How is the Mobile Internet Different?

Search Costs and Local Activities[1]

Anindya Ghose
New York University
aghose@stern.nyu.edu

Avi Goldfarb
University of Toronto
agoldfarb@rotman.utoronto.ca

Sang-Pil Han
New York University
shan2@stern.nyu.edu

Abstract

We explore how internet browsing behavior varies between mobile devices and personal computers. Smaller screen sizes on mobile devices increase the cost to the user of reading information. In addition, a wider range of locations for mobile internet usage suggests that the offline context can be particularly important. Using data on user behavior at a microblogging service (similar to Twitter), we exploit randomization in the ranking mechanism for the microblog posts to identify a random experiment in the cost of reading information. Using a hierarchical Bayesian framework to better control for heterogeneity, our estimates show: (1) Search costs are higher on mobile devices: While links that appear at the top of a page are always more likely to be clicked, this effect is much stronger on mobile devices; (2) The benefit of searching for geographically close matches is higher on mobile devices: Stores located in close proximity to a user are much more likely to be clicked on mobile devices. We speculate on how these changes may affect market outcomes in online commerce.

Keywords: Mobile Internet, Search Costs, Local Activities, Microblogging, Social Media, User Behavior, Binary Logit, Multinomial Logit, Econometrics, Hierarchical Bayesian, MCMC.

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1. Introduction

Consumers increasingly use mobile devices to access the Internet. We have little understanding of whether mobile user behavior matches behavior on personal computers (PCs). There are reasons to expect both similarities and differences. The two are similar because both provide instant access to roughly the same Internet sources with vast amounts of information. The browsing experience, however, is different for two main reasons. First, mobile devices typically have smaller screens than PCs. Second, mobile devices are, by definition, portable and not fixed to a location.

These differences in screen size and mobility suggest that two prominent findings about the PC-based internet may have distinct implications for the mobile internet: Specifically, that search costs are lower online (Bakos 1997, Brynjolfsson and Smith 2000, Baye et al. 2009, etc.) and that offline geographic location affects online behavior (Forman, Ghose, and Goldfarb 2009; Brynjolfsson, Hu, and Rahman 2009; Anderson et al. 2010; etc.). In this study, we compare behavior when the internet is accessed on a mobile device and when the internet is accessed on a PC. The purpose of this paper is to examine whether these characteristics of the PC-based internet will still apply to the mobile internet.

We do this comparison using data from a South Korean microblogging website, similar to Twitter. As on Twitter, users share their thoughts in short posts. The central feature of microblogging is a stream of messages (i.e. tweets) that a user receives from those they follow. In our setting, these messages are listed in reverse chronological order and contain clickable links. We have information on all such links related to brands for 260 distinct users between November 29, 2009 and March 6, 2010. We examine whether the user clicked on the link as a function of the access technology (mobile or PC), the rank of the link on the screen, and the distance between the user's home address and the retail location of the brand.

Rank allows us to measure the search costs. Higher search costs mean that it is more valuable to be ranked near the top. Distance allows us to examine the role of geography. For identification, we exploit a unique source of randomization in the ranking mechanism that generates these microblog posts. The rank is determined only by the timing of the posting by the creator, the frequency of log-in by the user, and the number of feeds that the user follows. Therefore, the same post will appear at a different rank for different users. By using post-specific fixed effects to control for post-specific quality, we can treat the posting mechanism as a natural experiment. To take advantage of this natural experiment, we develop a revealed preference econometric model of user clicking behavior and estimate it on a unique panel dataset of users encompassing their click-through decisions on microblog posts. In order to control for user-level hetergeneity, we characterize our model in a hierarchical Bayesian framework and estimate it using Markov Chain Monte Carlo methods, using an adaptive Metropolis-Hastings algorithm to gain efficiency in estimation.

Examining the value of clicking using this revealed preference model generates our main results. *First*, the negative and statistically significant relationship between a rank of a post and a click of that post is much stronger for mobile users than PC users. This result suggests that search costs are higher on mobile devices. *Second,* we find that the benefit of searching for geographically close matches is higher on mobile devices. This result suggests that there are stronger local interests for mobile users than PC users. These results are robust to number specifications and controls. In this way, the mobile internet is somewhat less "internet-like": search costs are higher and distance matters more. Speculatively, this suggests that the features of the internet market that depend on search costs and distance effects will change as the mobile internet becomes proportionately larger.

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 econometric models in Section 4. Section 5 presents estimation results, and Section 6 discusses implications of the result and concludes.

2. Related literature

In this section, we explain why it is important to examine search costs and distance effects. We also discuss some other related literature.

2.1 Why do search costs matter?

Much of the early management literature on the Internet documented the reduced search costs in the online environment (e.g. Bakos 1997; Shapiro and Varian 1998). This was followed by a rich literature examining the consequences of these lower search costs on economic outcomes. The reduction in search costs associated with the internet affected prices, price dispersion, product quality, market structure, unemployment and many other areas of economic life (see, Lynch and Ariely 2000; Autor 2001; Scott Morton 2006; Ellison and Ellison 2001; Brynjolfsson et al. 2009, etc.). We discuss the specific consequences of lower search costs below.

Drawing on the economic literature on search theory, Bakos (1997) developed a theory on how the reduced search costs in electronic marketplaces would affect market outcomes. In particular, he argued that lower search costs can prevent market failure by facilitating buyer-seller interaction. Furthermore, he showed that lower search costs facilitate price competition and reduce monopoly power. The wider literature on search also emphasized that lower search costs reduce price dispersion. These models were empirically tested in several dozen papers that examined online prices and price dispersion. Brynjolfsson and Smith (2000), for example, showed considerable support for the search cost models. Examining thousands of online and offline prices for books and CDs, they found that retail prices and the share-weighted price dispersion were lower online. Similar effects have been documented in life insurance prices (Brown and Goolsbee 2002), car prices (Scott Morton, Zettelmeyer, and Silva-Risso 2001), and elsewhere. Still, Lal and Sarvary (1999) emphasize that the internet only lowers search costs for attributes that can be understood digitally. For non-digital attributes, the internet does not lower search costs and that may explain why some studies have found persistent online price dispersion (Clemons et al. 2002; Baye, Morgan, and Scholten 2004; Pan, Ratchford, and Shankar 2002; Clay et al. 2001). Overall, however, the evidence suggests that lower search costs online leads to lower prices and lower price dispersion. If the search costs on the mobile internet differ from those on the PC-based internet, price dispersion online may change.

Another consequence of the reduced search costs online is increased variety of products offered and purchased. Because it is possible for consumers to find even obscure products relatively easily (and because inventory costs are lower), Brynjolfsson, Hu, and Smith (2003) argue that the internet increases the variety of products available. Similarly, Kuksov (2004) argues that lower search costs increase the incentives to differentiate. Brynjolfsson, Hu, and Simester (2006) show that, holding availability fixed, online users buy a wider variety of products and therefore the lower search costs online decrease the concentration of sales. Broadly, while the inventory costs do not change whether consumers access the internet through a PC or a mobile device, differences in consumer search costs might affect the benefit to firms of holding variety.

Therefore, lower search costs online appear to have had important market consequences. In this paper we examine whether a particular kind of search cost is different on the mobile internet. That type of search cost is the cost of scrolling down a list of links. A number of papers have shown that better ranked links are more likely to be clicked. Known as the "primacy effect", it has been documented in a variety of online contexts (Ansari and Mela 2003; Drèze and Zufryden 2004; Baye et al. 2009; Ghose and Yang 2009). This is widely interpreted as a search cost (e.g. Yao and Mela 2010; Brynjolfsson et al. 2010). Therefore, because we document a stronger primacy effect when the internet is accessed on a mobile phone, we argue that search costs are higher on the mobile internet.

2.2 Why do distance effects matter?

Much of the popular press has emphasized the ability of the internet to bring about the "Death of Distance" (Cairncross 1997) or a "Flat World" (Friedman 2005). In the academic literature, Balasubramanian (1998) analytically discusses the role of distance to offline stores in an online and offline substitution setting. Several empirical studies show that the online channel is more valuable when consumers have to travel further to reach an offline store (Forman et al. 2009l Anderson et al. 2010). Therefore, the online channel helps reduce the importance of distance in many ways. Still, much online behavior is local. In the context of social media, people look for constant updates about what's happening in the areas of proximity to where they live (Knowledge@Wharton 2010). Blum and Goldfarb (2006) show that surfing behavior is disproportionately local. And a broader literature documents a distance decay effect (Fellmann et al. 2000), in which interaction between two entities declines as the distance between them increases, and Tobler's first law of geography that "all things are related, but near things are more related than far things" (Tobler 1970). Overall, distance has been found to be an important determinant of online behavior. If the role of distance is different when people access the internet on a mobile device, it suggests that online behavior more broadly may change. For example, if surfing behavior becomes more local then local retailers may disproportionately benefit.

2.3 Other related literature

Our paper is related to the literatures on user generated content and on behavior across channels. By studying microblogs, we examine a form of user-generated content. An emerging stream of relevant work has investigated the economic impact of online user-generated content (UGC). For example, research has examined whether the textual information embedded in online UGC can have an economic impact in the context of reputation systems (Pavlou and Dimoka 2006), online reviews (Ghose and Ipeirotis 2010) and stock market discussion forums (Das and Chen 2007) by using automated text mining techniques. Other work has examined the economic and social impact of multimedia content generated by users in a mobile setting (Ghose and Han 2009, 2010). A handful of papers have focused on microblogs in particular, including Krishnamurthy et al. (2008), Java et al. (2007), Barnes and Böhringer (2009), and Zhao and Rosson (2009) on usage and Diakopoulos and Shamma (2010) and O'Connor et al. (2010) on sentiment. In addition, an emerging stream of research has investigated the economic impact of information diffusion and sharing on microblogging platforms (Boyd et al. 2010; Jansen et al. 2009).

Our paper is also related to the literature on consumer behavior across channels. Consumers interact with brands in many channels. A substantial body of prior research compares the PC-based online setting to the offline channel. For example, Brynjolfsson and Smith (2000) compare prices in online and offline retail settings and Danaher et al. (2003) compare brand loyalty online and offline. Our study examines how the mobile internet and PC-based internet differ.

3. Data Description

In this section, we describe the data that we collected from a microblogging service company in South Korea. Our sample is drawn from subscribers who used the microblogging service between November 29, 2009 and March 6, 2010. We have data on users' behavior at the microblogging site using both their PCs and their mobile phones. The dataset consists of posts related to 3,396 distinct brands viewed by 260 different users. The unit of analysis is the user-post and the data set contains 8,896 such observations.

Specifically, when subscribers use the service, they see a list of posts that looks much like the center window of the facebook screen or the search results from a search engine. Some of these postings are branded and others are not. Our data set contains all brand-related posts. Brands range from prominent international brands like Starbucks and McDonalds, to the relatively unknown (even locally).

There are two sources of brand posts in our setting: 1) brand-related updates from other members that one is following (i.e., followees) and 2) updates posted at a brand site that one has bookmarked (refer to Figure 1 for detail). Brand-specific variables include brand category (refer to Figure 2 for the complete list), brand profile tenure (days since brand first appeared on the website), post tenure (days since post first appeared on the website), and number of bookmarks. User-specific variables include age, gender, number of followees, and type of access channel. A user's access channel can include either a mobile phone or a PC and users access with a mobile phone 7.3% of the time. We focus our analysis on the 1940 posts seen by the 30 users who access the website at least once with each channel but show robustness to using the full sample of 260 users. We focus on the 30 who use both channels to ensure the results are not a result of unobserved heterogeneity across samples. The brand- and user-specific variables include whether a user clicked that brand post, the rank of a brand post on a user's login page, and the distance between the user and the brand store. Crucially, the rank of the same brand post varies across users and we exploit this variation for identification. Because many brands do not have a physical store (including several common categories such as books, computer games, and multimedia clips), we only have distance information for 24.3% of the users. Because we have brand post-level fixed effects, these capture the situations when distance is missing and therefore we do not require any further controls.

Table 1 shows summary statistics of the key variables used in our study.

4. Econometric Analysis

To formally characterize our econometric model, we model user click-through decisions in terms of brand attributes, user characteristics, and brand- and user-characteristics. A user can navigate all microblog posts when he logs on the microblog platform using a PC or a mobile phone. In our model, a user decides to explore the content of a post by clicking on the post that provides the maximum expected utility. To better control for heterogeneity, we characterize our model in a hierarchical Bayesian framework and estimate it using Markov Chain Monte Carlo methods. The rest of this section is organized as follows: a brief sketch of our research design using a natural experiment, the econometric model, the estimation method, and a discussion of the identification strategy.

4.1 Research Design: A Natural Experiment

We treat the posting of a new brand-related message by users as an “event” in a natural experiment setting. Upon a posting event, all followers of the post creator and bookmarkers of the brand will receive a clickable link of that post. In each posting event, we examine the impact of a post rank, geographical distance between a user and the location of the posting brand’s store and other factors upon clicking decisions. Thus, we control for any post-related unobserved quality issues when it comes to mapping their click-through rates. The rationale for this control is that some posts attract more user clicks than others for their unobserved inherent characteristics (i.e., timeliness, relevance). The natural experiment provides higher validity on causal inferences of treatment effects (Shadish et al. 2002).

In addition, the microblog service in our setting provides an ideal setting for identifying the impact of post rank since it provides a unique source of randomization in the ranking mechanism. When a user generates a post, the same post would appear at different positions (ranks) by users. However, the rank is determined independent of any prior click-through decisions (For detail, refer to Section 4.4 Identification). Hence, for each posting event, we pull the information about whether users who received the post (i.e., followers) in his log-in page actually clicked on it and other user-related and post-related characteristics such as post rank, post-user distance, user access channel, and so on.

Moreover, a brand post can appear not only to multiple users but also multiple times to the same user at possibly increasing ranks over time (i.e., an older post is located towards to the bottom of the screen). Thus, the rank of a subsequently appearing brand post can be affected on average by the frequency of up-date messages from followees (i.e., the more frequently a user receives updates from followees, the rank of a given post increases more quickly.) and by the frequency of self log-in (i.e., the less frequently a user log ins, the rank of a given post increases more quickly). We addressed this endogeneity issue in ranks by using only the first appeared brand post message on a user's screen as well, while excluding the subsequently re-peated appearances of the same brand post.[2] Thus, for a given post, we only included the message which appeared on a user's screen first time. We also excluded brand post messages which appeared to only one user, which prevents across-user comparison. Moreover, we have used users who have accessed via both mobile phones and PCs. This helps us to better identify the "within-user" moderating effect of access de-vices on user click decisions. The sample size of the post-level analysis using dual-channel users is 1,940.

4.2 Econometric Model

Our model consists of two-level specification models: 1) post-level latent utility model and 2) popula-tion-level model with user- and brand post-level heterogeneity. Notation and variable descriptions are pro-vided in Table 2.

4.2.1 Post-Level Model

The observed user binary response (i.e., clicks), y_{ijk}, can be modeled through a random-utility frame-work. We model that users click on a post when the utility for reading the post exceeds a threshold. The relation between the observed response and the latent utility of clicking can be written as:

$$y_{ijk} = \begin{cases} 0 & \text{if } u_{ijk} \leq 0 \\ 1 & \text{if } u_{ijk} > 0 \end{cases} \tag{1}$$

[2] For example, suppose user A and user B followed user C and both received a same brand post from user C. When user A first logged in, the brand post from user C appeared at 3rd position on his screen, and when user A logged in second time, the message appeared at 11th position. Likewise, assume that when user B first logged in, the brand post from user C appeared at 6th place, but he never logged in later. Then the way we collected the ranks for a unique brand post in this example is that we use 3rd place for user A and 6th place for user B, and related these ranks with click their decisions.

We model the latent utility u_{ijk} for post k at time j for user i as the function of observed and unobserved post and user characteristics in the following way. For a given brand post k, we specify that user i's latent utility at time j as follows, for k = 1, 2,…, s:

$$u_{ijk} = \beta_{ij0} + \beta_{ij1}\mathrm{Rank}_{ijk} + \beta_{ij2}\mathrm{Distance}_{ik} + \beta_{ij3}\mathrm{Rank}_{ijk}\mathrm{Distance}_{ik} + \mu_1\mathrm{Mobile}_{ij} + \mu_2\mathrm{Followee}_{ij} + \mu_3\mathrm{Bookmark}_{ij} + \mu_4\mathrm{Age}_i + \mu_5\mathrm{Gender}_i + \mu_6\mathrm{BrandTenure}_k + \mu_7\mathrm{PostTenure}_k + e_{ijk} \quad (2)$$

$$u_{ijs+1} = e_{ijs+1} \quad (3)$$

We assume the error term e_{ijk} is i.i.d from Type I extreme value distribution. The utility from not clicking on the brand post k is denoted as e_{ijs+1}.

We control for the user-level observed heterogeneity by including access channel (mobile phone vs. PC), number of followees, number of bookmarks, age and gender of each user. In addition, as the duration of time since the establishment of a brand microblog increases, the likelihood of a click on that brand may change. Similarly, as the duration of time since posting increases, the likelihood of a click on that post may change. We capture such brand-level and post-level observed heterogeneities by including tenure of brand profile and tenure of post, respectively.

4.2.2 Population-Level Model

The impact of key independent variables in equation (2) (e.g., *Rank*, *Distance*, and *RankDistance*) interacts with user-specific characteristics such as access channel (mobile phones vs. PCs), number of followees, and etc. Thus, we specify user-specific random slopes (i.e., β_{ij1}, β_{ij2} and β_{ij3}) to capture differences across users in their responses to post rank, post-and-user distance, and their interaction. We allow the coefficients of *Rank*, *Distance*, and *RankDistance* in equation (2) to vary along the respective population mean (i.e., $\bar{\beta}_1$, $\bar{\beta}_2$, and $\bar{\beta}_3$) and the user characteristics. We also model unobserved user heterogeneity by including λ_{i1}, λ_{i2} and λ_{i3} in each slope as follows:

$$\beta_{ij1} = \bar{\beta}_1 + \alpha_1\mathrm{Mobile}_{ij} + \alpha_2\mathrm{Followee}_{ij} + \alpha_3\mathrm{Bookmark}_{ij} + \alpha_4\mathrm{Age}_i + \alpha_5\mathrm{Gender}_i + \lambda_{i1} \quad (4)$$

$$\beta_{ij2} = \bar{\beta}_2 + \alpha_6\mathrm{Mobile}_{ij} + \alpha_7\mathrm{Followee}_{ij} + \alpha_8\mathrm{Bookmark}_{ij} + \alpha_9\mathrm{Age}_i + \alpha_{10}\mathrm{Gender}_i + \lambda_{i2} \quad (5)$$

$$\beta_{ij3} = \bar{\beta}_3 + \alpha_{11}\mathrm{Mobile}_{ij} + \alpha_{12}\mathrm{Followee}_{ij} + \alpha_{13}\mathrm{Bookmark}_{ij} + \alpha_{14}\mathrm{Age}_i + \alpha_{15}\mathrm{Gender}_i + \lambda_{i3} \quad (6)$$

In addition, each post may have inherent post-specific unobserved quality, hence the likelihood of clicking on a post will be associated with the brand post. In equation (7), we capture the brand post-level attractiveness, denoted as $\bar{\beta}_{0k}$, and allow unobserved heterogeneity across users with a random coefficient on the intercept, denoted as λ_{i0} as follow:

$$\beta_{ij0} = \bar{\beta}_{0k} + \lambda_{i0} \tag{7}$$

Further, we model the unobserved covariation among λ_{i0}, λ_{i1}, λ_{i2}, and λ_{i3}. We let the 4 error terms be correlated in the following manner:

$$\begin{bmatrix} \lambda_{i0} \\ \lambda_{i1} \\ \lambda_{i2} \\ \lambda_{i3} \end{bmatrix} \sim \mathrm{MVN}\left(\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \Sigma_{0,0}^{\lambda} & \Sigma_{0,1}^{\lambda} & \Sigma_{0,2}^{\lambda} & \Sigma_{0,3}^{\lambda} \\ \Sigma_{1,0}^{\lambda} & \Sigma_{1,1}^{\lambda} & \Sigma_{1,2}^{\lambda} & \Sigma_{1,3}^{\lambda} \\ \Sigma_{2,0}^{\lambda} & \Sigma_{2,1}^{\lambda} & \Sigma_{2,2}^{\lambda} & \Sigma_{2,3}^{\lambda} \\ \Sigma_{3,0}^{\lambda} & \Sigma_{3,1}^{\lambda} & \Sigma_{3,2}^{\lambda} & \Sigma_{3,3}^{\lambda} \end{bmatrix} \right). \tag{8}$$

4.2.3 Full Model

By replacing β_{ij0}, β_{ij1}, β_{ij2}, and β_{ij3} in equation (2) with equation (4) – (7), we can rewrite equation (2) for brand post k as follows:

$$\begin{aligned} u_{ijk} = {} & \bar{\beta}_{0k} + \mu_1 \mathrm{Mobile}_{ij} + \mu_2 \mathrm{Followee}_{ij} + \mu_3 \mathrm{Bookmark}_{ij} + \mu_4 \mathrm{Age}_i \\ & + \mu_5 \mathrm{Gender}_i + \mu_6 \mathrm{BrandTenure}_k + \mu_7 \mathrm{PostTenure}_k \\ & + (\bar{\beta}_1 + \alpha_1 \mathrm{Mobile}_{ij} + \alpha_2 \mathrm{Followee}_{ij} + \alpha_3 \mathrm{Bookmark}_{ij} + \alpha_4 \mathrm{Age}_i + \alpha_5 \mathrm{Gender}_i) \mathrm{Rank}_{ijk} \\ & + (\bar{\beta}_2 + \alpha_6 \mathrm{Mobile}_{ij} + \alpha_7 \mathrm{Followee}_{ij} + \alpha_8 \mathrm{Bookmark}_{ij} + \alpha_9 \mathrm{Age}_i + \alpha_{10} \mathrm{Gender}_i) \mathrm{Distance}_{ik} \\ & + (\bar{\beta}_3 + \alpha_{11} \mathrm{Mobile}_{ij} + \alpha_{12} \mathrm{Followee}_{ij} + \alpha_{13} \mathrm{Bookmark}_{ij} + \alpha_{14} \mathrm{Age}_i + \alpha_{15} \mathrm{Gender}_i) \mathrm{Rank}_{ijk} \mathrm{Distance}_{ik} \\ & + \lambda_{i0} + \lambda_{i1} \mathrm{Rank}_{ijk} + \lambda_{i2} \mathrm{Distance}_{ik} + \lambda_{i3} \mathrm{Rank}_{ijk} \mathrm{Distance}_{ik} + e_{ijk}. \end{aligned} \tag{9}$$

Note that equation (9) contains both main effects of *Rank*, *Distance*, and *RankDistance* (i.e., $\bar{\beta}_1$, $\bar{\beta}_2$, and $\bar{\beta}_3$) and moderating effects with individual-specific characteristics such as access channel, number of followees and bookmarks, and demographics (i.e., α_1-α_5, α_6-α_{10}, α_{11}-α_{15}). It also has control variables for brand post-specific intercept, mobile, followee, bookmark, age, gender, brand tenure, and post tenure (i.e., $\bar{\beta}_{0k}$, μ_1-μ_7).

4.3 Estimation

4.3.1 Choice Probability

We rewrite user i's latent utility above as being composed of a systematic part (i.e., v_{ijk}) and a stochastic part (i.e., e_{ijk}) as follows.

$$u_{ijk} = v_{ijk} + e_{ijk} \tag{10}$$

Recall that we assume that e_{ijk} is i.i.d from Type I extreme value distribution. Hence, the probability of user i clicking on brand post k at time j is then

$$\Pr\left(y_{ijk} = 1 | \underline{\beta}_i\right) = \frac{\exp\left(v_{ijk}\right)}{1 + \exp\left(v_{ijm}\right)} \tag{11}$$

where $\underline{\beta}_i$ denotes all parameters in the model.

4.3.2 Hierarchical Bayesian Modeling and Estimation

We cast our model in a hierarchical Bayesian framework and estimate it using Markov Chain Monte Carlo methods. We rewrite our main equations as follows.

$$\underline{u}_{ij} = X_{ij}'\underline{\beta}_i + \underline{e}_{ij} \tag{12}$$

$$\underline{\beta}_i = \underline{Z}_i'\underline{\mu} + \underline{\lambda}_i \tag{13}$$

where $\Pr\left(\underline{\mu}\right) = N\left(\underline{\eta}, C\right)$, $\underline{\lambda}_i = (\lambda_{i0}, \ldots, \lambda_{i3})' \sim N(0, \Lambda)$, and $\Pr(\Lambda^{-1}) = W(\rho, R)$.

The corresponding *mixed model* is as follows.

$$\underline{u}_{ij} = W_{ij}'\underline{\mu} + X_{ij}'\underline{\lambda}_i + \underline{e}_{ij} \tag{14}$$

Hence, the full conditionals are

$$\text{(1)}\ \Pr\left(\underline{\mu} | \Lambda, \{\underline{\lambda}_i\}_{i=1}^{n}, \{y_i\}_{i=1}^{n}\right) \tag{15}$$

$$\text{(2)}\ \Pr\left(\underline{\lambda}_i | \underline{\mu}, \Lambda, y_i\right) \tag{16}$$

$$\text{(3)}\ \Pr\left(\Lambda^{-1} | \{\underline{\lambda}_i\}_{i=1}^{n}\right) \tag{17}$$

where n is the total number of users in the sample.

It is important to note that conditional (3) can be computed using Wishart distribution. However, conditionals (1) and (2) cannot be directly computed because they are not conjugate. Hence, we use Metropolis-Hasting algorithm to compute conditional (1) and (2) (see Appendix A for detail).

Further, we use an adaptive Metropolis-Hastings algorithm with a random walk chain to generate draws (Atchadè 2006, Chib and Greenberg 1995, Hastings 1970). It enables us to adjust the tuning constant to vary by an individual. For example, a chain of draws for $\underline{\lambda}_i$ can be generated in the following way:

$$\underline{\lambda}_i^c \sim N\left(\underline{\lambda}_i^{(n)}, \Omega_n\right) \tag{18}$$

where Ω_n is a tuning constant at n. In addition, the adaptive Metropolis-Hasting algorithm enables to generate draws with higher efficiency while maintaining Markov chain properties (Andrieu and Atchade 2007). Lastly, the acceptance probability is as follows:

$$a\left(\underline{\lambda}_i^{(n)}; \underline{\lambda}_i^c\right) = \min\left\{1, \frac{L_i\left(\underline{\lambda}_i^c | y_i\right) \cdot \Pr\left(\underline{\lambda}_i^c | \underline{\mu}, \Lambda\right)}{L_i\left(\underline{\lambda}_i^{(n)} | y_i\right) \cdot \Pr\left(\underline{\lambda}_i^{(n)} | \underline{\mu}, \Lambda\right)}\right\}. \tag{19}$$

Similarly, a chain of draws for $\underline{\mu}$ can be obtained.

4.4 Identification

We briefly discuss identification issues in our model mathematically and empirically.

4.4.1 Mathematical Identification

First, we impose a location normalization restriction by setting the constant utility term for any one brand post to be zero. This is because one can change all the brand post-specific constant terms by adding/subtracting a constant k, without changing the choices implied by the model. As a referent brand post, we set the mean value for a brand post about a local restaurant to be 0. Our results do not change by the choice of a referent brand post. Second, we impose a scale normalization restriction by allowing the distribution for the error term, e_{ijk}, to be the type I extreme value distribution, whose variance is set to be $\pi^2/6$. This is because one can scale all the parameters in equation (2) by k, while scaling the error term by k, without changing the choices implied by the model.

4.4.2 Empirical Identification

The identification of the impact of rank depends on a unique source of randomization in the ranking mechanism. Unlike in the search engine context where the rank of posts determined by algorithm based on popularity and relevance, the rank of posts in our microblog setting is determined by "recency." Thus, the posts appear on a user's log-in screen in reverse chronological order (i.e., the most recent one appear at the top). This alleviates concerns for endogeneity issues in ranks because previous clicks by users on a post do not affect the rank of that post in any subsequent periods. Further, we consider the rank order of a post as random and exogenous for the following reasons: 1) the frequency that a content creator generates a brand post and the system automatically sends the brand post to a user is independent of that user's log-in frequency and 2) only after a user logs in, the user is able to see the ranks of a post. Hence a user's log-in decision can be considered as a sort of random stopping decision during the continuous post feeds from his followees or bookmarks, that is, we can consider users' log-in timing decisions as exogenous to the determination of ranks.

5. Results

We ran the MCMC chain for 60,000 iterations and used the last 20,000 iterations to compute the mean and standard deviation of the posterior distribution of the model parameters. We next present our key results on search costs and benefits across access technologies. We discuss the economic impact of our results to gain further insights. Further, we present a number of robustness check results.

We present the results on the coefficients of the main model in Table 3. The first column shows the effect of rank, distance, and their interaction on clicks when users access the microblogging site with a PC. Consistent with prior evidence on the primary effect, the first column shows that better rank increases clicks (rank is significantly negative). Furthermore, people click on nearby links (distance is significantly negative). These effects reinforce each other in combination as the interaction of rank and distance is significantly negative.

Our primary focus is on the difference between PCs and mobile devices. The second column of Table 3 shows that the estimate for interaction effect between the rank and the mobile phone access channel is negative and statistically significant (the coefficient is -0.078), implying that the primacy effect is strengthened in a mobile setting. This result reflects the fact that it is more difficult to read and browse posts using mobile phones with limited screen size compared to using PCs because of additional efforts involved in scrolling, thereby making real estate even more important in a mobile setting. Hence they are more likely to click on a highly ranked post, as opposed to in PC settings in which they see messages on a given screenshot.

We also find that distance matters more in the mobile setting than in the PC setting, even though our measure of the user's location reflects a physical address. Therefore, this result should not be interpreted as a contextual effect. Instead, it suggests that people tend to prefer local content on their mobile phones, perhaps because it is easier for them to travel there but perhaps for reasons unrelated to context. The interaction between distance and rank is also stronger in the mobile channel.

We discuss the economic impact of each effect using odds ratios. For PC users, one position upward increase in rank of a brand post yields an increase in the odds of clicking on that brand post by 26% (exp(-0.230) = 1.259) holding the other variables constant. This is similar in flavor to the 17.5% drop in click-through rates with position found in a shopbot setting by Baye et al. (2009) and a drop in click-through rates with position found in a search engine setting by Ghose and Yang (2009). For mobile phone users, one position upward increase in rank of a brand post yields an increase in odds of clicking on that brand post by 36%. Hence, the magnitude of the primacy effect (i.e., search costs) on the odds of clicking in mobile phone settings is 38% larger than that in PC settings.

For PC users, one mile decrease in distance between a user and a brand store yields an increase in the odds of clicking on that brand post by 11%. This result is consistent with anecdotal evidence that people generally have local interests – what's happening in the areas of proximity to where they live (Knowledge@Wharton 2010). For mobile users, one mile decrease in distance between a user and a brand store yields a decrease in the odds of clicking on that brand post by 23%. Hence, the magnitude of the distance decay effect (i.e., benefits from geographic matching) on the odds of clicking in mobile phone settings is 109% larger than that in PC settings.

Finally, some of the control variables yield interesting insights. Specifically, the estimate for mobile phone access is positive and statistically significant. This result suggests that a user accessing through mobile phones is in general more likely to click on brand posts, which is, in fact, consistent with higher click rates for mobile access (4.7%) as opposed to for PC access (2.5%) in the sample. In addition, the estimate for post tenure is negative and statistically significant (the coefficient is -0.074). This result suggests that the longer the duration of time since a new post is created the less likely that it is to be clicked. Further, the statistically significant results on unobserved heterogeneity suggest that controlling for the unobserved heterogeneity is crucial in our setting.

Table 4 shows that the results are robust to a number of alternative specifications. In particular, model (1) shows that the results on rank hold without controls for distance. Similarly, model (2) shows that the results on distance hold without the controls for rank. Model (3) shows that including the interaction between rank and distance does not affect the qualitative results on rank or distance. Models (4) and (5) show robustness to fewer interaction terms as controls. Model (6) includes all users, not just the dual channel users.

6. Discussion and Implications

We examine how the economics of the mobile Internet differ from the economics of the PC-based Internet. Focusing on search costs and benefits, we show that search costs are higher on the mobile Internet, but the benefits to searching for geographically proximate items are also higher.

This study provides several important insights for managers. First, and most directly, our results can provide microblogging service companies with insights about how they can target *access channel-based sponsored messages* using the information of whether a user accessed through a PC or a mobile phone. Our results show there exists a stronger primacy effect in a mobile phone setting compared to that in a PC setting. The asymmetric primacy effect suggests that microblogging companies can charge different prices to advertisers for sponsored messages based on the type of user access channel. For example, the stronger primacy effect on mobile phone users implies that for a given brand advertisement, microblogging platforms such as Twitter can charge more for a high ranking of sponsored messages displayed on mobile phone users as opposed to PC users. Further, this result suggests that advertisers that buy positions (rank) in sponsored search listings might have incentives to bid higher on sponsored links in mobile phones as compared to PCs.

Second, our results provide microblogging companies and advertisers with insights about how they can target *location-based sponsored messages* using geographical proximity between users and brand stores. Our results show that users in our microblogging setting exhibit strong local interests. Hence, when sponsored messages are accompanied with user-generated posts, they should be closely related to brand stores near the user's geographical location, as opposed to brand stores in random or faraway places.

While we showed these results in the context of microblogging, the implications are much wider. Mobile devices are increasingly important tools for accessing the Internet. While it is possible there are differences from setting to setting, our results broadly suggest that higher search costs and higher benefits to geographic targeting may impact all aspects of the mobile Internet including search engines, e-commerce sites, and social media sites. Furthermore, and more speculatively, higher search costs may mean higher equilibrium prices, price dispersion, and market concentration as the mobile internet grows in importance. Larger distance effects may mean an increasing role for local businesses (and even local social relationships) in determining online behavior.

Data availability issues suggest that some caution is warranted in this speculation. For example, we do not have information about the textual content in a microblog post (e.g., length, sentiment, theme, etc.) and therefore cannot examine how specific content matters across channels. Moreover, we do not observe users' Internet surfing location, only their address. Hence, we cannot claim a "contextual effect" here in which the immediate environment and vicinity plays a role in consumer's mobile usage behavior. Furthermore, our analysis focuses on brand posts in the microblogging setting and it is possible that the magnitudes of the differences across access channels will vary across settings.

Notwithstanding these limitations, our analysis documents higher search costs associated with the mobile internet as well as a greater role for geographic proximity. To the extent that search costs and geographic proximity affect market outcomes online, the increasing size of the mobile internet may have profound implications for the future direction of internet commerce.

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Appendix A: Computing Full Conditionals

The full conditionals for the mixed model are

(1) $\Pr\left(\underline{\mu}|\Lambda, \{\underline{\lambda}_i\}_{i=1}^{n}, \{y_i\}_{i=1}^{n}\right)$

(2) $\Pr\left(\underline{\lambda}_i|\underline{\mu}, \Lambda, y_i\right)$

(3) $\Pr\left(\Lambda^{-1}|\{\underline{\lambda}_i\}_{i=1}^{n}\right)$

where n is the total number of users in the sample.

Conditional (3) can be computed using Wishart distribution as follows:

$$\Pr\left(\Lambda^{-1}|\{\underline{\lambda}_i\}_{i=1}^{n}\right) = W\left(\rho + n, \left(\sum_{i=1}^{n} \underline{\lambda}_i \underline{\lambda}_i' + R^{-1}\right)^{-1}\right). \tag{A1}$$

However, conditionals (1) and (2) cannot be directly computed because they are not conjugate.

The conditional (1) can be written as follows:

$$\Pr\left(\underline{\mu}|\Lambda, \{\underline{\lambda}_i\}_{i=1}^{n}, \{y_i\}_{i=1}^{n}\right) \propto L\left(\underline{\mu}|\{\underline{\lambda}_i\}_{i=1}^{n}, \{y_i\}_{i=1}^{n}\right) \cdot \Pr\left(\underline{\mu}|\Lambda\right) \tag{A2}$$

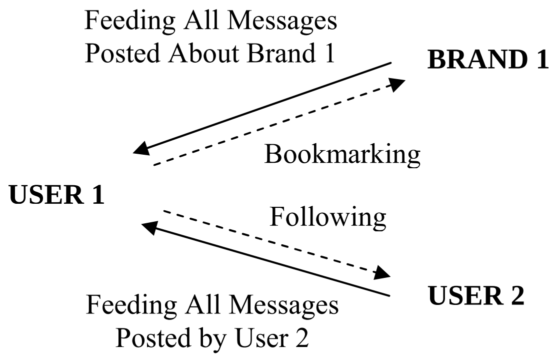
Recall that $L\left(\underline{\mu}|\{\underline{\lambda}_i\}_{i=1}^{n}, \{y_i\}_{i=1}^{n}\right)$ is the same as $L\left(\{y_i\}_{i=1}^{n}|\{\underline{\lambda}_i\}_{i=1}^{n}, \underline{\mu}\right)$ in a conceptual manner. Then, it is important to note that in conditional (1) we cannot apply normal-normal conjugacy because likelihood is based on Type 1 extreme value distribution whereas the prior is based on normal distribution. When we compute the posterior, we need to multiply the likelihood by the prior. Hence, we should use Metropolis-Hasting algorithm to compute the conditional (1).

The conditional (2) can be written as follows:

$$\Pr\left(\underline{\lambda}_i|\underline{\mu}, \Lambda, y_i\right) \propto L_i\left(\underline{\lambda}_i|\underline{\mu}, y_i\right) \cdot \Pr(\underline{\lambda}_i|\Lambda) \tag{A3}$$

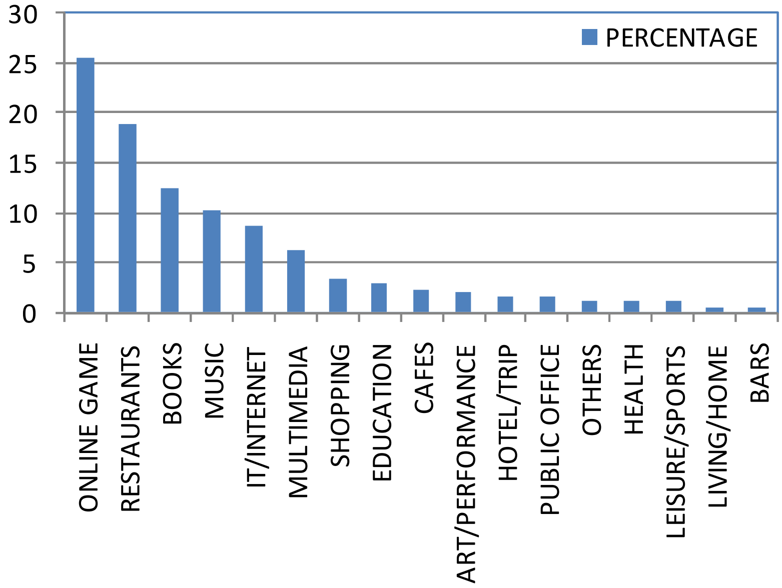
Again, recall that $L_i\left(\underline{\lambda}_i|\underline{\mu}, y_i\right)$ is the same as $L_i\left(y_i|\underline{\mu}, \underline{\lambda}_i\right)$ in a conceptual manner. Then, similar to conditional (1), in conditional (2) we cannot apply normal-normal conjugacy. Hence, we should use Metropolis-Hasting algorithm to compute the conditional (2).

Figure 1: Network Formation and Message Flows in a Microblogging Platform

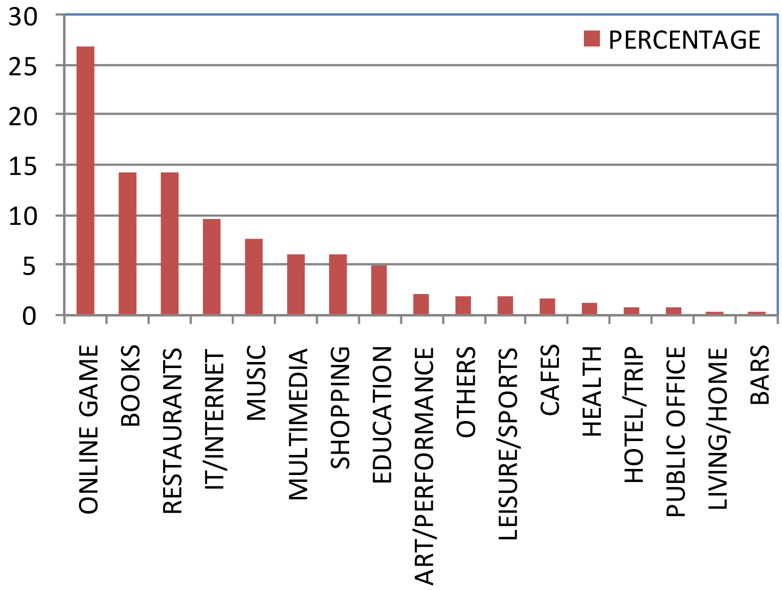


Note: Dotted lines represent network formation and solid lines represent message flows.

Figure 2: Brand Categories



All Brands



Clicked Brands Only

Table 1: Summary Statistics

Variable	Mean	Std. dev.	Min	Max
Brand-Level				
Brand profile tenure (days)	274	159	1	501
Post tenure (days)	8.380	14.269	0	97.1
Physical brand store rate	0.865	0.342	0	1
User-Level				
Age	24.987	11.818	0	54
Gender (Male =1, Female = 0)	0.769	0.422	0	1
Number of followees (those one follows)	10.414	30.609	0	373.6
Number of bookmarks	15.711	56.946	0	350
Mobile phone access rate	0.073	0.242	0	1
User- and Individual-Level				
Rank of brand post	39.107	26.859	1	90
Distance between a user and a brand store (km)	69.089	176.486	0.1	1169.5
Click-through rate on brand posts	0.030	0.171	0	1

Table 2: Notations and Variable Descriptions

$\mathrm{u}_{\mathrm{ijk}}$	Latent utility of clicking and visiting a brand post k by user i at time j
$\mathrm{Rank}_{\mathrm{ijk}}$	Rank of brand post k on user i's log-in screen at time j
$\mathrm{Distance}_{\mathrm{ik}}$	Euclidian log distance between user i's place and brand k's physical store
$\mathrm{Mobile}_{\mathrm{ij}}$	Access channel of user i at time j (1 = Mobile, 0 = PC)
$\mathrm{Followee}_{\mathrm{ij}}$	Number of users user i is following at time j
$\mathrm{Bookmark}_{\mathrm{ij}}$	Number of brand posts user i is following at time j
$\mathrm{Age}_{\mathrm{i}}$	Age of user i
$\mathrm{Male}_{\mathrm{i}}$	Gender of user i (1 = Male, 0 = Female)
$\mathrm{BrandTenure}_{\mathrm{k}}$	Days elapsed since brand profile k was created
$\mathrm{PostTenure}_{\mathrm{k}}$	Days elapsed since post k was created/posted

Table 3: Effect of Rank and Distance on Clicks (Dual Channel Users)

Coefficient estimates								
Variable	Main Effect	Moderating Effect						
		Mobile	Followee	Bookmark	Age	Male	Brand Tenure	Post Tenure
Intercept	Brand Post Fixed Effect	0.153*** (0.001)	0.003*** (0.001)	0.042*** (0.002)	-0.045*** (0.002)	-0.128*** (0.003)	-0.003*** (0.001)	-0.074*** (0.002)
Rank	-0.230*** (0.002)	-0.078*** (0.005)	0.0001 (0.0001)	-0.003 (0.003)	-0.001 (0.001)	-0.010*** (0.003)		
Distance	-0.107*** (0.002)	-0.098*** (0.002)	-0.001 (0.0006)	-0.014*** (0.002)	0.014*** (0.003)	0.003 (0.002)		
Rank × Distance	-0.068*** (0.002)	-0.007*** (0.003)	0.0003 (0.0002)	-0.001 (0.002)	-0.002** (0.001)	-0.007*** (0.003)		

Unobserved heterogeneity covariance estimates				
	Intercept	Rank	Distance	Rank × Distance
Intercept	0.026*** (0.006)	-0.001 (0.008)	-0.007* (0.004)	-0.004 (0.009)
Rank		0.125** (0.052)	-0.016** (0.009)	0.001 (0.027)
Distance			0.030*** (0.007)	-0.001 (0.009)
Rank x Distance				0.107* (0.060)

Notes: Posterior means and posterior deviations (in parentheses) are reported. Coefficients for brand post fixed effects are omitted due to brevity. *** denotes significant at 0.01, ** denotes significant at 0.05, and * denotes significant at 0.1.

Table 4: Robustness to Alternative Specifications

Variable	Main Effect	Moderating Effect						
		Mobile	Followee	Bookmark	Age	Male	Brand Tenure	Post Tenure
(1) Rank Only Model								
Intercept	Brand Post Fixed Effect	0.134*** (0.011)	0.002** (0.001)	0.033** (0.013)	-0.039*** (0.012)	-0.125*** (0.005)	-0.004*** (0.001)	-0.070** (0.007)
Rank	-0.241*** (0.015)	-0.082*** (0.004)	0.0004 (0.0003)	-0.005** (0.002)	-0.001 (0.001)	-0.017* (0.010)		
(2) Distance Only Model								
Intercept	Brand Post Fixed Effect	0.148*** (0.005)	0.001 (0.002)	0.062*** (0.015)	-0.075*** (0.013)	-0.185*** (0.063)	-0.002 (0.003)	-0.147 (0.091)
Distance	-0.163*** (0.055)	-0.155*** (0.059)	0.0005 (0.0008)	-0.029** (0.013)	0.008** (0.004)	-0.047 (0.045)		
(3) Rank and Distance Model								
Intercept	Brand Post Fixed Effect	0.150*** (0.007)	0.003*** (0.001)	0.050*** (0.003)	-0.061*** (0.007)	-0.127*** (0.008)	-0.003*** (0.001)	-0.057*** (0.008)
Rank	-0.233*** (0.004)	-0.089*** (0.007)	0.001 (0.001)	-0.005*** (0.001)	-0.001 (0.001)	-0.006 (0.010)		
Distance	-0.112*** (0.005)	-0.098*** (0.006)	-0.001 (0.001)	-0.010** (0.004)	0.009*** (0.003)	-0.007 (0.005)		
(4) Main Effects Only								
Intercept	Brand Post Fixed Effect	0.148** (0.062)	0.003*** (0.001)	0.039*** (0.009)	-0.012*** (0.004)	-0.210*** (0.048)	-0.002** (0.001)	-0.070*** (0.018)
Rank	-0.333*** (0.067)							
Distance	-0.157*** (0.055)							
Rank x Distance	-0.094*** (0.028)							
(5) Main and Mobile Effects Only								
Intercept	Brand Post Fixed Effect	0.181*** (0.026)	0.004** (0.002)	0.083*** (0.010)	-0.018*** (0.006)	-0.077*** (0.026)	-0.003*** (0.001)	-0.078*** (0.029)
Rank	-0.250*** (0.080)	-0.092*** (0.032)						
Distance	-0.131*** (0.038)	-0.109*** (0.041)						
Rank x Distance	-0.079*** (0.018)	-0.038*** (0.009)						
(6) All Users (Not Just Dual-Channel Users)								
Intercept	Brand Post Fixed Effect	0.163*** (0.004)	0.002** (0.001)	0.048*** (0.004)	-0.049*** (0.005)	-0.131*** (0.005)	-0.003*** (0.001)	-0.070*** (0.003)
Rank	-0.210*** (0.005)	-0.081*** (0.005)	0.0001 (0.0001)	-0.004 (0.005)	-0.002 (0.002)	-0.012*** (0.004)		
Distance	-0.116*** (0.004)	-0.095*** (0.003)	-0.001 (0.001)	-0.014*** (0.003)	0.011*** (0.003)	0.001 (0.002)		
Rank x Distance	-0.073*** (0.004)	-0.010*** (0.003)	0.0002 (0.0002)	-0.001 (0.003)	-0.002** (0.001)	-0.009*** (0.002)		

Notes: Posterior means and posterior deviations (in parentheses) are reported. Coefficients for brand post fixed effects and unobserved heterogeneity estimates are omitted due to brevity. *** denotes significant at 0.01,** denotes significant at 0.05, * denotes significant at 0.1.