HOW IS THE MOBILE INTERNET DIFFERENT?
SEARCH COSTS AND LOCAL ACTIVITIES

Completed Research Paper

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Abstract

We explore how internet browsing behavior varies between mobile phones and personal computers. Smaller screen sizes on mobile phones increase the cost to the user of reading information. A wider range of offline locations for mobile internet usage suggests that local activities are particularly important. Using data on user behavior at a (Twitter-like) microblogging service, we exploit exogenous variation in the ranking mechanism of posts to identify user search costs. We show (1) Search costs related to primacy effects are higher on mobile phones and (2) The benefit of searching for geographically close matches is higher on mobile phones. Thus, the mobile internet is somewhat less “internet-like”: search costs are higher and distance matters more. Our results suggest a possible exception: while primacy effect-related search costs are higher in a mobile phone, the cost of acquiring timely information appears to be lower on a mobile phone than on a PC.

Keywords: Mobile Internet, Search Costs, Local Commerce, Microblogging, Social Media, User Behavior, Hierarchical Bayesian
Introduction

After nearly two decades of research on the economic consequences of the internet, two findings have consistently appeared in the literature: search costs are lower online (Bakos 1997, Baye et al. 2009, etc.) and the internet can overcome geographic isolation (Balasubramanian 1998, Forman et al. 2009, Choi and Bell 2011, etc.). Both of these suggest that the addition of the internet channel has generated increased competition for both online and offline firms. While companies try to mitigate these effects with obfuscation, differentiation, and targeting (Ellison and Ellison 2009, Brynjolfsson et al. 2010, etc.), the fundamental shift is to an increasingly competitive e-commerce environment. As consumers increasingly use mobile phones to access the internet, it is important to understand when and how these results on search and geography transfer to the use of different devices. However, 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 phones typically have smaller screens than PCs. Second, mobile phones are, by definition, portable and not fixed to a location.

In this study, we compare behavior when the internet is accessed on a mobile phone 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. In other words, we empirically establish whether the models of Bakos (1997), Balasubramanian (1998), and others that have played a prominent role in the academic discussion of internet commerce are as fundamental in an online world that is increasingly accessed with mobile phones. 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 distributed by mobile phones- or PC-based Web. A microblog differs from a traditional blog in that its content is typically much smaller in size, consisting of a short sentence fragment described within a limit of 140 characters. 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 phones or PCs), the rank of the link on the screen, and the geographical distance between the user’s address and the retail location of the brand mentioned in the link.

Rank allows us to measure the search costs related to primacy effects. Higher search costs mean that it is more valuable to be ranked near the top. Distance allows us to examine the role of geography and local activities of users. For identification of rank effects, we exploit a unique source of randomization in the ranking mechanism that generates these microblog posting feeds. 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. Using post-specific fixed effects to control for post quality the posting mechanism provides exogenous variation in the ranking, under the assumption that our key controls (specifically, the time since posting and the number of followees) capture those potential confounds. In this way, variation in the posting mechanism can be seen as something like a natural experiment in ranking. To the extent that our covariates do not capture user-level heterogeneity in propensity to click on different types of posts, we include user-level random coefficients in a hierarchical Bayesian framework and estimate it with Markov Chain Monte Carlo methods, using an adaptive Metropolis-Hastings algorithm to gain efficiency in estimation. User decisions are captured with a revealed preference econometric model of user clicking behavior and estimated on a unique panel dataset of users encompassing their click-through decisions on microblog posting feeds.

Examining the value of clicking in 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. For PC users, moving one position upward in rank yields an increase in the odds of clicking on that brand post by 26%. For mobile phone users, a one position upward increase in rank yields an increase in odds of clicking on that brand post by 36%. This result suggests that

1 We use the term “mobile internet” and “mobile phone-based internet” interchangeably in this paper.
search costs are higher on mobile phones. *Second*, we find that the benefit of searching for geographically close brands is higher on mobile phones. For PC users, a 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%. For mobile users, a 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 23%. This result suggests that there are stronger local interests for mobile users than PC users. These results are robust to a variety of alternative 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. In addition, the coefficient estimates on one of our controls are suggestive of a possible exception to the finding of higher search costs on the mobile internet: time-related search costs may fall. That is, our results suggest that more recent posts are more likely to be clicked on a mobile phone. In other words, the cost of acquiring timely information may be lower on a mobile phone than on a PC. The coefficient estimates suggest that, for PC users, an increase in the recency of a post by one day yields an increase in the odds of clicking on that post by 7.1%. For mobile phone users, an increase in the recency of a post by one day yields an increase in odds of clicking on that post by 8.3%. Hence, the estimated magnitude of the post time-sensitivity effect on the odds of clicking in mobile phone settings is 17% larger than that in PC settings. Therefore, in considering the impact of search costs on equilibrium outcomes on the mobile internet, it may be important to consider the type of search cost: is it one related to primacy effects or to recency of information? If it is related to recency, many of the models emphasizing low online search costs become even more fundamental. On the other hand, if it is related to primacy, then these models are less likely to be fundamental.

Overall, this paper provides an understanding of how the mobile internet is different from the PC-based internet. As local commerce begins to explode on the internet, we are seeing an increasing number of high profile acquisitions in this industry such as Ebay’s recent acquisition of Milo, Google’s massive bid for Groupon, Amazon’s investment in LivingSocial, and so on. Recent industry reports have predicted that local commerce will be primarily conducted through the mobile internet (Marcus 2010). However, to our knowledge, no prior academic work has scientifically documented how the mobile Internet is different or similar to the PC-based internet. By demonstrating that users’ preferences for proximate brands are stronger when using a mobile phone, and that the primacy effect is higher when using a mobile phone, our paper provides insight for managers regarding the future potential of local and mobile commerce. For example, the asymmetric distance and primacy effects between mobile phones and PCs suggest that in many ways competition is likely to be less severe on the mobile internet than on the PC-based internet due to higher geographic frictions and search frictions.

**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.

**Why Do Search Costs Matter?**

Much of the early management literature on the internet documented 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, online demand, market structure, unemployment, and many other areas of economic life (see, Lynch and Ariely 2000, Autor 2001, Scott Morton 2006, Ellison and Ellison 2009, Kim et al. 2010, Brynjolfsson et al. 2011, etc.). Drawing on the economic literature on search theory, Bakos (1997) developed a model on how the reduced search costs in electronic marketplaces would affect market outcomes. He showed that lower search costs increase 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. These effects have been documented in a variety of industries such as books and CDs (Brynjolfsson and Smith 2000), life insurance (Brown and Goolsbee 2002), automobiles (Scott Morton et al. 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 (Baye et al. 2004, Pan et al. 2002). Overall, however, the evidence suggests that lower search costs online lead 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 et al. (2003) argue that the internet increases the variety of products available and Brynjolfsson et al. (2011) show that the internet's Long Tail is not solely due to the increase in product selection but may also partly reflect lower search costs on the internet. Similarly, Kuksov (2004) argues that lower search costs increase the incentives to differentiate. Broadly, while the inventory costs do not change whether consumers access the internet through a PC or a mobile phone, differences in consumer search costs in scrolling through these product listings on a computer screen might affect the benefit to firms of holding variety. Therefore, lower search costs have important market consequences. A number of papers have shown that better ranked links are more likely to be clicked in desktop environments. 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, Yang and Ghose 2010). This is widely interpreted as a search cost in an online setting (e.g. Yao and Mela 2011) and some work has quantified such search costs as quite substantial in online settings when users are exposed to multiple offers on a computer screen such as in a shopbot setting (Brynjolfsson et al. 2010).

In this paper, we examine whether a particular kind of search cost is different on the mobile internet as compared to on PC internet. That type of search cost is the cognitive effort consumers engage in while scrolling down a list of links displayed on small screens. They cognitively process incoming posting feeds before choosing to click one to learn more about it. Numerous studies have documented that the small screens of mobile phones create a serious obstacle to users' navigation activities and perceptions (Chae and Kim 2004), the effectiveness of the learning experience (Maniar et al. 2008), and in mobile marketing (Shankar et al. 2010). Since only a small amount of information can be shown on the screen, users need to scroll up/down and left/right continuously within a web page, making it difficult to find target information (Jones et al. 1999). These search processes place a heavy cognitive load on users (Albers and Kim 2000). Due to the small screen, users need to remember the content and context of a Web page that they have already viewed, which further increases the cognitive load and the potential for errors (Davison and Wickens 1999). Hence, adapting the presentation of web pages to the unique mobile context is critical to enabling effective mobile web browsing and information searching (Adipat et al. 2011). Because we find a stronger primacy effect when the internet is accessed on a (small-screen) mobile phone, we argue that this kind of search cost is higher on the mobile internet. Our real-world setting allows us to measure the overall magnitude, and the directional nature of search costs in mobile phones as opposed to in PCs.

Why Do Distance Effects Matter?

A long literature documents the role of distance in social and economic behavior. Tobler's (1970) first law of geography is that “all things are related, but near things are more related than far things”. The internet reduces the cost of communication. Therefore, the popular press has frequently emphasized the ability of the internet end this relationship and bring about the “Death of Distance” (Cairncross 1997) or a “Flat World” (Friedman 2005). In the academic literature, this idea has been explored in depth. Balasubramanian (1998) and Zhang (2009) analytically discuss 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. 2009, Anderson et al. 2010). Therefore, the online channel helps reduce the importance of distance in many ways, generally increasing the competition faced by any particular firm.

Still, the consequences of lowered communications costs depend on several local factors. Therefore, much online behavior is local. Blum and Goldfarb (2006) show that surfing behavior is disproportionately local and Hampton and Wellman (2002) document that online social interactions are also disproportionately local. Overall, the literature suggests an important role for distance in determining online behavior. If the benefit of accessing local information is different when people access the internet on a mobile phone, even though communication costs fall it suggests that online behavior more broadly may change. Hence, if
surfing behavior becomes more local then local retailers may disproportionately benefit. For example, people might access the internet on a mobile phone to sort or filter information by location to make it more relevant to their surroundings (Mountain et al. 2009). Location-based services are tools that tailor retrieved information based on the location at which a query was made (Brimicombe and Li 2006, Jiang and Yao 2006). The location-based services allow for ‘where’s my nearest’ services, for example, they include searches for local news, weather or sports reports, navigation, friend-finder services, location-based gaming, etc (Mountain et al. 2009). In this sense, distance between a user and brand stores interacts with whether the user accesses through a mobile phone or a PC.

Therefore, because we document a stronger impact of distance on click-through decisions when the internet is accessed on a mobile phone, we argue that the distance effects are higher on the mobile internet. To the best of our knowledge, no previous study has examined the distance effect in a mobile phone setting. Hence, the overall magnitude of the distance effect in mobile phones as opposed to PCs also remains an important empirical question.

Other Related Literature

Our paper is related to the literatures on user-generated content in social media platforms, on mobile marketing, and on user behavior across channels. By studying microblogs, we examine an increasingly popular form of user-generated content that can potentially have a strong economic and social impact. An emerging stream of relevant work has investigated the economic and social impact of user-generated multimedia content on the mobile internet by mapping the interdependence between content generation and usage (Ghose and Han 2011) and modeling how consumers learn about different kinds of content (Ghose and Han 2010). A handful of papers have focused on microblogs in particular, including for example, Java et al. (2007) and Boyd et al. (2010). Stephen et al. (2011) use data from Twitter to study transmission activity as a driver of retransmission and diffusion in online social networks.

Our paper builds on and relates to the literatures on mobile marketing. We examine user search costs and distance effects on the mobile internet. This can have important managerial implications for firms’ mobile marketing strategies. An emerging stream of relevant literature has discussed the role of mobile technologies in marketing, Shankar and Balasubramanian (2009) provide an extensive review of mobile marketing. Shankar et al. (2010) develop a conceptual framework on mobile marketing in the retailing environment and provide discussions on retailers’ mobile marketing practices. For example, retailers can communicate with consumers near their stores via mobile phones by transmitting relevant information such as the store’s location, product availability, quality, price, and coupon in its response to the customer’s mobile phone-initiated requests. Moreover, specific consumer segments such as the Gen Y youth market increasingly use mobile phones as single-source communication devices (Sultan et al. 2009) to gain greater access to social circles, location-based information and content. Sinisalo (2011) examines the role of the mobile medium among other channels within multichannel CRM communication.

Our paper is related to the literature on consumer behavior across channels. A large body of research examines behavior when consumers interact with firms through multiple channels (Ansari et al. 2008, Pauwels and Neslin 2009, Joo et al. 2010). A stream of relevant work has focused on user click and visit behaviors by modeling browsing behavior across websites (Park and Fader 2004) and examining evolving visit behavior in clickstream data (Moe and Fader 2004). Most directly related to our study, a portion of this prior research compares the PC-based online setting to the offline channel. For example, Danaher et al. (2003) compare brand loyalty online and offline, and Chu et al. (2008) compare price sensitivity online and offline. Our study examines how the mobile internet and PC-based internet differ.

Data Description

In this section, we describe the data that we collected from a microblogging service company in South Korea. The company was founded in November 2008. As of November 2009, there were about 40,000 registered members. Members can post a message about what they are doing or what they are thinking, and also they can read posts created by other members. Furthermore, there are mobile phone application versions of the service (i.e., iPhone and Android application). Hence, members can use the service anywhere and anytime. Our sample is randomly drawn from members 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 posting feeds viewed by 260 different users. The unit of analysis is the user-post and the data set contains 8,896 such observations (of 440 distinct posts). Specifically, when subscribers use the service, they see a list of posting feeds that looks much like the home page of a user’s Facebook account containing the latest news feeds from his social network or the search results from a query issued on a search engine. The initial views of the posts are limited to 140 characters. Most postings exceed this limit and therefore users often click to view the full posts. Furthermore, some posts contain marketing promotions that customers need to click to take advantage of them.

Some of these postings are branded and others are not. Our data set contains all brand-related posts (defined by a brand mentioned in the 140 characters listed). Brands range from prominent international brands like Starbucks and McDonalds, to the relatively unknown. 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. Brand-specific variables include brand category (refer to Figure 1 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. Our dataset has only two types of user access technologies/device - PCs vs. mobile phones, excluding tablets. So our definition of the mobile internet is internet access through mobile phones only.

![Figure 1: Brand Categories](image)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brand-level</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Brand profile tenure (days)</td>
<td>274</td>
<td>159</td>
<td>1</td>
<td>501</td>
</tr>
<tr>
<td>Post tenure (days)</td>
<td>8.380</td>
<td>14.269</td>
<td>0</td>
<td>97.1</td>
</tr>
<tr>
<td>User-level</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>24.987</td>
<td>11.818</td>
<td>11</td>
<td>54</td>
</tr>
<tr>
<td>Gender (Male =1, Female = 0)</td>
<td>0.769</td>
<td>0.422</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Number of followees (those one follows)</td>
<td>10.414</td>
<td>30.609</td>
<td>0</td>
<td>373.6</td>
</tr>
<tr>
<td>Number of bookmarks</td>
<td>15.711</td>
<td>56.946</td>
<td>0</td>
<td>350</td>
</tr>
<tr>
<td>User- and brand post-level</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mobile phone access rate</td>
<td>0.130</td>
<td>0.335</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Rank of brand post</td>
<td>39.107</td>
<td>26.859</td>
<td>1</td>
<td>90</td>
</tr>
<tr>
<td>Distance between a user and a brand store (miles)</td>
<td>43.180</td>
<td>110.303</td>
<td>0.06</td>
<td>730.9</td>
</tr>
<tr>
<td>Click-through rate on brand posts</td>
<td>0.030</td>
<td>0.171</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 1: Summary Statistics
We focus our analysis on the 1,940 total brand post views by those users who access the website at least once with each channel 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 or not, 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 brands in 48% of the observations in our main sample. 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.

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 posting feeds or notification messages when he logs on the microblog platform using a PC or a mobile phone. In our model, a user decides to click a post that provides the maximum expected utility to explore the content of the post. 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.

Research design: Exogenous Variation in Ranking

We treat the posting of a new brand-related message by users as an “event” in a natural experiment-like setting. Upon a posting event, all followers of the post creator and bookmarks of the brand will receive a notification message with a clickable link of that post. In each posting event, we examine the impact of a post rank, distance between a user and the offline 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 postings attract more user clicks than others for their unobserved inherent characteristics (i.e., timeliness, relevance).

In addition, the microblog service in our setting provides an ideal setting for identifying the impact of post rank because it provides a unique source of variation in the ranking mechanism. When a user generates a post, the same post would appear at different positions (ranks) for different users. However, the rank is determined independent of any prior click-through decisions. Instead, it is determined by time since last log-in (i.e., the more frequently a user logs in, the less quickly does the rank of a given post increase) and the number of other posts that have arrived in the interim (i.e., the more frequently a user receives updates from followees, the more quickly does the rank of a given post increase). We control for these factors directly with covariates and there ascribe all remaining variation in rank to factors that are exogenous to the propensity to click. In this way, it is something like a natural experiment. As described below, to the extent that our controls do not address all user-level heterogeneity in these dimensions, we further control for user-level differences with random coefficients in a Hierarchical Bayes framework.

We only use the first appearance of a brand post on a user’s screen in our analysis. We do this because any given brand post can appear multiple times to the same user at worse ranks over time (i.e., an older post will be located towards to the bottom of the screen). We also excluded brand posts which were displayed to only one user, in order to identify effects through across-user comparisons. Moreover, we emphasize results that include only those users who have accessed the microblogging platform via both mobile phones and PCs. This helps us to better identify the “within-user” moderating effect of access devices on user click decisions (i.e., dual channel users). However, our results are robust to the use of the entire sample of users in our data.

Econometric Model

Our model consists of two-level specification models: 1) post-level latent utility model and 2) population-level model with user- and brand post-level heterogeneity. Notation and descriptions are in Table 2.
Table 2: Notations and Variable Descriptions

<table>
<thead>
<tr>
<th>Notation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$u_{ijk}$</td>
<td>Latent utility of clicking and visiting a brand post k by user i at time j</td>
</tr>
<tr>
<td>$\text{Rank}_{ijk}$</td>
<td>Rank of brand post k on user i’s log-in screen at time j</td>
</tr>
<tr>
<td>$\text{Distance}_{ik}$</td>
<td>Euclidian log distance between user i’s place and brand post k’s physical store</td>
</tr>
<tr>
<td>$\text{Mobile}_{ij}$</td>
<td>Access channel of user i at time j (1 = Mobile, 0 = PC)</td>
</tr>
<tr>
<td>$\text{Followee}_{ij}$</td>
<td>Number of users user i is following at time j</td>
</tr>
<tr>
<td>$\text{Bookmark}_{ij}$</td>
<td>Number of brands user i is following at time j</td>
</tr>
<tr>
<td>$\text{Age}_{i}$</td>
<td>Age of user i</td>
</tr>
<tr>
<td>$\text{Gender}_{i}$</td>
<td>Gender of user i (1 = Male, 0 = Female)</td>
</tr>
<tr>
<td>$\text{BrandTenure}_{jk}$</td>
<td>Days elapsed since the brand profile of post k was created until day j</td>
</tr>
<tr>
<td>$\text{PostTenure}_{jk}$</td>
<td>Days elapsed since brand post k was created/posted until day j</td>
</tr>
</tbody>
</table>

**Post-Level Model:** The observed user’s binary response (i.e., whether to click or not) can be modeled using a random-utility framework. We posit that users click on a posting feed when the utility for reading the post exceeds a certain threshold. For a given brand post k, at time j, the relationship between the observed response $y_{ijk}$ and the latent utility $u_{ijk}$ of clicking for user i can be written as:

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

We model the latent utility $u_{ijk}$ from clicking on a post k at time j for user i as the function of observed and unobserved post and user characteristics in the following way. We are primarily interested in the effect of rank and distance on a user’s propensity to click on a brand posting that appears on his screen. Rank allows us to measure search costs. Higher search costs mean that it is more valuable to be ranked near the top, and hence such high ranked postings are likely to get higher click-throughs. Distance allows us to examine the role of geography and local activities of users. Higher click-through rates on postings involving brands located closer to the user mean that consumers have a preference for geographically local activities. We are interested in examining how these effects vary between a mobile phone and a PC.

Hence, for a given brand post k, we specify that user i’s latent utility at time j is a function of rank, distance and other factors as follows, for $k = 1, 2, \ldots, s$:

$$
u_{ijk} = \beta_i + \beta_{ij1}\text{Rank}_{ijk} + \beta_{ij2}\text{Distance}_{ik} + \beta_{ij3}\text{Rank}_{ijk}\text{Distance}_{ik} + \alpha_1\text{Mobile}_{ij} + \alpha_2\text{Followee}_{ij} + \alpha_3\text{Bookmark}_{ij} + \alpha_4\text{Age}_{i} + \alpha_5\text{Gender}_{i} + \alpha_6\text{BrandTenure}_{jk} + \alpha_7\text{PostTenure}_{jk} + \epsilon_{ijk}
$$

We assume the error term $\epsilon_{ijk}$ is i.i.d from Type I extreme value distribution. The utility from not clicking on the brand post k is denoted as $e_{ijk+1}$. As mentioned above, our choice model is binary rather than multinomial. This means we do not include information about the other posts that appear at the same time as the focal branded post of interest. Therefore, implicit in our i.i.d. error assumption is an assumption that the other (unmodeled) posts that appear along with the focal post are randomly drawn across observations. Further, 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 profile 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 in equation (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., $\beta_{ij1}$, $\beta_{ij2}$, and $\beta_{ij3}$) to capture differences across users in their responses to post rank, user-brand store distance, and their interaction. For example, we allow $\beta_{ij1}$ to vary by whether a user accesses through a mobile phone or...
a PC, in order to access to what extent mobile Internet moderate the effect of rank on user click-through decisions. Further, we allow the coefficients of Rank, Distance, and RankDistance in equation (2) to vary along the respective population mean (i.e., $\beta_1$, $\beta_2$, and $\beta_3$) and the user characteristics. We also model unobserved user heterogeneity by including $\lambda_{i1}$, $\lambda_{i2}$, and $\lambda_{i3}$ in each slope as follows:

\[
\beta_{ij1} = \bar{\beta}_1 + \alpha_8 \text{Mobile}_{ij} + \alpha_9 \text{Followee}_{ij} + \alpha_{10} \text{Bookmark}_{ij} + \alpha_{11} \text{Age}_i + \alpha_{12} \text{Gender}_i + \lambda_{i1} \\
\beta_{ij2} = \bar{\beta}_2 + \alpha_{13} \text{Mobile}_{ij} + \alpha_{14} \text{Followee}_{ij} + \alpha_{15} \text{Bookmark}_{ij} + \alpha_{16} \text{Age}_i + \alpha_{17} \text{Gender}_i + \lambda_{i2} \\
\beta_{ij3} = \bar{\beta}_3 + \alpha_{18} \text{Mobile}_{ij} + \alpha_{19} \text{Followee}_{ij} + \alpha_{20} \text{Bookmark}_{ij} + \alpha_{21} \text{Age}_i + \alpha_{22} \text{Gender}_i + \lambda_{i3}
\]

(4) (5) (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 post-level attractiveness with a fixed effect, denoted by $\beta_{i0}$, and allow unobserved heterogeneity across users with a random coefficient on the intercept, denoted by $\lambda_{i0}$ as follows:

\[
\beta_{ik} = \bar{\beta}_{i0} + \lambda_{i0}
\]

(7)

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

\[
[\begin{align*}
\lambda_{i0} \\
\lambda_{i1} \\
\lambda_{i2} \\
\lambda_{i3}
\end{align*}]
\sim \text{MVN}
[\begin{bmatrix}
0 & \Sigma_{0,1} & \Sigma_{0,2} & \Sigma_{0,3} \\
0 & \Sigma_{1,1} & \Sigma_{1,2} & \Sigma_{1,3} \\
0 & \Sigma_{2,1} & \Sigma_{2,2} & \Sigma_{2,3} \\
0 & \Sigma_{3,1} & \Sigma_{3,2} & \Sigma_{3,3}
\end{bmatrix}]
\]

(8)

Full Model: By replacing $\beta_{ij1}$, $\beta_{ij2}$, $\beta_{ij3}$, and $\beta_{ik}$ in equation (2) with equation (4) – (7), we can rewrite equation (2) for brand post $k$ as follows:

\[
u_{ijk} = \bar{\beta}_{i0} + \alpha_8 \text{Mobile}_{ij} + \alpha_9 \text{Followee}_{ij} + \alpha_{10} \text{Bookmark}_{ij} + \alpha_{11} \text{Age}_i + \alpha_{12} \text{Gender}_i + \alpha_6 \text{BrandTenure}_{jk} + \alpha_7 \text{PostTenure}_{jk}

+ \left(\bar{\beta}_1 + \alpha_8 \text{Mobile}_{ij} + \alpha_9 \text{Followee}_{ij} + \alpha_{10} \text{Bookmark}_{ij} + \alpha_{11} \text{Age}_i + \alpha_{12} \text{Gender}_i\right) \text{Rank}_{ijk}

+ \left(\bar{\beta}_2 + \alpha_{13} \text{Mobile}_{ij} + \alpha_{14} \text{Followee}_{ij} + \alpha_{15} \text{Bookmark}_{ij} + \alpha_{16} \text{Age}_i + \alpha_{17} \text{Gender}_i\right) \text{Distance}_{ik}

+ \left(\bar{\beta}_3 + \alpha_{18} \text{Mobile}_{ij} + \alpha_{19} \text{Followee}_{ij} + \alpha_{20} \text{Bookmark}_{ij} + \alpha_{21} \text{Age}_i + \alpha_{22} \text{Gender}_i\right) \text{RankDistance}_{ik}

+ \lambda_{i0} + \lambda_{i1} \text{Rank}_{ijk} + \lambda_{i2} \text{Distance}_{ik} + \lambda_{i3} \text{RankDistance}_{ik} + e_{ijk}
\]

(9)

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, number of bookmarks, and demographics (i.e., $\alpha_8$ – $\alpha_{22}$). It has control variables for brand post-specific intercept, mobile, followee, bookmark, age, gender, brand tenure, and post tenure (i.e., $\beta_{i0}$, $\alpha_6$ – $\alpha_7$).

Estimation

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.

\[
u_{ijk} = v_{ijk} + e_{ijk}
\]

(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

\[
\Pr\left(v_{ijk} = 1 | \beta_{i0}\right) = \frac{\exp\left(v_{ijk}\right)}{1 + \exp\left(v_{ijk}\right)}
\]

(11)

where $\beta_{i0}$ denotes all parameters in the model.
**Hierarchical Bayesian Modeling and Estimation:** We cast our model in a hierarchical Bayesian framework and estimate using Markov Chain Monte Carlo methods. We rewrite main equations as follows.

\[ u_{ij} = X_{ij}' \beta_i + e_{ij} \quad (12) \]

\[ \beta_i = Z_{ij} \mu + \lambda_i \quad (13) \]

where \( \Pr(\mu) = N(\eta, C) \), \( \lambda_i = (\lambda_{i0}, \lambda_{i1}, \lambda_{i2}, \lambda_{i3}) \sim N(0, \Lambda) \), and \( \Pr(\Lambda^{-1}) = W(\rho, R) \).

The corresponding mixed model is as follows.

\[ u_{ij} = W_{ij}' \mu + X_{ij}' \lambda_i + e_{ij} \quad (14) \]

Hence, the full conditionals are:

(A) \( \Pr(\lambda_i | \mu, \Lambda, y_i) \), (B) \( \Pr(\mu | \Lambda, \lambda_i \}_{i=1}^n, \{y_i\}_{i=1}^n) \), and (C) \( \Pr(\Lambda^{-1} | \lambda_i \}_{i=1}^n) \)

where \( n \) is the total number of users in the sample. We use an adaptive Metropolis-Hastings algorithm with a random walk chain (Atchadé 2006, Chib and Greenberg 1995, Hastings 1970) to generate draws of \( \lambda_i \) and \( \mu \) in conditional (A) and (B). Hence we can adjust the tuning constant to vary by an individual (see the Appendix for the detailed MCMC algorithm).²

**Identification**

**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 reference brand post, we set the mean value for a brand post in the “local restaurant” category to be zero. The qualitative nature of our results do not change based on the choice of a reference 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. 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.

**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 is determined by algorithms based on popularity and relevance, the rank 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 appears at the top). Because we control directly for recency and individual heterogeneity, this setting reduces 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, 2) the user is able to see the rank of a post only after the user logs in, and 3) we include post fixed effects and therefore identify off variation across users in the rank of the same post. Hence a user’s log-in decision can be considered as a random stopping decision during the process of continual posting feeds from his followees or bookmarks. Said simply, we can consider users’ log-in timing decisions as exogenous to the determination of the rank of a post. We can do this if we assume that our controls for recency, user characteristics, and user heterogeneous response (i.e. the random coefficients) adequately control for the differences in rank. The required assumptions for the main results of the paper are somewhat weaker. In particular, given that the main results of the paper rely on the interaction between access device and rank, we need to assume that the controls for recency, user characteristics, device-specific habits, and user heterogeneous response adequately control for all non-random differences in rank.

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² It is important to note that conditional (C) described above can be computed using Wishart distribution. However, conditionals (A) and (B) cannot be directly computed because they are not conjugate.
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 distance effects across the two kinds of access technologies (mobile vs. PC). We discuss the economic impact of our results to gain further insights. We also show robustness to a variety of alternative specifications and samples.

Table 3: Effect of Rank and Distance on Clicks (Dual Channel Users; N=1,940)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Main effect</th>
<th>Moderating effect</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mobile</td>
<td>Followee Bookmark</td>
</tr>
<tr>
<td>Intercept</td>
<td>-0.230***</td>
<td>-0.078***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>Rank</td>
<td>-0.107***</td>
<td>-0.098***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Distance</td>
<td>-0.068***</td>
<td>-0.007***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.003)</td>
</tr>
</tbody>
</table>

Unobserved heterogeneity covariance estimates

<table>
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<tr>
<th></th>
<th>Intercept</th>
<th>Rank</th>
<th>Distance</th>
<th>Rank x Distance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
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<td>-0.001</td>
<td>-0.007*</td>
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</tr>
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<td>(0.006)</td>
<td>(0.008)</td>
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<td>(0.009)</td>
</tr>
<tr>
<td>Rank</td>
<td>0.125**</td>
<td>-0.016**</td>
<td>0.001</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>(0.052)</td>
<td>(0.009)</td>
<td>(0.027)</td>
<td>(0.027)</td>
</tr>
<tr>
<td>Distance</td>
<td>0.030***</td>
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<td>-0.001</td>
<td>0.107*</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.007)</td>
<td>(0.009)</td>
<td>(0.060)</td>
</tr>
</tbody>
</table>

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.

Main Results

Estimation 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). People are more interested in proximate brands. This is consistent with a distance decay effect (Fellmann et al. 2000), in which interaction between two entities declines as the distance between them increases. 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 phones. The second column of Table 3 shows that the estimate for the interaction 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. In other words, users are more likely to click on a highly ranked post in a mobile setting, as opposed to in PC settings in which they see more messages on a given screenshot. As mentioned in Shankar et al. (2010), “real estate” is particularly important in a mobile setting. Therefore, search-related frictions are higher. 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.3

**Economic Important of the Effects:** We discuss the economic impact of each effect using odds ratios.
For PC users, moving one position upward in rank for a brand post yields an increase in the odds of
clicking on that post by 26% \( \exp(0.230) = 1.26 \) 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 the drop in click-through rates with position found in a search engine setting by Ghose and
Yang (2009) and Yang and Ghose (2010). For mobile phone users, one position upward increase in rank
of a brand post yields an increase in odds of clicking on that post by 36%. Hence, the magnitude of the
primacy effect on the odds of clicking in mobile phone settings is 38% larger than that in PC settings. For
PC users, a one mile decrease in distance between a user and a brand store yields an increase in the odds
of clicking on that post by 11%. This result is consistent with evidence that people generally have local
interests (Hampton and Wellman 2002). For mobile users, moving one mile closer in distance between a
user and a brand store yields a decrease in the odds of clicking on that 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 is consistent with evidence that a user accessing through mobile phones is in general more likely to
click on brand posts, which reflects the higher click rates for mobile access (4.7%) as opposed to for PC
access (2.5%) in the raw data. 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, controlling for rank. Further, the statistically
significant results on unobserved heterogeneity covariance estimates in Table 3 suggest that controlling
for 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 excluding 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.

---

3 Including an interaction term between a dummy for non-geographic brands and the mobile setting yielded qualitatively identical results. The coefficient on the interaction term was statistically insignificant and economically small. Therefore, we do not include it in the analysis.
### Table 4: Robustness to Alternative Specifications (N=1,940)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Main effect</th>
<th>Moderating effect</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Mobile</td>
<td>Followee</td>
<td>Bookmark</td>
<td>Age</td>
<td>Male</td>
<td>Brand tenure</td>
<td>Post tenure</td>
</tr>
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<td>(1) Rank only model</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>0.134***</td>
<td>0.002**</td>
<td>0.033**</td>
<td>-0.039***</td>
<td>-0.125***</td>
<td>-0.004**</td>
<td>-0.070***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.001)</td>
<td>(0.013)</td>
<td>(0.012)</td>
<td>(0.005)</td>
<td>(0.001)</td>
<td>(0.007)</td>
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<td>Rank</td>
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<td>-0.005**</td>
<td>-0.017*</td>
<td>0.001</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td>(0.004)</td>
<td>(0.0003)</td>
<td>(0.002)</td>
<td>(0.010)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(2) Distance only model</td>
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<td></td>
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<td></td>
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</tr>
<tr>
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<tr>
<td></td>
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<td>-0.029**</td>
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<tr>
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<tr>
<td>Intercept</td>
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<td>0.003***</td>
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<tr>
<td>Rank</td>
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<td>-0.089***</td>
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<td>0.039***</td>
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<td>(0.018)</td>
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**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.

In Table 5 we control for the recency of the information. Specifically, we also include an interaction between post-tenure (i.e., time elapsed since posting) and mobile variable into our main model. Importantly, the main results on rank and distance still hold. Importantly, the coefficient on recency has another interpretation as a type of search cost. In particular, the cost of acquiring timely information should be lower on a mobile phone than on a PC. The premise of this interpretation is that if the sign of this interaction term is negative, then it suggests that the screen-related search costs in a mobile phone are mitigated for timely information (i.e., more recent posts). Table 7 shows that the results confirm this notion (the coefficient of the interaction term is -0.011 and p-value < 0.01). Our key coefficient estimates still remain qualitatively the same in terms of the sign and the statistical significance. For PC users, an increase in the recency of a post by one day yields an increase in the odds of clicking on that post by 7.1% holding the other variables constant. For mobile phone users, an increase in the recency of a post by one day yields an increase in odds of clicking on that post by 8.3%. Hence, the magnitude of the post time-sensitivity effect on the odds of clicking in mobile phone settings is 17% larger than that in PC settings.
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 distance effects (local activities), we show that (primacy-related) search costs are higher on the mobile internet, but the preferences for geographically proximate brands 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 is a stronger primacy effect in a mobile phone setting compared to that in a PC setting. This has useful implications for the monetization of social media and user-generated content in such settings. In particular, 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 have an incentive to bid higher for the highest ranked sponsored links in mobile phones as compared to PCs. Of course, one would have to take into account the penetration and reach of such devices as well in any customized pricing strategy for ads.

Second, there may be an exception to the finding of higher search costs on the mobile internet: time-related search costs appear to fall. That is, the cost of acquiring timely information may be lower on a mobile phone than on a PC. This finding can have implications for how companies advertise and monetize time-sensitive content. As an example, for discount coupons embedded in sponsored messages that are valid for a very short period of time, advertisers are more likely to get higher redemption rates on mobile phones than PCs. Third, our results can 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, particularly on mobile devices. Hence, when sponsored messages are accompanied with user-generated posts, as the proportion of mobile users increases, such messages should be increasingly related to brand stores near the user’s geographical location.

Finally, and most generally, our results contrast with the literature on the PC-based internet that has hypothesized and documented that lower search frictions and geographic frictions mean that the PC-based internet is a particularly competitive environment. If search and geographic frictions are higher on the mobile internet than the PC-based internet, it suggests that competition on the mobile internet may be relatively muted compared to that on PCs. This would have implications for product pricing and price dispersion that are likely to be somewhat different on the mobile Internet than on the PC-based Internet.
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, more price dispersion, less product variety, and more market concentration as the mobile internet grows in importance. Larger distance effects in the mobile internet may mean an increasing role for local businesses (and perhaps 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) 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. Finally, our data on the mobile internet comes from mobile phones only. It does not address tablet computers such as the iPad, which have somewhat larger screens than phones but are somewhat less mobile. Future research can examine if consumer’s usage of the Internet on tablet devices are more similar to PCs or mobile phones. 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.
References


