloading). We consider the sequential nature of decisions therein. Content uploading or downloading is possible only if a user initiated his/her mobile data session (for example, by pushing a button in a keypad or by clicking an icon on a touchpad), so the mobile session initiation precedes the other two decisions. Moreover, given that a user started his/her mobile data session, we model the other two decisions over time by accounting for, for a content generation equation, a lag variable of a content usage, and vice-versa. Finally, we also postulate that for a given user content generation and content usage decisions can be associated with ones from network neighbors of the same user.

## *Econometric Issues*

Since some users are idle in certain periods and active in other periods in terms of their mobile phone-based content activities, the number of active weeks varies by users. This kind of selection process might occur non-randomly. Hence, we need to account for this issue in our estimation. Also, we need to account for the well-known initial conditions problem in our model because for each user the first observation in our sample may not be the true initial outcome of his/her mobile content generation and usage process. Further, we often observe that in a given time period some users behave similarly as they did in the previous period. We account for this phenomenon by incorporating both unobserved heterogeneity and dynamic state dependence in our model. Finally, there could be simultaneity issues between content generation and usage and we need to account for that too in our estimation. To summarize, there are four issues here: (i) selectivity bias (ii) initial conditions problem, (iii) heterogeneity and dynamic state dependence, and (iv) simultaneity. We address each of these issues in our model. Notations and variable descriptions are provided in Table 2.

## *Selection Equations*

We adopt Verbeek and Nijman's (1996) two-step method to correct for potential selectivity bias. In Step 1, a random effects (RE hereinafter) dynamic Probit model is run for selection equations and correction term estimates are obtained. In Step 2, we insert the correction term estimates into the main equations of content generation and usage and estimate these two equations simultaneously using a fixed effects model.

More specifically, we use the Heckman (1981) approach since it accounts for the potentially non-random selection process as well as allows for the endogeneity of the initial conditions. The covariates in the selection equation include whether the user started a mobile session in the immediate previous period or not, the frequency of session initiation by the user's network neighbors, the extent of total discretionary time available to a user, a user's demographical attributes and the age of the handset. Note that except for the behavior of social network neighbors, all other variables are time-invariant. Given this and consistent with Verbeek and Nijman (1996), we use a RE dynamic Probit model to account for a user's session start decision.

To account for the initial conditions issue, we specify a separate selection equation for the first time period of a user's session start decision which is distinct from the user's decision in the remaining time periods. We specify that user i decides whether to start his/her mobile sessions using an indicator function (i.e., 1 = Yes and 0 = No). Our model specification for the initial period (t = 1) is as follows:

$$\mathrm{Session}^{*}_{i,1} = \pi_0 + \pi_1 \sum_{m \in n(i)} \left(w_{i,m,1} \times \mathrm{Session}_{m,1}\right) + \pi_2 \mathrm{Age}_i + \pi_3 {\mathrm{Age}_i}^2 + \pi_4 \mathrm{Sex}_i + \pi_5 \mathrm{Handset\_Age}_i + u_i \qquad (1)$$

$$\text{Session}_{i,1} = 1\left(\text{Session}^*_{i,1} > 0\right). \tag{2}$$

For the remaining periods ($t \geq 2$), the specification is as follows:

$$\text{Session}^*_{i,t} = \alpha_0 + \alpha_1 \text{Session}_{i,t-1} + \alpha_2 \sum_{m \in n(i)} \left(w_{i,m,t} \times \text{Session}_{m,t}\right) + \alpha_3 \text{Age}_i + \alpha_4 {\text{Age}_i}^2 + \alpha_5 \text{Sex}_i + \delta_i + \eta_{i,t} \tag{3}$$

$$\text{Session}_{i,t} = 1\left(\text{Session}^*_{i,t} > 0\right). \tag{4}$$

**Table 2: Notations and Variable Descriptions**

| | |
|---|---|
| $\text{Session}_{i,t}$ | Whether user i started mobile session at time t (1 = Yes, 0 = No) |
| $n(i)$ | User i's network neighbors based on voice call records (i.e., users called by user i) throughout the sampling period |
| $\text{Session}_{m,t}$ | Whether user i's network neighbor m started his or her mobile session at time t |
| $w_{i,m,t}$ | Communication strength between user i and user m at time t, that is, $w_{i,m,t}$ is the number of calls user i made to user m at time t |
| $\text{Age}_i$ | User i's age |
| $\text{Sex}_i$ | User i's sex (1 = Male, 0 = Female) |
| $\text{Handset\_Age}_i$ | Days elapsed since user i's handset was launched in the market |
| $\delta_i$ | Unobservable, time-constant, individual-specific effect ($\delta_i \sim \text{IIN}(0, \sigma^2_\delta)$ ) where IIN is independent identical normal |
| $\eta_{i,t}$ | Unobservable, time-specific, individual-specific effect ($\eta_{i,t} \sim \text{IIN}(0, \sigma^2_\eta)$, $\sigma^2_\eta$ is set to 1 for normalization and $\delta_i$ are independent of $\eta_{i,t}$) |
| $\theta$ | Initial conditions parameter |
| $\text{Upload}_{i,t}$ | Number of times content is generated (uploaded) by user i at time t |
| $\text{Upload}_{m,t}$ | Number of times content is generated (uploaded) by user i's network neighbor m at time t |
| $\text{Download}_{i,t}$ | Number of times content is consumed (downloaded) by user i at time t |
| $\text{Download}_{m,t}$ | Number of times content is consumed (downloaded) by user i's network neighbor m at time t |
| $\beta_0, \gamma_0$ | Intercepts |
| $d_{i,j,t}$ | User-specific constant term where $d_{i,j,t} = 1(i = j)$ |
| $\kappa_j,\ \psi_j$ | User-specific parameters |
| $\nu_{i,t}, \varepsilon_{i,t}$ | Unobservable, time-specific, user-specific effect, $\nu_{i,t} \sim \text{IIN}(0, \sigma^2_\upsilon)$ and $\varepsilon_{i,t} \sim \text{IIN}(0, \sigma^2_\varepsilon)$ |

If the initial conditions are correlated with the unobserved, time-constant, individual-specific effect, as would be expected in most situations, estimators will be inconsistent. Since the $u_i$ in Equation (1) is correlated with $\delta_i$ in Equation (3), but uncorrelated with $\eta_{i,t}$ for t = 2, 3,...., T, we specify $u_i$ as follows:

$$u_i = \theta\, \delta_i + \eta_{i,1}. \tag{5}$$

Further, an orthogonality problem may arise in our model. Because our selection equation is based on a RE model, the estimator will be inconsistent if the unobservable, time-constant, individual-specific effect is correlated with the regressors therein. Hence, we follow the Mundlak (1978) and Zabel (1992) approach and add the mean values of time-varying regressors (in our case, the mean value of social network neighbor effect) in the selection equation. In sum, we specify these selection equations using a RE dynamic Probit model and use Maximum Likelihood Estimation methods based on Stewart (2007).

Note that for the main analysis, $w_{i,m,t} = w_{i,m}$ based on 5-week voice call communication records, since we do not have data on the strength of communications between users and their network neighbors over the entire 13 weeks.

**Main Equations: Content Generation and Usage**

Recall that only when a user initiates mobile sessions (i.e., $\mathrm{Session}_{i,t} = 1$), can we observe the user's content creation and usage activities. The content creation frequency and usage frequency are specified according to the following fixed effect (FE hereinafter) model, for t = 2, 3,…, T:

$$\mathrm{Upload}_{i,t} = \beta_0 + \sum_{j=1}^{N} \kappa_j d_{i,j,1} + \beta_1 \sum_{m \in n(i)} \left(w_{i,m,t} \times \mathrm{Upload}_{m,t}\right) + \beta_2 \mathrm{Download}_{i,t-1} + \beta_3 \mathrm{Selection}_{i,t} + \nu_{i,t} \quad (6)$$

$$\mathrm{Download}_{i,t} = \gamma_0 + \sum_{j=1}^{N} \psi_j d_{i,j,1} + \gamma_1 \sum_{m \in n(i)} \left(w_{i,m,t} \times \mathrm{Download}_{m,t}\right) + \gamma_2 \mathrm{Upload}_{i,t-1} + \gamma_4 \mathrm{Selection}_{i,t} + \varepsilon_{i,t}. \quad (7)$$

The estimation of the selection term requires estimation of the parameters in the selection equations. Given the parameter estimates from the selection equations, we compute the selection term using numerical integration by using Verbeek and Nijman (1996)'s formula.

### Estimation

In Step 1, the RE dynamic Probit model is run for selection equations and correction term estimates are obtained. In Step 2, we insert the correction term estimates into the FE model for the content generation and usage equations given by equations (6) and (7), respectively, and estimate them simultaneously. The RE model takes advantages of including observable, time-constant variables (e.g., age, gender, etc.), whereas the FE model benefits from capturing additional unobserved effects which are directly related to the individual-specific time-varying variables. This is consistent with Verbeek and Nijman (1996).[1]

In a system of multiple equations with endogenous variables, we can obtain more efficient estimators by estimating parameters by using a system procedure. In triangular structural systems, Lahiri and Schmidt (1978) show that GLS gives consistent estimates, if based on any consistent estimate of the disturbance covariance matrix. However, when the disturbance covariance matrix is not known, GLS is inefficient compared to full information maximum likelihood (FIML) and three stage least squares (Lahiri and Schmidt 1978). Also, it is well known that a traditional three-stage least-square (3SLS) allows simultaneous estimation of the system of multiple equations, in which interdependent relationships between equations are characterized. Therefore we implement the 3SLS estimation for the main equations (6) and (7).

For a given user, the content generation and usage equations across different time periods include unobserved, user-specific fixed effects ($\kappa_j$ and $\psi_j$, respectively). It is well known that the estimation of fixed effects model with a lagged endogenous variables is subject to potential finite-sample bias (Nerlove 1967, Nickell 1981, Godes and Maylin 2004, Duan et al. 2008). Our model may suffer from the bias because the number of observations per user is 13 for the full sample and only 5 for the subsample. To alleviate the potential bias from the fixed effects, we take first-differencing (FD) transformation to eliminate them (Wooldridge 2002) and run the 3SLS on the differenced equations of content generation and content usage.[2] We also implement alternative GMM-based dynamic pane l models to check robustness of the results and discuss it in Section 5.3.

### Identification

In Step 1, since the user selection decision is binary choice, we need location and scale normalizations on the latent dependent variable, $Session^*_{i,t}$ for identification. We set the user i's utility of not engaging in any mobile sessions in time t $Session^*_{i,t} = 0$ for location normalization. We also set the variance of unobservable, time-specific, individual-specific effect, $\sigma^2_\eta$ to 1 for scale normalization. In Step 2, we examine whether both necessary order condition and sufficient rank condition are satisfied for our first-differenced equations of content generation and usage. It is easy to

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[1] Verbeek and Nijman (1996) showed that a fixed effect estimator in the main equations is more robust to selectivity biases than the random effects estimator. Moreover, they also show that the conditions for the consistency of a fixed effect estimator are weaker than that for a consistent random effects estimator.

[2] This approach is similar to Verbeek's (1990) where he 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.

see that the order condition is met because each equation has three excluded exogenous variables (i.e., a social network neighbor effect, a lagged inter-dependent effect and a discretionary time effect) while it has no right-hand-side endogenous variable. Further, we check the rank condition using Baum (2007)'s Stata code and find that the rank condition for each main equation is satisfied, so our equations of content generation and usage are identified.

## Results

In this section, we discuss our results on how inter-temporal interdependencies are associated with users' content generation and usage behavior. We look at the selection equation result and the 3SLS analysis result.

### *Selection Equation Result*

Table 3 shows the results from the RE dynamic Probit model estimation. In the second week and thereafter (i.e., $t > 1$), we find the estimate for *Session(t-1)*, is positive (0.597) and statistically significant, implying a positive state dependence in initiating mobile sessions. The estimate for *Session SN(t)*, is positive (0.146) and statistically significant, suggesting a positive impact of social network neighbors. An interesting aspect is that user behavior greatly varies by age, given that the coefficient of *Age* is positive (0.043) and statistically significant and the coefficient of *Age Square* is negative (-0.001) and statistically significant, implying an inverted U-shaped relationship between age and mobile media usage. The other demographic variable, *Gender*, suggests that male users are more likely to create or consume mobile media content than female users.

For the first week of observation window (i.e., $t = 1$), we observe similar results as above. The estimate for *Handset Age* is positive (0.015) and statistically significant. This implies that experience with 3G mobile handset increases that user's propensity to engage in mobile content creation or consumption activities. Note that the significant estimate for theta suggests that the exogeneity of initial condition can be strongly rejected (refer equation (5) for theta). Finally, based on these selection equation results, we compute selection correction terms which are later inserted into content generation and usage equations.

### *3SLS Results*

We next present the results on the content generation and usage equations. Table 4 shows the result from three-stage least squares (3SLS) estimation. Results show that there are negative and statistically significant inter-temporal inter-dependencies between content generation and usage. This implies that an increase in content generation in previous period is associated with a decrease in content usage in the current period and vice-versa (-0.204 and -0.0001, respectively). These effects are also asymmetric – the negative impact of previous period's content uploading on current period's content downloading propensity is much higher than vice-versa. Further, a 1 standard deviation increase in the number of previous period's content downloading decreases the number of content downloading in current period by 0.0079. In our sample the average number of content uploading is 0.27; thus this 1 standard deviation increase translates into a 2.92% decrease when evaluated at mean. Similarly, a 1 standard deviation increase in the number of previous period's content uploading decreases the number of content downloading in current period by 0.7209. In our sample the average number of content downloading is 22.75; thus this 1 standard deviation increase translates into a 3.19% decrease when evaluated at mean. Therefore, the marginal effects also suggest the asymmetric effect of inter-temporal interdependencies.

**Table 3: Selection Equations Parameter Estimates**

| Equation | Variable | Coefficient |
|---|---|---|
| Session (t > 1) | Session (t-1) (1 = Yes, 0 = No) | 0.597 (0.003)*** |
| | Session SN (t) (1 = Yes, 0 = No) | 0.146 (0.007)*** |
| | Age | 0.043 (0.003)*** |
| | Age Square | -0.001 (0.0001)*** |
| | Gender (1 = Male, 0 = Female) | 0.110 (0.005)*** |
| | Mean of Session SN | 0.444(0.015)*** |
| | Constant | -1.359 (0.044)*** |
| Session (t = 1) | Session SN (t) (1 = Yes, 0 = No) | 0.225 (0.023)*** |
| | Age | 0.063 (0.006)*** |
| | Age Square | -0.001 (0.0001)*** |
| | Gender (1 = Male, 0 = Female) | 0.127 (0.009)*** |
| | Handset Age (Months) | 0.015 (0.001)*** |
| | Mean of Session SN | 0.359(0.029)*** |
| | Constant | -1.771 (0.077)*** |
| | Theta | 0.966 (0.007)*** |
| All Sessions | Variance of Delta | 0.968(0.036)*** |

***Notes*:** SN refers to social network, thus Session SN means whether at least one person in a given user's social network started a mobile session during that week. Mean of Session SN is the mean of Session SN variable. *** denotes significant at 0.01.

**Table 4: 3SLS Results on Content Generation and Usage Using 13-Week Sample**

| Equation | Variable | Coefficient |
|---|---|---|
| Upload (t) | Download (t-1) | -0.0001 (0.00004)** |
| | Upload SN (t) | -0.006 (0.004) |
| | Selection (t) | 0.039 (0.023)* |
| Download (t) | Upload (t-1) | -0.204 (0.046)*** |
| | Download SN (t) | 0.002 (0.005) |
| | Selection (t) | -0.144 (0.860) |

***Notes:*** SN refers to social network, thus Upload SN means upload frequency of a user's social network neighbors. Selection refers to correction terms by Heckman (1981)'s approach. * denotes significant at 0.1, ** denotes significant at 0.05 and *** denotes significant at 0.01.

However, the social network neighbor effect is not statistically significant in either of the two equations. This is most likely because the communication strength between users was not incorporated in imputing the structure of the social network for a given user. We address this issue in our future study. Note also that the estimates for *Selection(t)*, are positive (0.039) and marginally significant in the uploading equation and negative (-0.144) and insignificant in the downloading equation, suggesting the selection effect is marginally significant only in the uploading equation.

## Conclusion

Mobile media content based services constitute one of the fastest-growing applications on the Web. However, little is known about how the content generation behavior of users is related to their content usage behavior, and how user demographics, and social network behavior is associated with their behavior in mobile media settings.

Our results show the existence of negative inter-temporal interdependence between content generation and content usage behavior and vice-versa. It implies that users tend to dynamically balance their limited resources (e.g., time and money) by adjusting the frequency of their content generation and usage activities. Thus, our results are consistent with economic theories of resource allocation under constraints.

The insights from this study can have some managerial implications. The 3SLS analysis provides mobile phone companies with some insights on an increasingly important chicken-and-egg problem: i.e., whether a supply-side pricing strategy (e.g., lowering data transmission charges for uploading content) is more effective than a demand-side pricing strategy (e.g., lowering data transmission charges for downloading content and usage fees) in order to stimulate users' overall activity levels in mobile media, and thereby increase their profits. The asymmetric result on the magnitude of the inter-temporal interdependency between content generation and usage suggests that a supply-side approach might be more effective than a demand-side strategy in alleviating the negative feedback loop between the two kinds of user activities. This is because the absolute magnitude of the negative impact of content generation in the previous period on content usage in the current period is much stronger than vice-versa in 3SLS analysis. This suggests that companies could be better off by fixing any negative user experiences from content generation and uploading. For example, they could provide easy-to-use content preprocessing tools and less complicated content uploading procedures for the mobile web and monetize them through advertising.

Furthermore, the provision of monetary incentives to trigger users' content generation behavior might be more effective for a mobile phone company. In many ways, content diffusion in mobile media settings is similar to that in P2P networks because free riders (i.e., users who download content from others in the network without redistributing it to others) can create supply-side constraints. Hence, firms engaging in mobile content provision and advertising could think of offering distribution referrals in the form of monetary payments to users who generate and distribute content, similar to that in P2P networks (Hosanagar et al. 2008). Implementation can be done by providing discounts in data transmission charges to such users.

Our paper has several 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.). Future work could examine this information and develop and test more specific hypotheses. This will help companies perform a cost/benefit analysis for each content type, and finally help monetize such mobile content. Another area for future work is to study how content generated via mobile devices diffuse through social networks. This sort of analysis requires access to a sort of integrated databases that capture the identification of content created and uploaded by a given user and traces who download that content in subsequent sessions. It is conceivable that even without any social influence on each other, two users who like to use their mobile handset to upload photos on the Internet (for example, through Facebook mobile feed) meet offline and become friends. Future research can focus on identification issues involved in capturing social effects (Hartmann et al. 2008) in mobile media settings. We hope that our study will generate further interest in the emerging literature on the economics of user-generated content and more broadly, in mobile commerce.

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