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Working Paper #09-24

October 2009

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A Dynamic Structural Model of User Learning in Mobile Media Content[1]

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Consumer adoption and usage of mobile communication and multimedia content services has been growing steadily over the past few years in many countries around the world. In this paper, we develop and estimate a structural model of user behavior and learning with regard to content generation and usage activities in mobile digital media environments. Users learn about two different categories of content – content from regular Internet social networking and community (SNC) sites and that from mobile portal sites. Then they can choose to engage in the creation (uploading) and consumption (downloading) of multi-media content from these two categories of websites. In our context, users have two sources of learning about content quality – (i) direct experience through their own content creation and usage behavior and (ii) indirect experience through word-of-mouth such as the content creation and usage behavior of their social network neighbors. Our model seeks to explicitly explain how direct and indirect experiences from social interactions influence the content creation and usage behavior of users over time. We estimate this model using a unique dataset of consumers' mobile media content creation and usage behavior over a 3-month time period. Our estimates suggest that when it comes to user learning from direct experience, the content that is downloaded from mobile portals has the highest average quality level. In contrast, content that is downloaded by users from SNC websites has the lowest average quality level. Besides, the order of magnitude of accuracy of signals for each content type from direct experiences is consistent with the order of the quality levels. This finding implies that in the context of mobile media users make content choices based on their perception of differences in both the average content quality levels and the extent of content quality variation. Further we find that signals about the quality of content from direct experience are more accurate than signals from indirect experiences. Potential implications for mobile phone operators and advertisers are discussed.

Key words: structural modeling, mobile media, mobile portals, Internet websites, uploading content, downloading content, dynamic programming, simulated maximum likelihood estimation.

[1]We thank Tülin Erdem for very helpful comments. We also thank Sanjeev Dewan, Russ Winer, and participants at the 2009 Marketing Dynamics Conference, the 2009 SCECR conference 2009 and the 2009 Marketing Science conference for helpful comments. We thank the NET Institute for partial funding for this project. Anindya Ghose acknowledges the generous financial support from NSF CAREER award (IIS-0643847). The usual disclaimer applies.

1. Introduction

Taking cues from electronic commerce, different kinds of user-generated content (hereafter UGC) are becoming available in mobile media environments as well, spurred by rapid advances in the cellular telephony market. Besides content on regular websites and social networking sites, other examples of content created and accessed through mobile phones include photos, graphics, ring tones, videos, pod-casts, and other kinds of multi-media content. As of today, several content management systems and social media platforms have created lightweight versions of their hosted sites automatically for users that come in via a mobile phones or WAP (Wireless Application Protocol) browsers. These websites work in much the same way as the regular Internet. However, rather than viewing web pages designed for PC's/Mac's, mobile sites are especially designed to be viewed on the small screens of a phone, are quick to load and simple to use. This process has facilitated increased user adoption of mobile commerce. Increasingly, we see more and more companies and mainstream brands launching a mobile web presence so they can engage directly with their consumers.

In many countries, a unique aspect of the mobile digital media 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 electronic commerce where content usage and generation on blogs and opinion forums through a PC or laptop using an Internet connection (broadband or DSL) can be done without incurring any additional variable costs over and above the fixed monthly usage fees. With mobile phones becoming an increasingly significant medium for Internet access, mobile operators' portals offer an innovative and differentiated route for advertisers to reach users. Therefore, understanding what kinds of content users create and access using their mobile phones is a key issue towards examining its potential as an advertising medium.

In this paper, we develop and estimate a dynamic model of users' content generation and usage activities in a mobile media setting. Our data has explicit information on the two broad categories of websites that users can access through their cell phones – mobile portal sites and regular Internet social networking and community-oriented websites (more information on these two categories is provided in the 'Data' section). This distinction is important because of the fundamental differences in the operation of mobile portal sites from regular websites. Mobile portal sites are owned and hosted by mobile phone companies. Examples include Vodafone live, T-Mobile's Web'n'Walk, Planet3, Orange World and O2 Active. A substantial part of the original content on these sites comes from third-party content creators who have entered into contracts with mobile phone operators. As a result, mobile operators have control on the kinds and quality of content that is available on these websites. This is as opposed to off-portal, regular Internet websites where these mobile phone operators can exercise less control on the content that is available to be shared, for obvious reasons. Hence, an understanding of differences in user behavior (both upload and download) between mobile portal sites and off-portal, social networking and community (SNC, hereafter) websites can be useful from the point of view of monetization of user-generated content through mobile advertising.

The context of our empirical analysis is akin to that of user dynamics and learning in experience goods. We model user behavior and learning with respect to two different categories of content – content from SNC websites and that from mobile portal sites and with respect to two different kinds of activities – content creation (uploading) and consumption (downloading). We do so in a dynamic structural model setting with Bayesian updating.[2] In our context, there are several reasons why user behavior might exhibit dynamics. First, as is known in the prior literature on state dependencies, choices made in previous periods might causally affect a user's current period utility and behavior. Second, as is known from the work on habit persistence there are temporal dependences in the random component of utility users derive from products (Heckman 1981). Third, users can exhibit forward-looking behavior in which they maximize the stream of expected utilities over a planning horizon rather than maximizing their immediate utility. As an example, current choices might depend on their information value and their impact on future utility, like in strategic consumer trial or sampling behavior (Eckstein et al. 1988). If this were so, then decision makers need to take into account the impact of their current actions on their future stream of utilities.

In fact, there is evidence of user dynamics in mobile media content settings. Specifically, prior work has shown that there are positive state dependencies in the content generation and content usage behavior of the users in mobile multi- media usage settings (Ghose and Han 2009). In addition, we have seen a positive association between the behavior of social network neighbors and the content generation and content usage behavior of a user in our prior work (Ghose and Han 2009). However, existing work does not model how and why users' current choices depend on past choices. Nor does it explain how and why one's choices depend on the choices of their social network neighbors.

Furthermore, user uncertainty can arise in situations with imperfect information about product characteristics and in fast-changing environments. Under uncertainty, past experience with brands (products) as well as marketing mix elements may affect a consumer's information set, which in turn affects his/her current choices (Erdem and Keane 1996). It is easy to see how there can be uncertainty and learning incentives in a mobile media content setting. Users can be uncertain about the benefits from spending time

[2] There are a couple of reasons why we choose to adopt such an approach. First, incorporating user dynamics into structural econometric models can enhance our understanding of user behavior. A dynamic structural approach takes into account the fact that when current choices influence future pay-offs, and hence the behavior of a rational decision-maker must be forward-looking (Chintagunta et al. 2006). Second, dynamic structural models may be able to explain certain empirical patterns that are not captured by static models especially when it comes to situation involving uncertainty and learning. Hence, ignoring the dynamics could potentially "throw away" valuable information and in the worst case could generate misleading conclusions about behavior (Chintagunta et al. 2006).

and monetary resources towards content generation and content usage activities. Further, they may lack information about the benefits from content generation and usage at the specific content category level. For example, downloading audio files from mobile portal sites can provide information about the direct benefit from audio content but provide little information about the utility from downloading other types of content (such as video files) from SNC sites. Similarly, users may be uncertain about the quality from a video file uploaded on SNC sites as opposed to one that is uploaded on mobile portal sites. Finally, there are additional quality-signaling in our context which could facilitate reduce uncertainty and facilitate learning – such as the behavior of social network neighbors.

These reasons suggest that a dynamic structural model of uncertainty and user learning is well suited for our context. Our paper builds and estimates a structural model of user behavior in which forward-looking users learn about mobile media content quality. The learning occurs through direct signals such as their own content creation and usage behavior as well as through indirect word-of-mouth (WOM) signals such as the content creation and usage behavior of their social network neighbors. Hence, our model seeks to explicitly explain how direct usage experience and indirect experience from social interactions affect the content creation and usage behavior of users over time.

Our parameter estimates suggest that there is substantial heterogeneity in the mean quality values across different content types. Downloads from mobile portal sites have the highest quality level, followed by upload to mobile portal sites, upload to SNC sites and download from SNC sites. Besides, the order of magnitude of signal accuracy for each content type from the direct experience is consistent with the order of true quality level. For example, we find that for learning based on direct experience, signals about the quality of download from mobile portals are the most accurate while signals about the quality of download from regular SNC sites are the least accurate. In addition we find that signals about the quality of content from direct experience are more accurate than signals from indirect experiences. This is consistent with what one would expect - learning based on direct experience is more reliable (has less variability) than learning based on indirect experience.

To summarize, the key contributions of this paper are the following. *First*, it addresses a key question unexplored in the emerging stream of literature in the economics of user-generated content: how users learn the quality of mobile media-related content (both content generation and usage activities) from two distinct categories of websites – (i)mobile portal sites and (ii) Internet social networking and community sites. *Second*, it develops a structural framework of user content generation and usage and tests a "true content quality" model in the spirit of Erdem et al. (2008). The content quality model is based on the notion that there is a true quality value for each content type, and a user's experience with a content type may vary due to situational circumstances. We find evidence that in the context of mobile media users make content choices based both on their perception of differences in content quality. *Third*, it distinguishes between the effects of two different sources of learning (i.e., direct experience and indirect word-of-mouth) on user behavior, and finds evidence for both. We do this by using a novel panel dataset encompassing individual user-level mobile activity information and the same users' social network information, and accordingly develop a complex modeling procedure for value function derivation and simulation-based estimation. To our knowledge, no prior research using structural modeling has employed an individual-level word-of-mouth interactions data among users to capture the indirect source of learning in consumer behavior, or explicitly incorporated the individual-level indirect word-of-mouth effect in the value function of forward-looking consumers.

The rest of this paper is organized as follows. Section 2 outlines the prior work in related areas. In Section 3, we provide the theoretical framework for the structural model. This includes information on user decision-making process, description of the utility specification with posterior mean and variance, the formulation of the dynamic optimization problem and econometric estimation. Section 4 describes the data that we deploy with some summary statistics that provide interesting insights into user behavior. We describe the key results in Section 5. Section 6 discusses implications and concludes.

2. Prior literature

A number of recent papers have developed dynamic structural demand estimation models. The main focus of prior work has been on modeling direct learning and too in the context of durable or storable goods (Erdem and Keane 1996 , Hendel and Nevo 2006, Gowrisankaran and Rysman 2007, Ching and Ishihara 2009). There is also existing work in the domain of nondurable experience-goods markets (for example, Ackerberg 2001, Israel 2005, Crawford and Shum 2005, Erdem et al. 2008) of which the latter two papers are most closely related to our work. Crawford and Shum (2005) look at user learning from direct experience such as symptomatic signals and curative signals in the pharmaceutical industry. Erdem et al. (2008) incorporate user experience, advertising content, advertising intensity, and price as signals of product quality in a learning model in a product category like ketchup. However, none of these papers consider the possibility of any kind of indirect learning through word-of-mouth (WOM).

Erdem et al. (2005) look at consumers' active learning in a fast-changing market (e.g., computers) and develop a structural model of consumers' decisions about how much information to gather prior to making a purchase. However, they employed survey data where they asked subjects about the source of information without using the actual communication history between consumers or the strength of the WOM communications. Iyengar et al. (2007) look at a wireless service industry and model the dual learning process of service provider's quality and consumer's consumption quantity within a Bayesian learning framework. Narayanan et al. (2005) propose a Bayesian learning process model that incorporate the impact of direct (perceived product quality) and indirect (through goodwill accumulation) effects on consumer utility in the context of physician learning for new drugs. We also incorporate the effect of social network neighbors on users' content generation and usage behavior. A small but growing number of papers have investigated peer effects in new product adoption (Van den Bulte and Lilien 2001, Manchanda et al. 2004, and Iyengar et al. (2008) in drug adoption and Nam et al. (2006) in video-on-demand adoption. Nair et al. (2008) document the presence of asymmetric social interactions. See Hartmann et al. (2008) for a comprehensive survey of the social interactions literature. However, these papers do not analyze learning with respect to content creation and usage behaviors in the mobile media setting nor do they distinguish the *indirect WOM* effect from the *direct usage* effect, as we do in this paper.

Finally, our work is also related to the stream of literature on the economic impact of user-generated content (UGC). Studies have used the numeric review ratings (e.g., the number of stars) and the volume of reviews in their empirical analyses (Chevalier and Mayzlin 2006, Dellarocas et al. 2007, Forman et al. 2008, Duan et al. 2008) as well as tested whether the textual information embedded in online UGC can have an economic impact (Ghose et al. 2005, Ghose and Ipeirotis 2007, Das and Chen 2007, Archak et al. 2008, Ghose 2009) using automated text mining techniques. Related to this stream of work, Trusov et al. (2008) find that in an online world, if an influential member in a social networking site creates content, then the people connected to him or her increase their content usage. Our paper is distinct from all of the above in that we consider the content generation and usage behavior in a multi-media context as opposed to one consisting of only numeric or textual content.

In summary, there are two aspects we aim to address in our paper: a dynamic structural model of user uncertainty and learning about content quality in a Bayesian manner, and users' dynamic learning about quality of content based on their own behavior as well as from indirect WOM experience of their network neighbors. Whereas previous work has examined some of these issues separately, we address these aspects together. The Bayesian learning-based structural model gives a different picture of the value of information than would be obtained by simply estimating a static discrete choice model. This is because the Bayesian learning-based model incorporates the fact that information from either of the two sources can be valuable by inducing people to switch choices, and thus both positive and negative signals are valuable. Moreover, our study is in the context of multi-media content access and creation through mobile phones which has not been explored in prior work.

3. Model

We model user behavior in an environment where users are uncertain about the "true quality" level of content that is being consumed or generated through mobile phones and attempt to learn about it. There are two sources that can shape a consumer's evaluation: own consumption behavior which we refer to as the *direct effect* and the consumption behavior of their network neighbors which we refer to as the *word-*

of-mouth or indirect effect. Users may be risk averse with respect to variation in content quality. This is reasonable to assume in a context where sampling is costly since users need to pay transmission charges based on the amount of traffic that is being downloaded or uploaded. We first start with the discussion of the true quality model.

We adopt a single agent problem framework. A user's objective is to determine an optimal sequence of content generation and usage choices. Users update their expectations in a Bayesian manner as they receive additional signals of quality. We set our time period of analysis to be a 'day.' Posterior beliefs are updated once at the end of each day. This helps us synchronize the incidence timing of two sources of information that can influence their behavior and learning – direct experience and indirect experience.

In our paper, we focus on distinguishing between the two broad classes of websites described before. Hence, in order to model the set of user choices, we allow users to choose amongst the following five distinct options: (i) upload content to Internet SNC sites, (ii) upload content to mobile portal sites, (iii) download content from Internet SNC sites, (iv) download content from mobile portal sites, and (v) do nothing.

We model users' information set and choice timings as follows. Based on users' own prior experiences and the information they have received from their social networks, they start with a pair of prior beliefs about each activity at the beginning of time *t*. Users receive activity-specific information from their social networks through time period, *t*.[3] Then they calculate the choice-specific value using their value functions, evaluate their choices amongst the various alternatives, and choose the one with the highest value. Thereafter, users update their posterior on perceived content quality from their own usage experience as well as that of their social networks at the end of time *t*.

3.1 User Decision and Content Quality Uncertainty

A user *i* can engage in a given content activity *j* as many as *s* events on day *t*. Since users are forward-looking in our model, their current choices can influence their preferences in future periods. Hence, they select the sequence of choices that maximizes their expected utility over an infinite time horizon. We specify user *i*'s expected utility as follows:

$$\max_{D \equiv \left\{\left\{\left\{d_{ijt}^{s}\right\}_{j=1}^{J}\right\}_{s=1}^{N_{Sit}}\right\}_{t=1}^{\infty}} E_D\left(\sum_{t=1}^{\infty} \beta^t \sum_{s=1}^{N_{Sit}} d_{ijt}^{s} U_{ijt}^{s}\right) \tag{1}$$

[3] In order to incorporate the impact of indirect signals from network neighbors and the associated communication strength of each signal, we fix the maximum number of network neighbors for each user to five based on the call frequencies between them. The qualitative nature of our results is robust to the use of other numbers as well ranging from one to five. It is also robust to the use of call duration (rather than call frequency) to determine the social network, for a given user.

where $j \in \{1$ = upload to SNC sites, 2 = upload to mobile portal sites, 3 = download from SNC sites, 4 = download from mobile portal sites and 5 = doing nothing$\}$, N_{Sit} is the number of times user *i* is involved in an activity at time *t*, β is a discount factor, d^s_{ijt} denotes 1 if user *i* chooses activity *j* at the s^{th} event on day *t* and 0 otherwise, and U^s_{ijt} denotes the associated utility.

We model user uncertainty about content quality as follows. Users are imperfectly informed and uncertain about the mean attribute levels of each of the four kinds of content, similar in spirit to prior work (Erdem and Keane 1996). User experiences with respect to content quality vary. There could be a number of reasons why user experiences may vary. First, in our setting, a user's experience of content quality is very likely to be context dependent. In our mobile context, since users may access mobile services from very diverse locations (e.g., on the road in a bus, car or train, at home, at work, etc.), there could be substantial variation in the perceived quality of the content that is consumed as well content that is created. Hence, each direct experience of content usage (downloading) or generation (uploading) provides a noisy but unbiased signal of quality for the different activities. We denote the quality of the direct experience signal received by user *i* about activity *j* at s^{th} event on day *t*, Q^s_{Eijt}, as follows:

$$Q^s_{Eijt} = Q_j + \xi^s_{ijt} \qquad \text{where} \quad \xi^s_{ijt} \sim N\left(0, \sigma^2_{\xi j}\right). \qquad (2)$$

That is, $Q^s_{Eijt} \sim N\left(Q_j, \sigma^2_{\xi j}\right)$. Here, Q_j and $\sigma^2_{\xi j}$ are the "latent quality index" and the "choice-specific direct experience variability," respectively, similar in spirit to prior work (Erdem et al. 2008).

In addition to variation in the direct experiences of users, there can be variation in the indirect experiences of users. This can happen because the network neighbors of a user, like the users themselves, receive a noisy signal of content quality from the upload and download activities across both the kinds of websites. Moreover, when the information regarding content quality is transferred via (say) word-of-mouth, there could be additional sources of noises such as incorrect delivery of the information by a sender, misunderstanding by a recipient, etc. Hence, to allow for this possibility, we model the information from network neighbors as providing a noisy but unbiased signal.

A complication arises from the fact that users can receive multiple indirect experience signals on a given day. Instead of specifying each indirect signal that the users receive within a given day, we aggregate all indirect signals within a day into one cumulative indirect signal whose accuracy increases in the number of indirect signals. This is similar in spirit to Mehta et al. (2008). Further we assume that each indirect experience signal comes only from those network neighbors who have experienced it in that period. We denote the indirect experience signal of user *i* from a network neighbor *k* who has participated in activity *j* at the same time *t* as follows:

$$Q^f_{WOMijt} = Q_j + \delta^f_{ijt} \tag{3}$$

where

$$\delta^f_{ijt} \sim N\left(0, \sigma^2_{\delta j}\right),$$

$$f \in N_{WOMijt} = \sum_{k \in n_i} \sum_{f=1}^{N_{Ekjt}} w_{ik} d^f_{kjt}\,.$$

That is, $Q_{WOMijt} \sim N\left(Q_j, \sigma^2_{\delta j}\right)$. We refer to $\sigma^2_{\delta j}$ as the "choice-specific indirect experience variability." Because own experience is likely to provide a less noisy signal of the quality of a given activity than indirect experience, we expect that $\sigma^2_{\delta j} \geq \sigma^2_{\xi j}$ for each activity *j*.

We posit that we can derive N_{WOMijt} by computing the weighted count of frequency of engaging in each activity by user *i*'s network neighbors. Specifically, to incorporate the communication intensity between users, we use voice call frequency as a weight. This is motivated by the possibility that higher the number of voice calls between a caller and a receiver, higher the probability of receipt of an indirect experience signal by that user. Thus, user *i* receives $\sum_{k \in n_i} \sum_{s=1}^{N_{Ekjt}} w_{ik} d^s_{kjt}$ indirect experience signals from network neighbors at time *t*. Here w_{ik} is *relative* call frequency between user *i* and user *k* (who is a network neighbor of user *i*) and d^s_{kjt} is an indicator variable indicating whether or not user *k* engaged in activity *j* at *s*th event on day *t*.[4]

We note that the information set I_{it} includes all quality signals that user *i* received through time *t*. Then, under the assumption that all signals are unbiased, $E\left[Q^s_{Eijt} | I_{it}\right] = E\left[Q_{WOMijt} | I_{it}\right]$. This implies that the expected level of the direct experience signals and the expected level of indirect experience signals, given the information available to user *i* at time *t*, are equal.

3.2 User Utility Function

Let U^s_{ijt} denote user *i*'s single-period utility from activity *j* at s^{th} event on day *t*. Let Q^s_{Eijt} denote user *i*'s quality signal from directly experiencing activity *j* at s^{th} event on day *t*. This follows from the fact that utility is a function of experienced attribute levels and not the mean attribute levels (Erdem and Keane 1996). p_j is the average price of activity *j*. We posit that users are risk averse with their utility being concave in quality and linear in price. Similar in spirit to Erdem et al. (2008), we assume users have a per-period utility function of the form, for activity *j* = 1,..., 4:

[4] For example, suppose that user A has 3 network neighbors who engaged in activity 1 on a given day. Suppose they engaged four, five and two times, respectively in this activity. Further suppose that user A made calls to each other the network neighbor 4, 2, and 10 times on that day, thus the weight of the intensity of communication of user A with each of these network neighbors is 4/16, 2/16, and 10/16, respectively. Then the count of number of times user A receives indirect signals about content activity 1 is computed as (4/16) x 4 + (2/16) x 5 + (10/16) x 2 = 2.875.

$$U_{ijt}^{s} = w_g * Q_{Eijt}^{s} + w_g * r_g * \left(Q_{Eijt}^{s}\right)^2 - a_g * P_j + \varepsilon_{ijt}^{s}. \tag{4}$$

Subscript *g* denotes the number of latent segments. Note that *w* is user *i*'s utility weight on quality, *r* captures the extent of the risk aversion towards variation in quality (*r* < 0: utility is concave, so the user is risk averse), *a* is the price coefficient, and ε_{ijt}^{s} captures a taste shock known to user *i* but not to the econometrician. Letting $\mu_{ij,t} \equiv E\left[Q_j | I_{it}\right]$ denote user *i*'s expectation of activity *j*'s true quality level at time *t*, we re-write Equation (2) as follows:

$$Q_{Eijt}^{s} = \mu_{ij,t} + \left(Q_j - \mu_{ij,t}\right) + \xi_{ijt}^{s}. \tag{5}$$

Then, based on Equation (4), the expected utility to user *i* from choosing activity *j* on day *t* in state I_{it} is given as follows:

$$E\left[U_{ijt}^{s} | I_{it}\right] = w_g * Q_{Eijt}^{s} + w_g * r_g * \left(Q_{Eijt}^{s}\right)^2 + w_g * r_g * E\left[\left(Q_j - \mu_{ij,t}\right)^2 | I_{it}\right]$$
$$+ w_g * r_g * \sigma_{\xi}^{2} - a_g * P_j + \varepsilon_{ijt}^{s}. \tag{6}$$

There are two sources of expected variability in direct experience quality, Q_{Eijt}. First is the experience variability, σ_{ξ}^{2}. Second is the variability of true quality around perceived quality, $E\left[\left(Q_j - \mu_{ij,t}\right)^2 | I_{it}\right]$. Note that this is similar to a "risk term". That is, if a user has little information about the activity, then true quality will tend to depart somewhat from expected quality, and thus the risk term is large (Erdem et al. 2008). Also we simply assume that the expected utility associated with "doing nothing" to be a constant plus a stochastic error component as follows:

$$E[U_{i5t} | I_{it}] = \Phi_0 + \varepsilon_{i5t}, \tag{7}$$

3.3 Users Updating Perceived Content Quality

Users have prior beliefs about the "mean" quality levels for each activity *j*. We model them as follows:

$$Q_j \sim N\left(Q_0, \sigma_{Q_0}^{2}\right). \tag{8}$$

That is, all activities have a mean quality level of Q_0 but the true quality of activity *j* has variance $\sigma_{Q_0}^{2}$. Following Erdem et al. (2008), we restrict the prior mean Q_0 to be equal to the mean of the all activity-specific quality levels Q_j for *j* = 1,..., 4.[5]

[5] We also model an alternative setting where users have idiosyncratic "match values" to each activity *j*. As a robustness check, we discuss the result in Section 5.

User *i* does not know the true quality of any of the four possible options, but receives signals which allow that user to update his perceived quality about activity *j* from direct experience as well as indirect experience of his network neighbors. Note that user *i* may receive multiple quality signals at time *t* as many as N_{WOMijt} times. In terms of the updating process, we assume that users use information (i.e., either the direct experience signal or the indirect experience signal, or both) that they receive over time. To be specific, they learn about the mean and variance of quality levels in a Bayesian fashion (DeGroot 1970) according to the process described below in (a) and (b).

(a) Posterior Mean of Perceived Content Quality

Unlike cases where there is only one signal per a source at a given time (e.g., Crawford and Shum 2005, Erdem et al. 2008), in the mobile media context users can receive *multiple* signals of direct and indirect experience in a given day. This is because in a mobile digital media context, users create and consume content far more frequently compared to products like computers and drugs. This setting is, in spirit, similar to Mehta et al. (2008). Moreover, in our setting they communicate more frequently with friends and colleagues so that opinions or ideas about one's experience are more likely to be shared with each other. To address the modeling complication arising from this, we posit that although users can receive multiple quality signals within a day, they update their posterior beliefs once at the end of a day.

Let the posterior mean of perceived quality about activity *j* at time *t*+1 be denoted as $\mu_{ij,t+1}$. At the end of day *t*+1, the posterior mean can be written as the sum of three separate components - (i) prior mean at the end of day *t*, (ii) sample mean of the realized quality signals from direct experience during day *t*, and (iii) sample mean of the realized quality signals from indirect experience during day *t*. This is written as follows:

$$\mu_{ij,t+1} = \left(\beta_{1ij}^{t+1} * \mu_{ij,t}\right) + \left(\beta_{2ij}^{t+1} * \overline{Q_{Eijt+1}}\right) + \left(\beta_{3ij}^{t+1} * \overline{Q_{WOMijt+1}}\right) \tag{9}$$

where

$$\overline{Q_{Eijt+1}} = \frac{1}{N_{Eijt}} \sum_{s=1}^{N_{Eijt}} Q_{Eijt+1}^{s},$$

$$\overline{Q_{WOMijt+1}} = \frac{1}{N_{WOMijt}} \sum_{f=1}^{N_{WOMijt}} Q_{WOMijt+1}^{f},$$

$$\beta_{1ij}^{t+1} = \frac{\frac{1}{\sigma_{Q_{ij,t+1}}^2}}{\frac{1}{\sigma_{Q_{ij,t+1}}^2} + \frac{N_{Eijt}}{\sigma_{\xi j}^2} + \frac{N_{WOMijt}}{\sigma_{\delta j}^2}},$$

$$\beta_{2ij}^{t+1} = \frac{\frac{N_{Eijt}}{\sigma_{\xi j}^2}}{\frac{1}{\sigma_{Q_{ij,t+1}}^2} + \frac{N_{Eijt}}{\sigma_{\xi j}^2} + \frac{N_{WOMijt}}{\sigma_{\delta j}^2}}, \text{ and}$$

$$\beta_{3ij}^{t+1} = \frac{\frac{N_{WOMijt}}{\sigma_{\delta j}^2}}{\frac{1}{\sigma_{Q_{ij,t+1}}^2} + \frac{N_{Eijt}}{\sigma_{\xi j}^2} + \frac{N_{WOMijt}}{\sigma_{\delta j}^2}}. \tag{10}$$

The intuition behind the above updating Equation (9) is that the posterior mean of perceived quality at the end of time *t*+1 is a weighted average of the three components described above. In doing so, we consider the weight for each component by its relative accuracy. To compute the extent of relative accuracy of each signal, as shown in Equation (10), we use the inverse of variance of each source such that the less diverse a signal generated from a source, the more accurately it represents the true quality. Note that $1/$variance of a signal is equivalent to the accuracy of the signal. For example, β_{1ij}^{t+1} represents the ratio of accuracy of the prior belief to the sum of the accuracy of the prior belief, the direct experience signal, and the indirect experience signal. β_{2ij}^{t+1} represents the ratio of accuracy of the direct experience signal to the sum of the accuracy of the prior belief, the direct experience signal, and the indirect experience signal. Similarly, we can interpret β_{3ij}^{t+1} as.

For simplicity, we posit that the network neighbors and the communication strength between them remain fixed throughout the sample period. This knowledge is public in the sense that the econometrician can treat this information as exogenously given. Also, $\sigma_{Q_{ij,t+1}}^2$ is the variance of user *i*'s belief of activity *j*'s mean quality at time *t*+1. We explain this in the next section.

(b) Posterior Variance of Perceived Content Quality

Let the posterior variance of perceived quality of activity *j* at time *t*+1 be denoted by $\sigma_{Q_{ij,t+1}}^2$. We compute it according to the following. There are three components of relevance here - (i) the inverse of prior variance of perceived quality at the start of estimation sample (*t*=0), (ii) the sum of the inverse of the variance of the direct experience signals, and (iii) the sum of the inverse of the variance of the indirect experience signals. Higher the value of (ii) or (iii), lower the posterior variance implying the higher the posterior accuracy. This is written as follows:

$$\sigma_{Q_{ij,t+1}}^2 = \frac{1}{\frac{1}{\sigma_{Q_{ij,0}}^2} + \frac{\sum_{\tau=1}^{t+1} N_{Eij\tau}}{\sigma_{\xi j}^2} + \frac{\sum_{\tau=1}^{t+1} N_{WOMij\tau}}{\sigma_{\delta j}^2}}. \tag{11}$$

Note that N_{Eijt} denotes the count of number of times that user *i* chooses activity *j* at time *t*, and N_{WOMijt} denotes the count of number of times that user *i* receives an indirect signal about the quality of activity *j* from his network neighbors at time *t*.

Table 1: Notations and Variable Descriptions

β	discount factor
Q_j	true quality of activity *j*
N_{Sit}	count of the number of times user *i* is involved in content choices at time *t*
d^s_{ijt}	whether user *i* chooses activity *j* at *s*th event on day *t* (1 = Yes, 0 = No)
U^s_{ijt}	user *i*'s immediate utility from activity *j* at *s*th event on day *t*
N_{Eijt}	count of number of times that user *i* engages in activity *j* at time *t*
Q^s_{Eijt}	user *i*'s received direct experience quality signal about activity *j* at *s*th event on day *t*
N_{WOMijt}	count of number of times that user *i* receives indirect signal about content activity *j* from his or her network neighbors at time *t*
n_i	user *i*'s network neighbors based on voice call records (i.e., users called by user *i*)
Q_{WOMijt}	user i's received indirect word-of-mouth quality signal about activity *j* at time *t* from network neighbors
$\sigma^2_{\xi j}$	Variance of the direct experience signal of activity *j*
$\sigma^2_{\delta j}$	Variance of the indirect experience signal of activity *j*
w_g	weight on quality for *g*th latent segment
r_g	extent of risk aversion towards variation in quality for *g*th latent segment
a_g	weight on price for *g*th latent segment
P_j	average price of activity *j*
Q_0	mean of the all activity-specific quality levels
$\mu_{ij,t}$	user *i*'s posterior mean of perceived quality about activity *j* at time *t*
w_{ik}	tie strength between user *i* and user *k* who is a network neighbor of user *i* based on call frequencies therein
k_0	initial condition parameter; log of prior standard deviation at the beginning of the pre-estimation sample
k_1	initial condition parameter; the impact of cumulative experiences in the pre-estimation sample period on prior variance at the start of estimation sample period
$\sigma^2_{Q_0}$	user *i*'s prior variance of perceived quality at the beginning of pre-estimation period (*t*<0)
$\sigma^2_{Q_{ij,o}}$	user *i*'s prior variance of perceived quality at the end of pre-estimation period (*t*=0)
$\sigma^2_{Q_{ij,t}}$	user *i*'s posterior variance of perceived quality about activity *j* at time *t (t>0)*
I_{it}	user *i*'s state variables at time *t*
l^t_{ij}	count of number of times that user *i* has done activity *j* up to and through time *t*
m^t_{ij}	count of number of times that network neighbors of user *i* have engaged in activity *j* up to and through time *t*
V_{it}	user *i*'s value function at time *t*
$\bar{V}$	user *i*'s integrated value function at time *t*
V_{ijt}	user *i*'s choice-specific value function at time *t*

(c) Specifying Initial Conditions

We 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 behavior. The initial conditions issue has implications for what we assume about the prior mean and variance of the quality perceptions. If one does not control for initial choice history, the implicit assumption is that every user has the same prior mean and variance across all content types. However, it is possible that a user that has engaged in an activity multiple times in the past would have more informed priors than another user who has engaged very little in that activity. Hence, one needs to account for the heterogeneity of priors in the sample.

We follow an approach that is similar in spirit to that used in Erdem et al. (2006) and Mehta et al. (2008) and use a part of the data as a pre-estimation sample to estimate the distribution of priors. Because our data contain social network data only for the last 35 days (5 weeks), we use first 56 days (8 weeks) to estimate each user's initial conditions and the last 35 days to estimate the model. We posit that user *i*'s prior standard deviation of the quality level of activity *j* at the start of our estimation period is as follows:

$$\log\sigma_{Q_{ij,0}} = k_0 - k_1 \ln\left(\sum_{t=-55}^{0} \sum_{s=1}^{N_{Eijt}} d_{ijt}^{s}\right), \tag{12}$$

where k_0 and k_1 are parameters to be estimated. We can interpret k_0 as log of prior standard deviation at the beginning of the pre-estimation sample when the user has no cumulative prior experience. That is, $k_0 = \ln\sigma_{Q_0}$. Equation (12) shows that the initial uncertainty about activity *j* is less if a user had engaged in content activity *j* more during the pre-estimation period by reducing its prior variance from $\sigma_{Q_0}^2$ to $\sigma_{Q_{ij,0}}^2$. So we expect the sign of the estimate of k_1 to be positive.

3.4. Users' Dynamic Optimization Problem

(a) State Variables

State variables completely summarize all information from the past that is needed for the forward-looking optimization problem (Adda and Cooper, 2003). In our dynamic structural model, there are five kinds of state variables, I_{it}. Note that users can observe these state variables at time *t* before they make content choice decisions for time *t*. The first is user *i*'s time *t* priors for perceived quality from choosing activity *j*, denoted as $\mu_{ij,t}$. The second is user *i*'s time *t* priors for variance of perceived quality from choosing activity *j*, denoted as $\sigma_{Q_{ij,t}}^2$. The third is the count of number of times that user *i* has chosen activity *j* up to time *t*. This is given as follows:

$$l_{ij,t} = \sum_{\tau=1}^{t-1} N_{Eij\tau}. \tag{13}$$

The fourth is the count of number of times that network neighbors of user *i* have chosen activity *j* up to time *t*, weighted by the frequency of communication. This is given as follows:

$$m_{ij,t} = \sum_{\tau=1}^{t} N_{WOMij\tau}. \tag{14}$$

And finally, we have the idiosyncratic errors denoted by ε_{ijt}.

(b) Dynamic Decision-Making

A user's optimal decision rule is to choose the option that maximizes the expected present value of utility over the planning horizon. This leads to a dynamic programming problem. One can apply the Bellman's principle to solve this problem by recursively finding value functions corresponding to each alternative choice. Based on the Bellman's equation, we evaluate the value function in the infinite-horizon setting, given as follows:

$$V_{it}(I_{it}) = \max_j E\left[U_{ijt} + \beta * E\left[V_{it}(I_{it+1}) | d_{ijt}, Q_{Eijt}, Q_{WOMijt}, N_{WOMijt}\right] | I_{it}\right] \tag{15}$$

where β is a discount factor. Hence, the optimal decision rule is $\mathrm{argmax}_j\{V_{ijt}(I_{it})\}$ where, for every *j*,

$$V_{ijt}(I_{it}) = E\left[U_{ijt} | I_{it}\right] + \beta * E\left[V_{it}(I_{it+1}) | d_{ijt}, Q_{Eijt}, Q_{WOMijt}, N_{WOMijt}, I_{it}\right] \tag{16}$$

is the choice-specific value function.

Recall that signals received by users are random variables and these are only observable to the users but unobservable to researchers. In order to derive the value function, we need to eliminate the random component of these signals. The way to do this is to generate a sequence of signals for the current period own experience and for both the direct and indirect experience in the next period. Note that in the above equation we have two components: one outer "expectation" term and the other inner "expectation" term. Hence, towards computing this value function, we take the outer expectation over Q_{Eijt}^{s} and the inner expectation over both Q_{Eijt+1} and $Q_{WOMijt+1}$. We employ a variant of the Keane and Wolpin (1994) approximation method for computing the value function.

(c) Integrated Value Function

The integrated value function is the expectation of the value function over the distribution of unobservable state variables (e.g., ε_{ijt}), conditional on the observable state variables: (for simplicity, we drop out subscripts *it* in $\overline{V}$)

$$\overline{V}(I_{it}) = \int V(I_t, \varepsilon_{ijt}) dG_\varepsilon(\varepsilon_{ijt}). \quad (17)$$

This function is the unique solution to the integrated Bellman's equation:

$$\overline{V}(I_{it}) = \int \max_j E\{U_{ijt} + \beta * E[\overline{V}(I_{it+1}|d_{ijt}, Q_{Eijt}, Q_{WOMijt}, N_{WOMijt})]|I_{it}\} dG_\varepsilon(\varepsilon_{ijt}). \quad (18)$$

Hence, the choice-specific value function becomes:

$$V_{ijt} = E[U_{ijt}|I_{it}] + \beta * E[\overline{V}_{it}(I_{it+1})|d_{ijt}, Q_{Eijt}, Q_{WOMijt}, N_{WOMijt}, E[U_{ijt}|I_{it}]]. \quad (19)$$

We use this choice-specific value function with the integrated value function to compute the choice probability. We will explain this in the estimation section. Note that if ε_{ijt} are i.i.d. type-1 extreme value random variables, this becomes the dynamic problem conditional on logit model with Bellman's equation:

$$\overline{V}(I_{it}) = \log\Bigg(\sum_{j=1}^{4} \exp\Big\{w_g * Q_{Eijt}^s + w_g * r_g * (Q_{Eijt}^s)^2 + w_g * r_g * \sigma_{Q_{ij,t}}^2 + w_g * r_g * \sigma_\xi^2 - \alpha_g * p_j$$
$$+\beta * E[\overline{V}(I_{it+1})|d_{ijt}, Q_{Eijt}, Q_{WOMijt}, N_{WOMijt}]|I_{it}\Big\}$$
$$+\exp\{\Phi_0 + \beta * E[\overline{V}(I_{it+1})|d_{ijt}, Q_{Eijt}, Q_{WOMijt}, N_{WOMijt}]|I_{it}\}\Bigg). \quad (20)$$

Note that the idiosyncratic error term is integrated out. We can also interpret the value from the integrated value function as "inclusive value" for deciding which activity to engage in conditional on a set of state variables. Also note that the last additive term represents the utility from the fifth option, "doing nothing" and we integrate out the indirect experience signals.

3.5 Estimation

We start by outlining the choice probabilities and the likelihood function. Then we discuss the estimation procedure followed by a discussion of our identification restrictions.

(a) Choice Probability

Let Ξ_g denote the complete set of model parameters for a user of latent class g. We define the deterministic part of the choice-specific value function is as following (for simplicity, we drop the superscript *s* denoting the s^{th} event):

$$V^*_{ijt}\left(I_{it}\middle|\Xi_g\right) = V_{ijt}\left(I_{it}\middle|\Xi_g\right) - \varepsilon_{ijt}. \tag{21}$$

If ε^s_{ijt} are i.i.d. type-1 extreme value random variables, the probability of user *i* doing activity *j* at time *t* is given by:

$$\mathrm{Prob}\left(d_{ijt} = 1|I_{it}, \Xi_g\right) = \frac{\exp\left\{V^*_{ijt}\left(I_{it}\middle|\Xi_g\right)\right\}}{\sum_{e=1,5}\exp\left\{V^*_{iet}\left(I_{it}\middle|\Xi_g\right)\right\}}. \tag{22}$$

(b) Likelihood Functions

Let $H_i = \left\{\left\{\left\{d^s_{ijt}\right\}^5_{j=1}\right\}^{N_{Eijt}}_{s=1}\right\}^T_{t=1}$ denote user *i*'s choice history, where *T* is the last observation period. Recall that we have five options ranging from 1 (upload to SNC sites) to 5 (doing nothing). Then,

$$\mathrm{Prob}\left(H_i|\Xi_g\right) = \prod_{t=1}^{T}\prod_{s=1}^{N_{Eijt}}\prod_{j=1}^{5}\mathrm{Prob}\left(d^s_{ijt} = 1|I_{it}, \Xi_g\right)^{d^s_{ijt}}. \tag{23}$$

Also, let $\tilde{\xi}_{it} = \left\{\left\{\left\{d^s_{ijt}\xi^s_{ijt}\right\}^4_{j=1}\right\}^{N_{Eijt}}_{s=1}\right\}^t_{t=1}$ and $\tilde{\delta}_{it} = \left\{\left\{\left\{\sum^{N_{Ekjt}}_{s=1} w_{ik} d^s_{kjt}\right\}_{k\in n_i}\right\}^4_{j=1}\right\}^t_{t=1}$ denote the sets of direct experience signals and indirect WOM signals, respectively, received by user *i* up to and through time *t*, such that $I_{it} = I_{it}\left(\tilde{\xi}_{it}, \tilde{\delta}_{it}\right)$. Then we can write the probability of observed history of user *i* as follows:

$$\int_{\tilde{\xi}_{ijt}}\int_{\tilde{\delta}_{ijt}}\prod_{t=1}^{T}\prod_{s=1}^{N_{Eijt}}\prod_{j=1}^{5}\mathrm{Prob}\left(d^s_{ijt} = 1|I_{it}\left(\tilde{\xi}_{it}, \tilde{\delta}_{it}\right), \Xi_g\right)^{d^s_{ijt}} dF\left(\tilde{\xi}_{it}, \tilde{\delta}_{it}\right). \tag{24}$$

Finally, let $\tilde{x}_{it} = \left\{\left\{x_{ij}\right\}^4_{j=1}\right\}$ denote a set of hypothetical quality signals with variance $\sigma^2_{xij} = \left[1/\sigma^2_{Q_{ij,0}} - 1/\sigma^2_{Q_0}\right]^{-1}$. We can think of the user as receiving one cumulative signal that results in this decrease in variance (that is, an increase in signal accuracy). Thus, as shown in Erdem et al. (2006) and Mehta et al. (2008), we represent this cumulative signal as follows:

$$x_{ij} \sim N\left(Q_j, \sigma^2_{xij}\right). \tag{25}$$

Thus, given the cumulative signal in Equation (26) and the distribution of the user's prior mean belief about content activity *j* at the beginning of the pre-estimation sample in Equation (8), we can calculate the mean quality belief at the end of the pre-estimation sample using Bayesian updating formula as follows:

$$\mu_{ij,0} = \begin{cases} \dfrac{Q_0/\sigma_{Q_0}^2 + x_{ij}/\sigma_{xij}^2}{1/\sigma_{Q_0}^2 + 1/\sigma_{xij}^2}, & \text{if user i has at least one prior experience of activity j,} \\ Q_0, & \text{otherwise.} \end{cases} \tag{26}$$

We use $\mu_{ij,0}$ as the initial mean quality belief for user *i* for content activity *j* at the beginning of the estimation sample.

(c) Simulation Estimation

We adopt the simulated maximum likelihood estimation (see Stern 2000). We integrate over direct signals, indirect signals, and initial conditions as follows: Let $\left(\tilde{\xi}_{it}^{u}, \tilde{\delta}_{it}^{u}, \tilde{x}_{it}^{u}\right)$ denote the u^{th} draw for user *i*, where *u* = 1,..., *U*, we have an unbiased and consistent simulator:

$$\widehat{\mathrm{Prob}}\left(H_i|\Xi_g\right) = \frac{1}{U}\sum_{u=1}^{U}\prod_{t=1}^{T}\prod_{s=1}^{N_{Eijt}}\prod_{j=1}^{5}\mathrm{Prob}\left(d_{ijt}^{s} = 1|I_{it}\left(\tilde{\xi}_{it}^{u}, \tilde{\delta}_{it}^{u}, \tilde{x}_{it}^{u}\right), \Xi_g\right)^{d_{ijt}^{s}}. \tag{27}$$

Then the simulated likelihood for the sample is:

$$\prod_{i=1}^{N}\sum_{g}\pi_g * \widehat{\mathrm{Prob}}\left(H_i|\Xi_g\right). \tag{28}$$

In finding the maximums of the simulated likelihood for the sample, we adopt the quasi-Newton methods. To be specific, we use the BHHH numerical maximization, which makes use of the outer product of the gradients (see Berndt et al. 1974). Also, we obtain consistent estimates of the variance of $\hat{\Xi}_g$ using the outer product of gradients variance estimator. In sum, we solve a dynamic optimization problem and estimate the simulated likelihood function recursively.[6]

(d) Identification

We briefly discuss identification issues in our model mathematically and empirically. First, we impose a scale normalization restriction by setting $Q_3 = 1$ for the quality of content download from Internet SNC sites. This is because one can scale all the Q_j by a positive constant κ, while scaling all the $\sigma_{\xi j}$ and $\sigma_{\delta j}$ by κ, without changing the choices implied by the model. So quality of uploads to SNC sites is set to 1 while other activities' qualities are measured relative to download from SNC sites. This normalization is in the spirit of Erdem et al. (2008) and ensures identification of the true content quality levels associated with each activity.

[6] We adopt our overall estimation strategy from the nested fixed point algorithm (NFXP) to obtain the maximum likelihood estimator of the structural parameters (see Aguirregabiria and Mira 2009 for detail).

We can identify k_0 and k_1 from the dynamics of the model. Consider a subset of users with sufficient prior experience of all mobile content activities such that $\sigma_{Q_{ij,o}} = 0$. This implies that these users have no uncertainty about content features. In this case, our model would reduce to a static model without learning. In our data, there are users not only with sufficient prior experience, but also users with limited prior experience. This variation across users helps us identify the parameter, k_0 and k_1. Further, the parameters, w and α, are identified by stationary choices from users with sufficient experience in engaging in various content activities, as discussed in Erdem et al. (2008). Note that the location normalization like setting $\Phi_0 = 0$ is not required in our dynamic structural model. [7]

The identification of the risk aversion parameter, r, depends on the dynamics of our model. This is because only when users face uncertainty about content features like in our dynamic learning setting, do they reveal the risk preference (i.e., risk aversion) in their choices. Our panel data satisfies this condition.

The parameters representing the dispersion of the direct and the indirect information signals, $\sigma_{\xi j}$ and $\sigma_{\delta j}$, are identified by the extent to which users in our sample update their choice probabilities after receiving each type of signal. Also, we separate the impact of *direct experience* from the impact of *indirect experience* on a user's learning process with respect to content quality associated with each activity. The main identification restriction is that the direct experience from own usage and generation behaviors impacts a user's utility whereas indirect experience from the usage and generation behaviors of network neighbors influence the kinds of quality signals received but does not impact the utility function of the user directly. This is consistent with the approach of Crawford and Shum (2005). In this sense, we are fortunate in that our data includes instances where users have either zero or little direct experience or where users have zero or little indirect experience from their social network. Moreover there is a lot of variation in the data in terms of how different users engage in each of the four different kinds of activity (see Figures 1 and 2 and our discussion of empirical identification in Section 4). Each of these unique attributes of our data is useful because variation in the mix of direct and indirect experiences both within and across users is important for identifying the parameters related to the perceived content quality associated with each activity.

Finally, note that prices are not endogenous in our model. This is because prices charged by the mobile phone operator does not vary by content type (whether it is from SNC websites or from mobile portal sites) or by activity (upload or download). The charges incurred by a user are simply based on the number of bytes that are transmitted or received. So we can treat prices as pre-determined.

[7] Erdem et al. (2008) elaborate on this in great detail in their Online Appendix.

4. Data Description

Our data is drawn from 3G mobile users in Korea who used the services of the company between March 15, 2008 and June 15, 2008. 3G mobile services enable users to upload their content faster than conventional mobile services. Further, these services are more commonly available in the large screen handsets that facilitate more user-friendly content generation and usage compared to the small-screen devices. The dataset that we employ in our analysis consists of 32,036 mobile data transaction records encompassing 430 users' content uploading and downloading behaviors over the 3-month period. We also have data on voice calls made by the same users that enables us to construct their social networks. We randomly selected 250 users for calibration and 180 users for validation. Because the data are collected on a daily basis over a 3-month period, the calibration and validation samples consist of 19,326 and 12,710 observations, respectively.

As briefly outlined in the introduction, there are two broad categories of websites users can access through their mobile phone, either for uploading content or for downloading content. The first category is one consisting of regular social networking and community websites that any user can browse through a PC or laptop. Examples of such websites in our data include Cyworld and Facebook. By forcing these off-portal sites to comply with mobile web standards, mobile operators try to ensure visitors a consistent and optimized experience on their mobile device. The second category of websites includes portal sites specifically created by the mobile phone company. Examples of such websites in our data include Nate Portal and KTF Portal, which are the Asian equivalent of US sites like Vodafone live and T-Mobile's Web 'n' Walk. The content on these sites can be accessed through a mobile phone by users who subscribe to the services of the mobile operator. These mobile portals are community-oriented sites that allow users to download and upload (in order to share with others) ringtones, wallpapers, videos, screen savers, video games, etc. Users pay transmission charges for every upload and download, just as they would have to do when accessing the regular Internet sites. The transmission charges are in general the same, irrespective of whether users upload or download content.

We have precise transmission data and time stamp information from individual-specific transactions that involve either an upload or download of content. Table 2 shows summary statistics of our data. The first interesting observation is that users are more actively engaged in content usage instead of content creation. This suggests that most users' content creation activities are still in a nascent stage. Further, their content usage activities primarily focus on content download from mobile portals. Hence, users may engage in experimentation through content creation in order to learn about its benefits. This helps us capture users' dynamic learning behavior in the mobile media setting.

As noted before, there are two *sources* of learning in our setting. First, users can learn through their own usage over time. We refer to this as *direct experience*. Second, users can learn from the behavior of their social networks (i.e., some kind of a word of mouth from their network neighbors). We refer to this as word-of-mouth (WOM) or *indirect experience*. In our model and data, the extent of such indirect learning can be adjusted by communication strength (i.e., call frequency or call duration). We have tried both combinations and found that the qualitative nature of the results remain unchanged.

Table 2: Summary Statistics (N=32,036)

Variable	Mean	Std. Dev	Min	Max
Direct Experience				
Frequency of activity 1: content upload to the SNC sites	0.007	0.134	0	8
Frequency of activity 2: content upload to the mobile portal site	0.006	0.097	0	3
Frequency of activity 3: content download from the SNC sites	0.001	0.028	0	2
Frequency of activity 4: content download from the mobile portal site	0.624	3.088	0	120
Indirect Experience				
Frequency of activity 1: content upload to the SNC sites	0.004	0.088	0	7.485
Frequency of activity 2: content upload to the mobile portal site	0.001	0.050	0	4.514
Frequency of activity 3: content download from the SNC sites	0.0003	0.024	0	1.711
Frequency of activity 4: content download from the mobile portal site	0.357	5.198	0	267.2

Notes*: Frequency is the count of number of non-zero packet transmission for each activity across all users computed on a daily basis. The frequency of indirect WOM experience is a weighted average of the number of times the network neighbors of a given user have engaged in a given activity on a given day. Hence, it may exceed 1.*

Table 3: Matrix Highlighting Conditional Switching Probability Between Activities

Prob(Activity at t+1 | Activity at t) in Percentage		**Time t+1**				
		Activity 1	**Activity 2**	**Activity 3**	**Activity 4**	**Activity 5**
Time t	**Activity 1**	47.2	0.0	2.8	44.4	5.6
	Activity 2	0.0	21.2	0.0	51.5	27.3
	Activity 3	16.66	0.0	16. 66	50.0	16. 66
	Activity 4	0.2	0.3	0.0	94.3	5.1
	Activity 5	0.1	0.3	0.0	8.4	91.2

Notes: *Activity 1-5 denote uploading content to SNC sites, upload contenting to the mobile portal sites, downloading content from SNC sites, downloading content from the mobile portal sites, and doing nothing, respectively.*

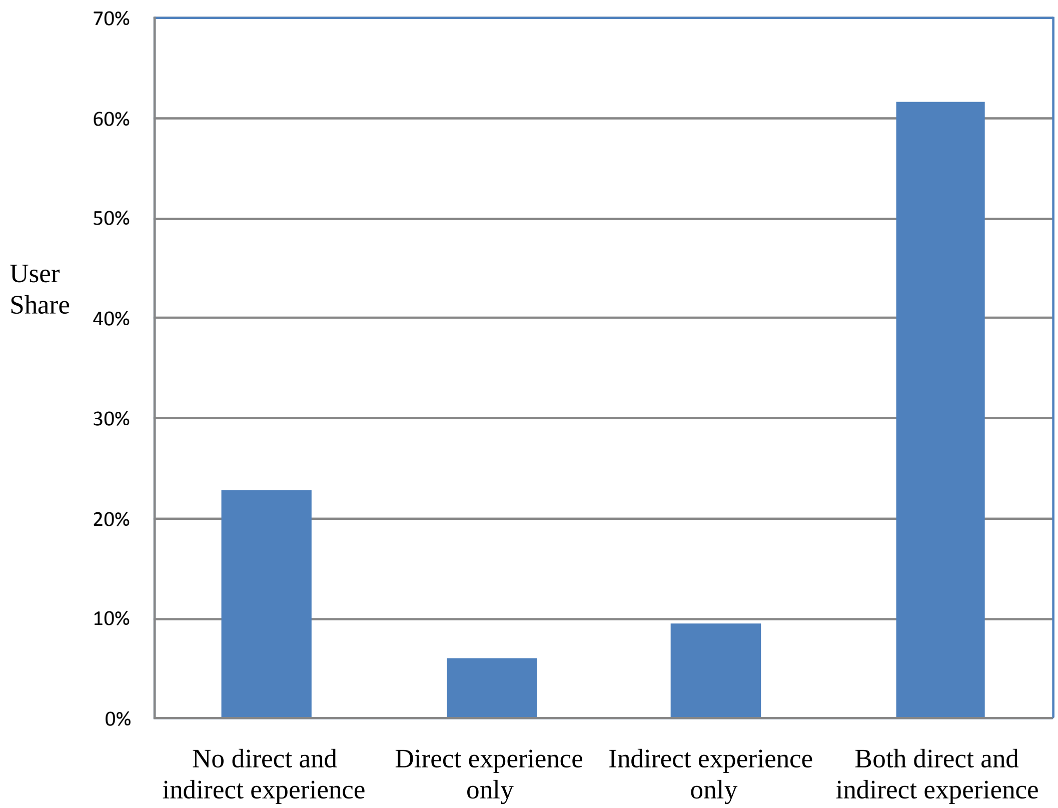
In addition, there are two kinds of content-specific learning. The first is when users learn about the "true quality" of content associated with each of the four activities. This is based on the notion that some multi-media content (such as video files) could be vertically differentiated where all users agree on the quality-levels of different types of content. The second is when users learn about their "taste" for different kinds of content-related activities. This is based on the notion that some content (like ringtones or video games) could be horizontally differentiated and hence, such content may be more appealing to distinct user groups than others. For instance, younger users are more likely to engage in uploading or downloading of content from SNC sites since they care about their reputation and popularity on these sites. In contrast, older users are more likely to engage in content download from mobile portal sites since they care more about applications they can use in their professional lives such as podcasts. Indeed, anecdotal reports in the trade press suggest that there is evidence about this kind of behavior.

Our main model is based on the first kind of learning that is, learning about the true quality of content associated with each of the four kinds of activities.

We find that users typically receive a higher number of information signals from their indirect experiences compared to their own direct experiences. This is not surprising given that the average number of calls made by users in our sample is 6.1 times in a day and the average number of unique call-recipients is 3.3 users per day. Based on our sample statistics, we compute that a user can receive as many as 1.65 indirect signals per day on an average from their network neighbors. Also, since we do not observe when users actually began their first downloading or uploading activity since the inception of the service, there could be potential initial condition or left-censoring problems. To avoid such issues, we include only those users in our sample whose content-related activities we first observe after the first month.

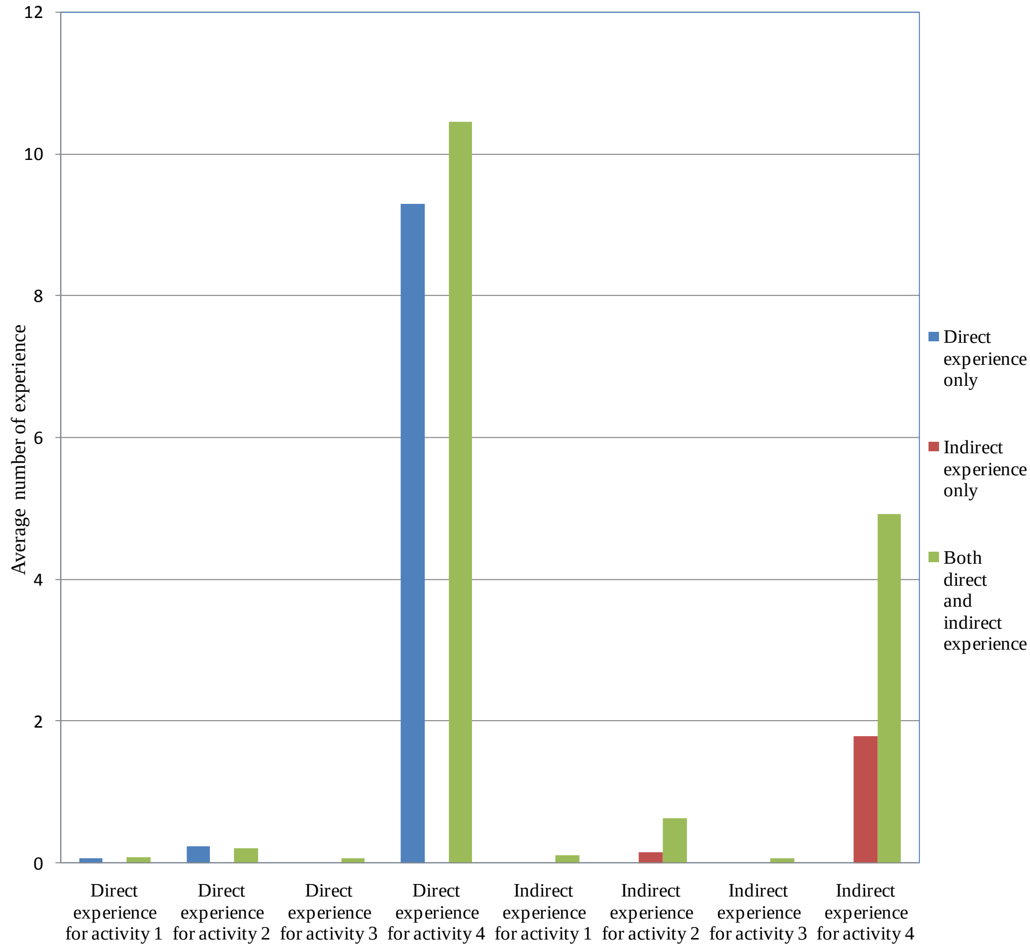
We next present some suggestive evidence of learning through users' conditional switching propensities across the five options available to them in Table 3. First, these probabilities suggest that some activities tend to elicit a relatively higher probability of switching (activities 1, 2 and 3) while other activities tend to elicit a relatively lower probability of switching (activities 4 and 5). For any given activity, this phenomenon is evident from comparing the off-diagonal elements with the diagonal elements. Interestingly, we find that for the various activities there are non-zero probabilities of users switching to other activities across adjacent time periods. The off-diagonal elements are quite different from zero for activities 1 to 3. Even for activities 4 and 5, we see that there is a non-trivial probability of users switching from these activities to other activities, 1-3. Recall that activities 1 through 4 denote content upload to SNC websites, upload to mobile portal sites, download from the SNC websites and download from mobile portal sites. The first three of these are relatively recent service features enabled in the mobile setting, as opposed to content download from mobile portal sites which has existed for a much longer time period. This indicates that to some extent users often engage in new types of content usage and creation, further suggesting the experimental nature of their content-related activities. These descriptive statistics motivate further examination of exactly how the learning process works in this setting.

Figure 1: Plot Showing Variation in Users' Experiences



In addition, our data presents evidence of empirically identifying the impact of *direct experience* from the impact of *indirect experience* on a user's learning process with respect to content quality. Figure 1 shows that a large proportion of users (62%) experience both direct and indirect signals. However, there also exist users who have either very little direct or very little indirect experience (6% and 10%, respectively). Further, Figure 2 shows that for each activity, there exist a great deal of variation in the average number of experiences per user across each of the two sources of learning. For example, with respect to activity 4, instances of *direct* experience are observed for users who belong to either the "direct only" experience or "both direct and indirect" experience categories, or both. In contrast, for the same activity, instances of *indirect* experience are observed for those users who belong to either the "indirect only" experience or "both direct and indirect" experience categories, or both. In a similar vein, for activity 2, more instances of *direct* experience are observed for those users who belong to the "direct only" category. In contrast, more instances of *indirect* experience are observed for those users who belong to the "both direct and indirect" category. Thus, we can see that due to significant amount of variation in the data, the impact of direct experience is identified by the extent of variation in the activities of users who only have direct experiences, whereas the impact of indirect experience is identified by the extent of variation in the users who only have indirect experiences from their social networks.

Figure 2: Variation in Experience by User, Activity, and Source



5. Empirical Results

5.1 Goodness of Fit Tests

Our model allows for user heterogeneity in the quality weight (w_g), risk coefficient (r_g), and price coefficient (a_g). Hence, we first choose the number of latent classes, *g*. We estimated models with 1 and 2 latent classes, and we calculate the AIC and the BIC for both models in the estimation sample, and we compute the log likelihood in the holdout sample.[8] As we know, the model with the lower value of AIC and BIC is preferred. Increasing the number of latent classes (*g*) from one to two deteriorates AIC and BIC in Model 1 (content true quality model). We find that our model in 1 latent class setting does slightly better than in 2 latent class setting (AIC of 44270.8 in the one-latent class case and AIC of 44278.0 in the

[8] The AIC and the BIC are given as $-2 \ln (L) + 2k$ and $-2 \ln (L) + k\ln(n)$, respectively, where L is the likelihood, k is the number of parameters, and n is the sample size.

two-latent class case) even though the difference in number of parameters is only 3. A similar trend can be seen from the comparison of the BIC results.

To further validate these results in a holdout sample, we implement a comparison of choice frequencies between sample data and simulated data from models. The usage share comparison between sample data and simulated data from models in Table 4 shows that our model predicts the usage share distribution well. Also we find the hit rate for individual observed usage to be 49.6%. In sum, based on results from in-sample and out-of-sample fitness comparison, we discuss our parameter estimates based on the result from the 1 latent class model.

Table 4: Usage Share Comparison Between Simulated and Sample Data

Activity	**Usage Share Comparison**	
	Holdout Sample	Simulated Data
1: uploading to SNC sites	0.27%	0.31%
2: uploading to portal sites	0.31%	0.29%
3: downloading from SNC sites	0.11%	0.01%
4: downloading from portal sites	54.17%	55.56%
5: doing nothing	45.15%	43.83%

5.2 Parameter Estimates

The results of the parameter estimates for the model are shown in Table 5. First, we discuss the estimates on the quality levels. We find that there is substantial heterogeneity in the mean values across different content types. Downloads from mobile portal sites have the highest quality level, followed by upload to mobile portal sites, upload to SNC sites and download from SNC sites. Also, we find that consumers are significantly risk averse in this category ($r = -0.006$). This is consistent with prior literature (Erdem and Keane 1996), which has also emphasized the importance of controlling for risk aversion to obtain unbiased estimates of advertising effects.

With respect to direct experience, signals about the quality of download from mobile portal sites are the most accurate, whereas signals about the quality of download from SNC sites are the least accurate. In addition, the order of magnitude of signal accuracy for the direct experience is consistent with the order of true quality level. For example, download from mobile portal sites has both the highest quality level and the highest signal accuracy (lowest signal standard deviation). In terms of magnitude of estimates, the standard deviation of indirect experience signals is much higher than the standard deviation of direct experience signals. This is consistent with what one would expect - learning based on direct experience is more reliable (has less variability) than learning based on indirect experience because the information signals of neighbors may be not fully observed by or communicated to a user. Also we find that cumulative prior experience significantly reduces the user's initial uncertainty about the content quality.

Table 5: Parameter Estimates (True Content Quality Model)

Parameter	Description	Estimates	Standard Error
Utility function			
w	Quality coefficient	2.458	0.391***
r	Risk-aversion coefficient	-0.006	0.000***
α	Price coefficient	1.013	0.015***
Φ_0	Constant utility from doing nothing	6.240	0.329***
Quality			
Q_1	Quality level of activity 1	1.716	0.084***
Q_2	Quality level of activity 2	1.749	0.055***
Q_3	Quality level of activity 3	1	-
Q_4	Quality level of activity 4	2.801	0.000***
Signals			
$\sigma_{\xi 1}$	Std. dev. of direct experience signal of activity 1	0.117	0.030***
$\sigma_{\xi 2}$	Std. dev. of direct experience signal of activity 2	0.060	0.027**
$\sigma_{\xi 3}$	Std. dev. of direct experience signal of activity 3	0.177	0.092*
$\sigma_{\xi 4}$	Std. dev. of direct experience signal of activity 4	0.002	0.006
$\sigma_{\delta 1}$	Std. dev. of indirect experience signal of activity 1	594.2	150.3***
$\sigma_{\delta 2}$	Std. dev. of indirect experience signal of activity 2	15.10	1.308***
$\sigma_{\delta 3}$	Std. dev. of indirect experience signal of activity 3	65.07	3.454***
$\sigma_{\delta 4}$	Std. dev. of indirect experience signal of activity 4	254.1	0.346***
Initial conditions			
k0	Initial condition parameter 1	2.397	0.000***
k1	Initial condition parameter 2	0.052	0.019***

Notes: *Activity 1-4 denote uploading content to SNC sites, upload contenting to the mobile portal sites, downloading content from SNC sites, and downloading content from the mobile portal sites, respectively. These estimates are based on g=1. *** denotes significant at 0.01.*

6. Discussion and Implications

In this paper, we present a dynamic structural model in which users learn about content quality about four different activities through two distinct channels: (i) direct experience from own content creation and usage behavior, and (ii) indirect experience from the content creation and usage behavior of social network neighbors. The model is estimated on a dataset consisting of mobile media content usage and creation behavior where we have information on the content upload and download behavior of users from two different categories of websites - regular Internet social networking and community (SNC) sites and mobile portal sites.

Our estimates suggest that when it comes to user learning from direct experience, the content that is downloaded from mobile portals exhibits a higher level of quality than the content that is downloaded from SNC sites. This is consistent with the anecdotal fact that content provision to users via mobile portals (which are typically owned and hosted by mobile operators) preceded content provision via Internet SNC websites. In the early stages after the launch of their mobile services, most mobile phone operators implemented "closed" content management systems to exercise control on the kinds and quality of content that is available to users on their mobile devices. Subsequently, users had access to WAP-enabled regular Internet websites. Hence, the option of accessing third-party content via mobile portal sites was available to users much before the option of accessing multi-media content via regular Internet SNC sites. In addition, increasingly explicit monetary incentives are being given to users to create content on portal sites. Such practices have resulted in higher quality multi-media content being available to users on portal sites.

We are seeing mobile sites that combine social networking, UGC and messaging applications are establishing large user bases across a number of regions and monetizing services via a combination of advertising, revenue-share (with operators) and subscription models (Chard 2008). Our results can provide some insights for online advertising, given that advertisers are increasingly using the mobile Web as platform to reach users. The total value of advertising on mobile was 2.5 billion dollars in 2008. A recent study reports that about one-in-ten mobile Web users said they have made a purchase based on a mobile Web ad, while 23% said they have visited a Web site, 13% said they have requested more information about a product or service (OPA News 2007). Our result suggests that when it comes to embedding advertisements within multi-media content like audio or video files, advertisers would find it more profitable to insert their ads (such as intromercials or rich media ads) within multi-media content that is available on mobile portal sites, which are perceived as high quality for content they provide, compared to content that is available regular Internet sites.

These behavioral traits suggest that there may be several interesting opportunities for firms to monetize multi-media content in the process of reaching consumers through mobile phones. For example, firms could design programs or contests that lead to more frequent and high quality user-generated content updates on online social networking sites. Indeed, anecdotal evidence also suggests that there is a growing trend of cell phone users creating and sharing video and photo content on mobile portals as well as regular SNC websites, pushed by the popularity of video-camera embedded phones, and content-sharing mobile applications. And increasingly, there are incentives for users to engage in content creation and uploading to mobile portals. Even in the U.S., mobile operators like Cingular offer a "Messaging Awards" program, where customers vote on the best user-generated video, photo and text submissions. From the firms' perspective, mobile carriers are looking to take advantage of user-generated mobile content, given it doesn't cost the carrier anything to create, and motivates the consumer to transmit content over the pipes that is more profitable than the transmission of low-margin voice services.

Our paper has several limitations, which could be avenues for future research. Two in particular are worth some discussion. For example, we do not consider the actual amount of content generation and usage activities in our analysis. Instead, we focus only on frequency of these activities. Second, we do not have information on the specific types of content that are being generated or downloaded (such as audio files or video files) in our data. If one had access to such data, one could build a model that associated specific features of content to the magnitude of the direct and indirect effects. Notwithstanding these limitations, we hope our study paves the way for future research in the area of mobile media usage and commerce.

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