

**CONSUMER ADOPTION AND USAGE  
BEHAVIOR ON THE MOBILE INTERNET**

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The Academic Faculty

by

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To my beloved parents, husband Kaibo and son Jiaye.

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## SUMMARY

Although the availability and popularity of the mobile Internet has increased dramatically in recent years, its effect on consumers' online behaviors and subsequent implications for mobile service providers, marketers, and policy makers remains poorly understood. This dissertation focuses on consumers' cross-platform consumption behavior on mobile devices by studying how the adoption of a new mobile technology might depend on or affect the use of existing complementary or substitute platforms. In this dissertation, I specifically study the interrelationships of different platforms for accessing the mobile Internet.

The first study of this dissertation addresses how the adoption of mobile applications (apps) influences the use of corresponding mobile websites. The media industry has undergone a fundamental shift over the last decade as new online distribution channels have proliferated in an unprecedented manner. Although mobile devices have experienced rapid adoption among consumers, their effect on consumer behavior and their subsequent implications for publishers and advertisers have yet to be understood. I examine consumers' news consumption behavior on mobile news websites in response to the introduction of a mobile news app. Pseudo-panel analysis based on repeated cross-sectional data suggests that the introduction of a mobile app by a major national media company leads to a significant increase in demand at the corresponding mobile news website. In addition, I report that this effect is greater for consumers with higher appreciation for concentrated news content, with stronger propensity for a particular political viewpoint, and with fewer time constraints. The results are consistent with the interpretation that adoption of a provider's news app stimulates corresponding mobile news website visits. I discuss the implications of these findings for advertisers, media publishers, and policy makers.

The second study of this dissertation examines whether the quality of local fixed-line Internet service influences mobile Internet adoption and usage. An empirical analysis shows that local fixed-line Internet speed relates negatively to mobile Internet adoption and usage; if the local fixed-line connection is insufficient, consumers tend to get online through their mobile phones. Further, better local mobile Internet coverage increases the likelihood of adopting and using the mobile Internet. Neither fixed-line nor mobile Internet speed has significant impacts on mobile-specific offline services such as taking photos or videos. In some circumstances, substitution between the two platforms is stronger, such as among younger consumers and those living in areas with lower fixed-line Internet speeds. I discuss the implications of these findings for policy makers, consumers, and mobile service providers.

The last chapter of this dissertation reviews the literature on consumers' adoption and usage behavior on the mobile Internet to identify future research directions. Although a large volume of literature is available on how consumers adopt and use the mobile Internet, the topic is still under development and offers potential opportunities for further research and applications.

# **CHAPTER 1**

## **INTRODUCTION**

More and more people rely on their mobile phones to do various online activities, like online communicating, searching, browsing, and purchasing behavior. According to estimates by the International Telecommunication Union (2013), the 2.1 billion active mobile Internet users in the world at the end of 2013 represented 29.5% of the global population. Mobile Internet subscriptions grew 40% annually between 2010 and 2013, roughly three times the growth rate for fixed broadband subscriptions (International Telecommunication Union 2013). This rapid growth has been accompanied by increasing research interest in how consumers adopt and use the mobile Internet (e.g., Ghose, Goldfarb and Han 2012; Ghose and Han 2011; Xu et al. 2014).

One stream of prior work on consumer behavior on the mobile Internet particularly focus on users' multichannel consumption behavior on the mobile Internet (e.g. Bang et al. 2013; Ghose, Han and Xu 2013). In the first two studies of my dissertation, I follow this stream of literature that studies the interrelationships of different platforms for accessing the mobile Internet. In particular, I examine consumers' cross-platform consumption behavior on mobile devices by studying how the adoption of a new mobile technology might depend on or affect the use of existing complementary or substitute platforms.

The first chapter of this dissertation addresses how the adoption of mobile applications

(apps) influences the use of corresponding mobile websites; I examine the interrelationship of the uses of different mobile media channels to access online news. The media industry has undergone a fundamental shift as new online distribution channels proliferate, raising a critical question for practitioners: How do people consume media in multichannel environments? Addressing this question requires an understanding of an even more basic issue, namely, whether new media channels complement or substitute for existing channels. Prior literature has studied whether the introduction of new Internet-enabled online channels complement or substitute for existing offline channels, but with this article, I offer a new framework and data to understand user consumption of media contents across multiple mobile device channels. That is, I examine whether the adoption of mobile news apps is associated with more or less visitation of mobile news websites.

As an empirical investigation of consumer responses to the introduction of a new mobile news app, I consider the introduction of the Fox News app in 2010 and determine whether consumers who adopted the app increase or decrease their news consumption through the Fox News mobile website. I also study consumer characteristics that might explain their heterogeneous responses. The empirical analysis includes a quarterly survey of U.S. mobile smartphone users during 2009 and 2010. Adoption of the Fox News app increased news consumption on the Fox News mobile website, indicating their complementarity. Furthermore, this complementarity was stronger among consumers with narrower media consumption tastes and preferences for a particular ideological slant to the news; consumers who are time constrained instead exhibit weaker complementarity.

This study thus provides substantive contributions to mobile advertising and media channel consumption research. In particular, it enhances understanding of mobile advertising

in a multichannel environment. The emergence of a potentially disruptive channel makes it imperative for marketers to monitor changes in consumer behavior and understand their implications. For example, substitution or switching across new and existing media channels might make it harder for advertisers to reach their target audiences, which disperse across more channels, whereas complementarity implies that advertising on complementary channels could create repeated impressions. To the best of my knowledge, no prior empirical work addresses cross-channel news consumption behavior on mobile devices, which is a critical gap, considering the rapid growth of the mobile Internet in general and its uses for media consumption in particular. Furthermore, this research helps define when complementarity or substitution is more likely to occur in mobile channels. The content and capabilities of apps and mobile news channels are similar in many ways—leading to a potential expectation of substitution—but I offer evidence of their complementarities. The proposed framework should generalize to other digital media settings. It identifies circumstances in which complementarities or substitutions are more likely, including how consumer characteristics may influence this likelihood.

The second chapter of this dissertation investigates how the availability and quality of fixed-line Internet access influences the adoption and usage of mobile Internet services by examining the impact of the local speed for fixed-line Internet service on consumers' decisions to adopt and use the mobile Internet. The emerging mobile Internet technology invites analyses of the substitutability or complementarity of fixed-line and mobile services; we lack sufficient understanding of consumers' decision making across different Internet platforms. On the one hand, fixed-line and mobile networks provide many of the same basic functions for performing online activities, so consumers might use them interchangeably as

substitutes. On the other hand, important differences mark the two platforms, in terms of mobility, quality, and reliability. Thus, consumers might use both services simultaneously as complements. The local availability and quality of an incumbent technology (fixed-line Internet) thus might influence the adoption and usage of an emerging technology (mobile Internet), but the question of how requires an empirical analysis.

The question of whether fixed-line and mobile services are substitutes or complements also determines the market structure for Internet service provision. Telecommunication policy makers cite potential concerns about a lack of competition in the mobile service market. For this reason, regulatory opposition has prevented the recent proposed merger of AT&T wireless and T-Mobile. However, if the mobile networks substitute for fixed-line networks, the structure may alleviate these competitive concerns, because competition would include not just the limited number of mobile carriers but also fixed-line Internet providers. By demonstrating the levels of substitution or complementarity between fixed-line and mobile Internet and identifying consumer segments for whom these effects are greater, this paper provides insight for policy makers regarding competition and for mobile carriers regarding their optimal infrastructure investment plans.

In this empirical analysis, I examine whether the speed of local fixed-line Internet is associated with more or less mobile Internet adoption and usage. I also reveal how the average effects of local Internet speeds can mask significant heterogeneity in consumer responses. A two-stage logit model uses novel data pertaining to U.S.-based mobile phone users and local Internet coverage data. Consumers first choose whether to adopt a mobile data plan, and then choose whether to perform online activities on their mobile phones. With a control function approach, I identify the effects of fixed-line and mobile Internet speed, using

instrumental variables for the fixed-line and mobile Internet speeds. I also conduct falsification analyses to show that the effects do not exist when they shouldn't.

The impact of local fixed-line Internet speed on mobile Internet adoption and usage is negative, suggesting that the two are substitutes. I quantify customers' sensitivity to local mobile Internet speeds when they decide to adopt and use the mobile Internet service. But local fixed-line and mobile Internet speed do not have significant impacts on the usage of mobile specific offline activities that can be undertaken only on mobile phones, not on personal computers (e.g., taking photos/videos). The substitution also is stronger among younger consumers, who are less sensitive to slower mobile Internet speeds, and for consumers living in areas with relatively low fixed-line Internet speed, because fixed-line and mobile Internet speeds then are comparable.

The third study of this dissertation reviews the literature on consumers' adoption and usage behavior on the mobile Internet. The mobile Internet services markets are currently growing rapidly, and a future of promising but yet uncertain possibilities with potential new technology innovations. At this point of the development, I take a look at the current state of consumers' behavior on the mobile Internet from a literature review perspective. I review prior literature on the relationship between the mobile Internet and traditional Internet on personal computers or laptops, consumer's multi-channel consumption behavior on the mobile Internet and other mobile usage behavior on the mobile Internet such as mobile social media and mobile marketing, and suggest directions for future research in this still emerging field.

## CHAPTER 2

# NEWS MEDIA CHANNELS: COMPLEMENTS OR SUBSTITUTES? EVIDENCE FROM MOBILE PHONE USAGE

### 2.1 Introduction

The increasing digitization of news is fundamentally reshaping the news industry: U.S. newspaper advertising revenues fell 47% from 2005 to 2009 (Athey, Calvano and Gans, 2013; FCC 2011) as online advertising spending climbed to over \$100 billion in 2012 (eMarketer 2013).<sup>1</sup> The changing news channel environment has raised a classic problem for marketers: how to appropriately target and reach consumers in the multichannel environment. This problem has been intensified by the proliferation of new digital media outlets that has increased the number of consumers who meet their news needs through multiple outlets, or “multi-home” (Gentzkow and Shapiro 2011; Varian 2010). As a result, while new online digital tracking technologies such as web bugs or cookies have made it possible for advertisers to track online consumers (e.g., Goldfarb and Tucker 2011a), they must still place ads on multiple online properties to ensure impressions, potentially reaching the same consumer multiple times (Athey, Calvano and Gans, 2013).

With the emergence of a potentially disruptive channel, it is imperative for marketers to monitor changes in consumer behavior and to understand their implications for marketing strategy (Ahonen 2011). Advertisers, for instance, may need to adjust their cross-channel

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<sup>1</sup> Other theories have also been used to explain the decline in advertising. For example, one theme has highlighted an increase in the supply of advertising space (e.g., Rice 2010). Some authors have also argued that online ads are less effective, although this view is inconsistent with some recent evidence (e.g. Goldfarb and Tucker 2011b).

advertising strategies so that they can reach their target audience effectively and efficiently. To that end, they need to start by understanding the most basic and critical question: whether a new media channel complements or substitutes for existing channels. We follow prior literature in economics in saying that two products or services are complements when the utility of consuming two products together is greater than the combined utilities of consuming them separately, similarly two goods are substitutes when the utility of consuming two products together is less than the combined utilities of consuming them separately (e.g., Gentzkow 2007). If there is substitution or switching across new and existing media channels (e.g., Deleersnyder et al. 2002; Gentzkow 2007; Geyskens, Gielens and Dekimpe 2002), it may be harder for advertisers to reach their target audience since it may now be more dispersed across channels. However, if a new media channel complements an existing channel (e.g., Chiou and Tucker 2011; Smith and Telang 2009), advertisers who are active on both channels will face the possibility of wasted impressions.

In this paper, we empirically investigate consumer response to the introduction of a new mobile news application, or app, on mobile devices<sup>2</sup> and discuss its implications. To that end, we focus on the introduction of the Fox News app in 2010 and analyze whether consumers who adopted the Fox News app increased or decreased their news consumption at the corresponding Fox News mobile website. We then study consumer characteristics that explain heterogeneity in consumer response to the new channel.

Our study of the news category in general and Fox News in particular is guided by several considerations. First, the news category is one of the most popular mobile data

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<sup>2</sup> A mobile application (or mobile app) is a software application designed to run on smartphones, tablet computers, and other mobile devices.

activities among U.S. consumers after e-mail and texting (comScore 2012). As a result, it is critical for advertisers to understand any changes in consumers' news consumption behavior in response to the additional news channel. Second, Fox News is a very popular news outlet with a large audience base: its Cable News subsidiary has been ranked as the most popular news outlet for over a decade (Fox News Press, 2012) and its online website attracted more than 32 million unique monthly visitors in 2012 (Schneider, 2012). Further, among major news outlets, Fox News has the highest proportion of readers who report being politically conservative (Gentzkow and Shapiro 2011). Therefore, in addition to our main research question, our empirical setting offers a unique opportunity to study how differences in media tastes across consumers—in particular, their tastes for a particular political viewpoint—influence their response to the new mobile channel (Gentzkow and Shapiro 2010).

For our empirical analysis, we use a quarterly survey of U.S. mobile smartphone users during 2009 and 2010. We use repeated cross-sectional data, and so are unable to introduce individual-level fixed effects to remove unobserved time-invariant consumer characteristics to help identify our focal effect. To overcome this data limitation, we use a pseudo-panel data analysis approach (Deaton 1985) in which we transform the cross-sectional data into a synthetic panel by grouping individuals into cohorts. That is, the unit of our empirical analysis is cohorts and not individuals. While the pseudo-panel method has been widely used in areas such as labor economics where repeated cross-sectional data are common, to the best of our knowledge its use in marketing has been more limited.<sup>3</sup> Our study provides an example of this method for marketing researchers.

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<sup>3</sup> To the best of our knowledge, our paper is the first marketing application of the pseudo-panel approach.

We find that the adoption of the Fox News app leads to increased news consumption at the Fox News mobile website, providing strong evidence of complementarity between the Fox News app and mobile website. We further show that this average effect masks significant heterogeneity in consumer response. Drawing from recent literature on audience fragmentation and ideological segmentation in online media consumption, we find that the complementarity is stronger among groups of consumers with more focused tastes in media consumption in terms of a penchant for selective exposure (Webster and Ksiazek 2012) and preferences for a particular ideological “slant” to news (Gentzkow and Shapiro 2010; Mullainathan and Shleifer 2005). Lastly, we also find that consumers who are time-constrained exhibit weaker complementarity between different media channels.

Our research aims to provide the following substantive contributions to the area of mobile advertising and news media channels. First, we seek to enhance our understanding about the media consumption behavior of consumers in the emerging area of mobile channels. With a couple of notable exceptions (e.g., Ghose and Han 2011; Ghose, Goldfarb and Han, 2012), to the best of our knowledge there is no prior empirical work on cross-channel news consumption behavior on mobile devices. Given the rapid growth of the mobile Internet in general and mobile news media consumption in particular, we believe this is an important gap in our understanding. In addition, by showing that consumers with focused and more politically-aligned tastes are more likely to exhibit complementarity, we identify consumer segments for whom segmentation and targeting will be easier, and for whom the value of advertising will be greater (Bergemann and Bonatti 2011). This will have important implications for publishers and marketers and their advertising decisions.

## 2.2 Research Setting

We empirically investigate consumer responses at conventional mobile websites in response to mobile apps introduced by news providers. Before investigating whether and to what extent complementarity or substitution occurs between both channels, we first discuss how news apps differ from news websites on mobile devices. To begin with, we briefly discuss mobile applications (“mobile apps” or simply “apps”) and mobile websites, two distinct ways for consumers to access digital content on mobile devices such as smartphones and tablet computers.

Apps have comparative advantages and disadvantages compared to mobile websites. Figure 2.1 shows the bottom part of the front pages from the Fox News mobile website (panel A) and the Fox News mobile app (panel B). As Figure 2.1 suggests, mobile apps tend to be more user-friendly than mobile websites since mobile apps allow publishers to take full advantage of mobile operating systems. In contrast, content on a mobile web page is rendered in a more generic environment that is not necessarily tailored for specific mobile operating systems (Alang 2010). This limits a publisher’s ability to customize its content. On the other hand, mobile websites typically offer more news content than apps.<sup>4</sup> The marginal cost of adding a new article on a mobile app is higher than that for a mobile website. It is easier to convert news content from a traditional website to a mobile website, as a mobile website is similar to any other website in that it consists of browser-based HTML pages (Summerfield 2011). However, adding content to a mobile app requires additional programming effort (Alang 2010; Summerfield 2011). Therefore, the news content of a mobile website and traditional website are similar, but mobile apps typically offer fewer news articles. Another

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<sup>4</sup> Among the 22 providers in our sample that have mobile apps and mobile websites, 17 provide more diverse content on their mobile websites than on their applications. For the other 5 providers, the amount of content is the same across the two channels.

advantage of a mobile website is that it can be easily reached from other websites, such as social media, search engines, or news aggregators. Mobile apps cannot be reached from other external websites, and during our sample period the Fox News app did not link to any articles on its own mobile website.

In sum, given the strengths and weaknesses of each channel, it is unclear a priori whether one will complement or substitute the other. One recent industry report indicates that a substantial percentage of mobile consumers access content from both apps and mobile websites (comScore 2012), suggesting that one channel may not completely substitute the other. In this paper we provide a more systematic answer to this question by carefully analyzing a large survey data set using the pseudo-panel data analysis technique.

#### A: Fox News Mobile Website



#### B: Fox News App



Notes: Screen shots are obtained by scrolling down to the bottom of the first page on the Fox News website and Fox News mobile app. The number of top stories shown on the Fox News app is approximately 10, whereas the number of top stories that can be found on the Fox News mobile website is almost 100.

**Figure 2.1: Screenshots of the Bottom Part of the Fox News Mobile Website and the Fox News App**

## **2.3 Related Literature**

The effect of a new channel on the demand for an existing channel is often a priori unknown and hence is treated as an empirical question (Deleersnyder et al. 2002; Gentzkow 2007; Smith and Telang 2009). For instance, recent research continues to discuss the various relationships between Internet commerce and brick-and-mortar commerce (e.g., Geyskens, Gielens and Dekimpe 2002; Ansari, Mela and Neslin 2008; Avery et al. 2012) or free file-sharing services and recorded music (Liebowitz 2008; Smith and Telang 2009). In this section, we review the relevant literature on new and existing channels from multiple disciplines, and relate them to our research setting.

### **2.3.1 Substitution vs. Complementarity**

Our main research question— whether the use of apps complements or substitutes use of mobile websites – is empirical in nature since past research on consumer response to new channels has found evidence supporting both alternatives. Consumer adoption of a news app may lead to lower demand for the provider’s corresponding mobile news website if the new channel closely duplicates the capabilities of the existing channel (e.g., Deleersnyder et al. 2002) or offers new ones (Alba et al. 1997). More pertinent to our setting, multi-channel media research has shown that new technology-enabled media channels have consistently substituted older channels; this has been the pattern for television (Mendelsohn 1964), cable television (Sparkes 1983), and Internet news and traditional print media (e.g., Athey, Calvano and Gans, 2013; Deleersnyder et al. 2002). Substitution also occurs when people have a limited amount of time to spend on media consumption (Deleersnyder et al. 2002). Therefore, if consumers perceive a mobile news app to be similar to the mobile website along key

dimensions, the adoption of the mobile app may substitute for demand for the mobile news website.

It is also possible that consumer adoption of a provider's mobile news app results in a higher demand for the provider's corresponding mobile news website. A separate stream of multichannel research notes different comparative advantages among channels. For example, the Internet may offer convenience, selection, and price (Forman, Ghose and Goldfarb, 2009) relative to traditional brick-and-mortar retail stores, while traditional stores provide instant gratification and lower transaction costs such as shipping and handling charges (Avery et al. 2012). Different channels can also serve as a form of advertisement for one another (Avery et al. 2012; Jacoby and Mazursky 1984; Keller 1993). Within the media category, it is well documented that consumers who borrow or rent access to music, television, or movies may later choose to buy (Liebowitz 1985; Peitz and Waelbroeck 2004); in this context consumers use the lower cost channel to sample products or services for later choice, which is usually referred to as a "sampling effect" (Liebowitz 1985). In our research setting, the corresponding mechanism is that consumers may learn about a news topic using the app due to its superior user interface, and later visit the corresponding mobile website to obtain more news. Under these conditions, the mobile news app articles would serve as "samples" for articles offered by the news provider at its mobile news website. These findings support the view that when different channels have different comparative advantages, the use of one may increase the use of the other. That is, a new channel may complement the existing channel.

We note that substitution and complementary effects might operate on the same consumer simultaneously. While our data do not allow us to separately identify these two

competing effects, we are able to study the net effect of adopting mobile news apps on mobile news website visits.

### **2.3.2 Implications of Consumer Heterogeneity for Substitution or Complementarity**

In this subsection, we review and discuss recent research on online content supply and demand to identify consumer segments that may exhibit greater substitution or complementarity between the two mobile channels. Our discussion and empirical analysis are motivated by recent research on content diversity and audience fragmentation in digital media (Gentzkow and Shapiro 2011; Webster and Ksiazek 2012), and research on the ideological segregation of online consumers (Mullainathan and Shleifer 2005; Yildirim, Gal-Or and Geylani 2013). Our main interest in this section is to identify consumers who will show higher or lower complementarity or substitution between mobile apps and mobile websites, if any.

The digitization of media content on the Internet has led to a large increase in the media sources available to consumers. The main question in this research stream has been whether the growing content availability leads consumers to consume a steady diet of their preferred news genre or a diverse range of materials (Gentzkow and Shapiro 2011; Webster and Ksiazek 2012). One key finding is that consumers have responded to the increase in content using a strategy of “selective exposure” in which they consume greater quantities of similar news from a small number of news providers, rather than consuming a greater variety of content by sampling from a larger number of news providers (Hollander 2008; Iyengar and Hahn 2009; Ksiazek, Malthouse, and Webster 2010). While much of the prior research in this area focuses on the dispersion of online content consumption across different sources at one point in time (e.g., Fox News website and Facebook.com), our setting allows us to study consumer responses to increased content availability through multiple channels from the same

provider (e.g., Fox News app and Fox mobile website) and how their responses depend on their news tastes. That is, we investigate whether substitution or complementarity is stronger or weaker among consumers with narrower news tastes conditional on a news provider's app adoption. Building on the findings in audience segmentation, we posit that, conditional on mobile news app adoption, consumers with narrow news tastes are more likely to display higher levels of complementarity between channels while we posit substitution for consumers with diverse news tastes. If our expectation about the content demand relationship between the mobile app and the corresponding mobile website holds, it implies that the selective exposure documented in audience fragmentation holds not only across news providers but also across different channels for one provider. These results will have targeting implications for content providers in terms of advertising reach and frequency.

Our empirical analysis is also informed by the latest developments on the ideological segregation of online consumers, especially in the news category (Mullainathan and Shleifer 2005; Gentzkow and Shapiro 2011). This stream of research argues that, due to the increasing proliferation of news outlets, consumers with a particular political preference will be more likely to consume from news outlets that match their own value beliefs. This behavior results in a penchant for ideological segregation (e.g., Ksiazek, Malthouse, and Webster 2010; Stroud 2008).<sup>5</sup> Applying these findings to our context, we expect stronger channel complementarity for consumers whose political preferences are better aligned with that of the news provider. In contrast, all else equal, we expect consumers whose political preferences are less aligned with that of a content provider will exhibit weaker complementarity or even substitution between the mobile news app and website. Given that marketers are beginning to recognize the implications of the ideological propensity on online consumer behavior and media company

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<sup>5</sup> Empirical evidence on ideological segregation is mixed (see, for example, Gentzkow and Shapiro 2011).

strategy (Yildirim, Gal-Or and Geylani 2013), we believe that this study also adds more insights on this topic.

Lastly, we consider the effects of a consumer's temporal budget on the degree of complementarity or substitution conditional on mobile app adoption. As the prior literature has shown, time-constrained consumers are more likely to substitute between new and existing channels (e.g., Alba et al. 1997; Deleersnyder et al. 2002). Assuming that consumers' overall temporal budgets for a news category do not change over time, which we believe is a reasonable assumption during a relatively short time window, we expect more time-constrained consumers to be less likely to exhibit complementarity between the mobile news app and website.

## **2.4 Data**

We begin by discussing comScore MobiLens, the data source for our study. Next, we discuss in detail the construction of the pseudo panel data from the MobiLens data.

### **2.4.1 comScore MobiLens**

For our empirical analysis we use a large quarterly data set, comScore MobiLens, which is based on a detailed survey of the mobile Internet activities of a nationally representative sample of the U.S. population. Participants in the survey are recruited from a large, demographically diverse population of about 30,000 individuals assembled through a variety of recruitment methods. Participants answer questions about basic demographic information, ownership of mobile devices, and behavior on the mobile Internet.<sup>6</sup> The data are a repeated cross-section (consumers usually do not overlap over time) and for our study we

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<sup>6</sup> For data accuracy, comScore conducts the survey across three months in a given quarter. That is, a survey respondent recruited at the end of each month is asked about their behaviors in the preceding one month and not the past quarter, which is designed to minimize the potential respondent errors in the survey.

use data from the fourth quarter (Q4) of 2009 and the second quarter (Q2) of 2010. Because not all respondents own smartphones, our data contain information on news consumption on mobile websites and apps for approximately 5,600 smartphone users. The survey queries these smartphone users on their use of news apps and mobile news websites. In particular, it asks whether the user accessed a particular mobile news website (e.g., CNN, Yahoo, and Fox), and whether she adopted and used a particular app to access news.

Our decision to focus on consumer response to the introduction of the Fox News app is guided in part by some limitations of our data. comScore began measuring app adoption among consumers during the second quarter of 2010, however most of the popular news providers introduced their apps before this period. Because our empirical approach requires data on changes in consumer behavior over time, this makes analysis of these providers unsuitable for our empirical approach. Therefore, we focus on Fox News, a major news provider that released its app in early 2010 and we compare use of the Fox News website before (Q4 2009) and after (Q2 2010) the introduction of the Fox News app (March 2010) to study the effect of app adoption on Fox mobile website consumption.

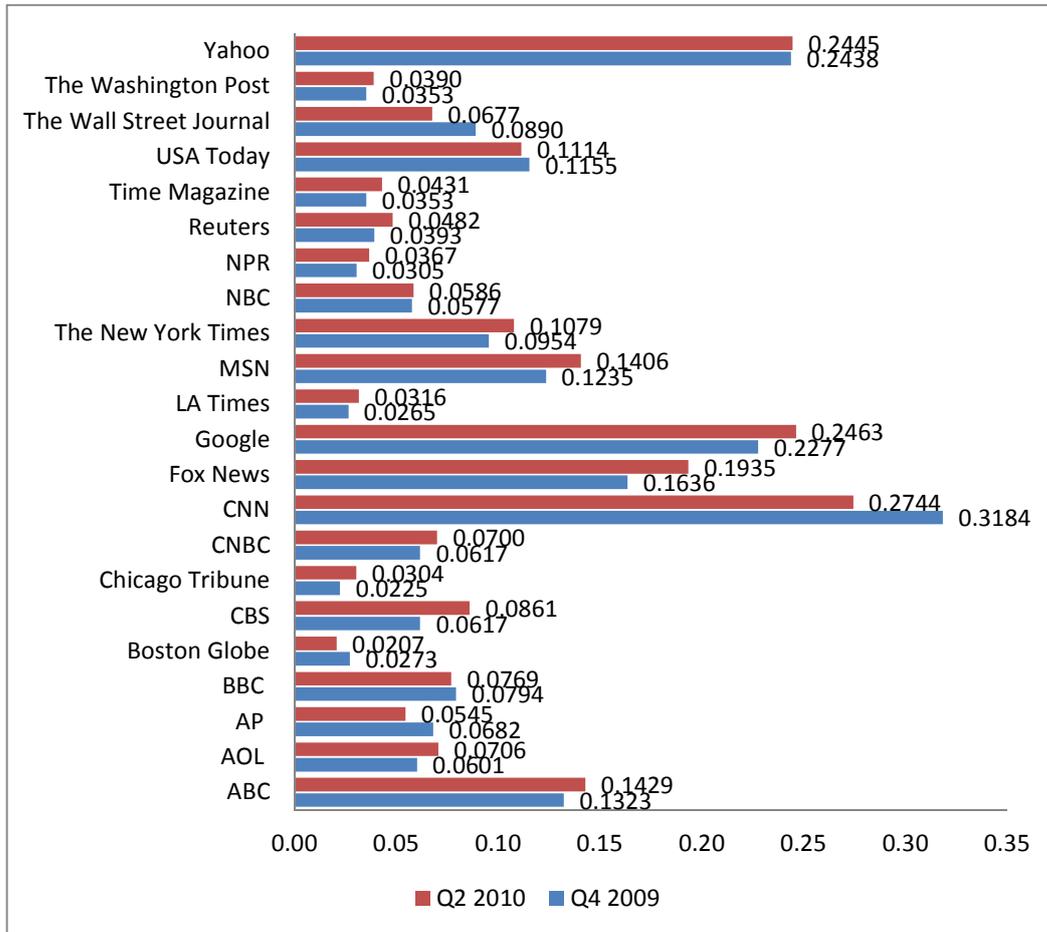
Like other prior research based on self-reported measures, one potential concern of our survey data is that they may be subject to respondent errors. Respondent errors will introduce measurement errors in the dependent and independent variables. If the measurement error is uncorrelated among the explanatory and dependent variables, it will lead to an attenuation bias (e.g., Hausman 2001) that will bias our estimates towards zero. However, if measurement error for the key independent (Fox News app adoption) and dependent (Fox News website visits) variables are correlated, then this could lead to a spurious finding of complementarity. In this section, we discuss why we believe the potential measurement error generated by

respondents is likely to be small and is unlikely to influence our estimates. Next, we present a series of econometric tests that empirically investigate whether our findings could be the result of the correlation between the measurement error and key variables.

First, the survey is organized in multiple steps that force respondents through a few gateways before reaching the target questions. This helps the instrument to elicit more reliable answers from the respondents. For instance, for each category of mobile phone usage the survey first asks a question about general frequency of use (for example, did the respondent consume news media during the previous month), regardless of access method. The survey next asks a question about the access method (app or web) for that category, and then follows up with questions about the “brand” of websites visited, followed by a similar question for apps. News website and app questions come after questions about social networking and information search on mobile phones. This helps to reduce the likelihood of “title confusion” where respondents might confuse a news app with a news website. Second, while MobiLens data are aggregated on a quarterly basis, the survey occurs each month and asks respondents about their mobile phone usage behavior in the preceding month. Focusing on the previous month, rather than prior three months, will limit the recall bias and elicit a more accurate response.

A series of detailed data analyses also suggest that the effect of measurement error may be limited. First, the average number of installed news apps for a smartphone consumer in the data is 0.85, and the average number of news websites accessed is 1.92. Hence, we observe that consumers are very selective in which news apps and news websites they visit. This suggests that a positive bias in our measurement in the key dependent and explanatory variables due to the effects of title confusion is likely to be small. Second, we conducted a set

of analyses within the MobiLens data to obtain evidence of overall data integrity. Although this may only serve as indirect evidence for validity of the reported Fox app adoption rate in the paper, we see this as a critical test towards evaluating the validity of the reported values in a broader context. Specifically, we computed and compared the adoption rates of major apps (e.g., FoxNews app, CNN app etc.) and their corresponding mobile website consumption. We found that the app adoption rate is highly correlated with the corresponding mobile website consumption rate within our data: Spearman's rank correlation for app adoption and mobile website consumption rate is 0.88. We believe these comparisons provide indirect but rather strong evidence for the validity of the measures on app adoption and mobile web consumption. Lastly, we compared the probability of visiting different online news providers during the time periods in our data. Figure 2.2 shows that the probability of visiting the Fox News website increased from 0.176 in Q4 2009 to 0.185 in Q2 2010. This compares to Fox App adoption of 0.045 in Q2 2010 and suggests that the overall traffic to Fox sites on the mobile platform increased over our sample period. We also compared our data to several public data sources on news consumption via traditional web browsers (Pew Research Center 2012, 2013). Direct comparisons are difficult because of differences in time period and the way digital traffic is measured. However, despite these disparities there is substantial overlap among the top providers in our data set and those viewed through desktop browsers as measured by comScore, Nielsen, and Pew Research.



Notes: Data are constructed as the sample average of users in each of the two quarters who indicate they had visited the website in the previous month.

**Figure 2.2: Probability of Smartphone Users Visiting Mobile Websites**

### 2.4.2 Pseudo-Panel Data

The main empirical challenge in evaluating whether consumer behavior exhibits complementarity or substitution between channels is to separate their effects from correlation in consumer preferences (Arora, Forman, and Yoon 2010; Gentzkow 2007). In our empirical setting, some consumers may have a greater taste for certain news content or a particular news provider. A potential source of identification in the presence of correlated preferences is panel data in which repeated observations of the same consumer will enable us to separate

correlation and complementarity (Gentzkow 2007).<sup>7</sup> However, as we discussed in the preceding section, the MobiLens survey participants do not overlap in each quarter, so the data are not a panel but rather a series of cross-sectional data. To facilitate panel-type analysis, we adopt a pseudo-panel approach. Originally proposed by Deaton (1985) and further developed in past studies (e.g., Browning et al. 1985; Verbeek and Vella 2005; Campbell and Cocco 2007), the pseudo-panel method has been widely used in macro and labor economics, where repeated cross sectional data are relatively common (e.g., U.S. Consumer Expenditure Survey and British Family Expenditure Survey). Pseudo panel analysis is undertaken by aggregating the observational units in the cross-sectional data into “cohorts”, matching cohorts across time, and running panel analysis on the synthesized cohorts. Therefore, our analyses will be conducted at the cohort level rather than at individual level. For a more detailed econometric discussion on pseudo-panel analysis, please refer to the Appendix A.

Constructing a pseudo-panel requires identifying a set of reliable, time-invariant criteria to identify cohorts so that the same individual remains in the same cohort over time (Prince and Greenstein 2014). We construct our cohorts using demographic characteristics in the data that we believe will give rise to stable cohorts over a short period of time. Our choice of demographic variables to construct the cohorts—age group, income, education, and location (urban vs. rural)—follow prior analyses (e.g., Blundell, Browning, and Meghir 1994; Campbell and Cocco 2007; Prince and Greenstein 2014). Each characteristic is coded as a categorical variable. For example, the categories for the age group variable are 18–24, 25–34, 35–44, 45–54, 55–64, and 65 and over.<sup>8</sup> Among the cohorts in our pseudo-panel, one cohort

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<sup>7</sup> This is similar to "reflection" problem that arises when a researcher observing the distribution of behavior in a population tries to infer whether the average behavior in some group influences the behavior of the individuals that comprise the group (Manski 1993).

<sup>8</sup> Similarly, the categories for the income-level variable are <\$25,000, \$25,000–\$50,000, \$50,000–\$75,000,

consists of consumers who range in age from 25 to 34, have an income of \$50,000–\$75,000, have a bachelor’s degree, and live in an urban area. In our pseudo-panel data, the average number of consumers per cohort is 44, with a standard deviation of 16.<sup>9</sup> Table 2.1 provides summary statistics for the cohorts in our pseudo-panel.

**Table 2.1: Descriptive Statistics: Cohort-level summary statistics**

Variable	Q4 2009				Q2 2010			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Fox News app adoption	.00	.00	.00	.00	.05	.17	.00	1.00
Number of household members	2.92	.59	1.00	5.00	2.98	.54	1.00	5.00
Length of mobile phone use (year)	3.69	.27	1.00	4.00	3.71	.22	2.00	4.00
Monthly cost of mobile phone service(USD)	105.69	13.64	36.67	150.00	112.69	12.69	50.00	150.00
First to buy new technology (1-10)	5.21	.88	.33	10.00	5.32	.90	2.00	8.33
Ask for opinion to buy new e-product (1-10)	5.55	.86	1.40	9.33	5.58	.92	2.33	10
Keep track of cell phone technology (1-10)	5.43	.91	.75	10.00	5.48	.86	2.00	8.29
Number of cohorts	151							

## 2.5 Empirical Analysis

### 2.5.1 Model

As was discussed earlier, the main empirical challenge in our identification strategy is to separate true substitutability or complementarity from intrinsic or correlated consumer preferences. For instance, in our empirical context, a consumer who simply likes the “news” category will be more likely to consume news using both apps and mobile news websites in a purely cross-sectional data set. A potential solution to this problem is the use of instrumental

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\$75,000–\$100,000, and greater than \$100,000. The categories for education level are grammar school or less, some high school, high school completed, some college, associate degree, bachelor’s degree, and postgraduate degree. We define urban locations as those located within a metropolitan statistical area.

<sup>9</sup> In our empirical analysis, we experimented with alternative cohort definitions such as including employment status in our cohort definition. Our results are robust to these changes.

variables. If we could identify variables that are correlated with mobile news app adoption but not with mobile news website consumption, we could use those variables to estimate the effect of app adoption on mobile news website demand. Unfortunately, after careful and extensive searching, we were not able to identify such instrument variables.

We use an alternative approach for causal inference: difference-in-difference estimation. The idea behind difference-in-difference estimation is to examine a set of treated units before and after some treatment. Given that other factors often change around the time of the treatment, researchers use a control group to control for such factors to try to isolate the effects of the treatment. Indexing units by  $d$  and time by  $t$ , the basic framework is as follows:

$$\text{Outcome}_{dt} = \lambda_0 + \lambda_1 \text{TreatmentGroup}_d + \lambda_2 \text{AfterTreatment}_t + \lambda_3 \text{TreatmentGroup}_d \times \text{AfterTreatment}_t + \theta \text{RegressionControls}_{dt} + \varepsilon_{dt}.$$

One can plug in zeros and ones for the various binary variables in this equation, and the difference across units after treatment is  $\lambda_3$ . If  $\lambda_3$  is positive, then it is viewed as having a positive effect on the outcome (e.g., Angrist and Pischke 2009).

In our setting,  $\text{Outcome}_{dt}$  is whether an individual visits the Fox News mobile website,  $\text{TreatmentGroup}_d$  is whether the individual adopts the Fox News app, and  $\text{AfterTreatment}_t$  indicates the second period of our sample period. In this case, the control group is the set of Fox News app non-adopters. Specifically, one equation that we could estimate using this approach would be as follows:

$$y_{dt} = \alpha + \beta \text{FoxApp}_d \times \text{time}_t + \gamma \text{time}_t + \theta X_{dt} + \tilde{\mu}_d + \varepsilon_{dt},$$

where  $\text{TreatmentGroup}_d$  ( $\text{FoxApp}_d$ ) is absorbed in the fixed effect  $\tilde{\mu}_d$ . Under this model,  $\tilde{\mu}_d = \mu_d + \mu_d^F$ ,  $\mu_d$  indicates individual  $d$ 's preference for news and extent to which she uses her smartphone more generally, i.e., the extent to which she is a “technology savvy” user. In

contrast,  $\mu_d^F$  indicates a preference for Fox News, i.e., the fit between the individual and the ideological slant provided by Fox News. Note that omitting these variables could create biased estimates for  $\beta$ .

To address this issue, we utilize another source of variance within our data, namely differences in the effects of the Fox News app adoption on the Fox News website visits compared to the effects of visiting other mobile news websites. This estimation approach is in the spirit of other papers that have compared the effects of a treatment across heterogeneous contexts to obtain identification (e.g., Chevalier and Mayzlin 2006). Specifically, we model  $y_{djt}$ , individual  $d$ 's likelihood of visiting mobile news website  $j$  in time  $t$ , as

$$(1) \quad y_{djt} = \alpha + \beta_1 \text{FoxApp}_d \times \text{time}_t + \beta_2 \text{FoxWeb}_j \times \text{time}_t + \beta_3 \text{FoxApp}_d \times \text{FoxWeb}_j \times \text{time}_t + \gamma \text{time}_t + \theta X_{dt} + \mu_{dj} + \varepsilon_{djt},$$

where  $\text{FoxApp}_d$  is an indicator variable equal to 1 if individual  $d$  adopts Fox News app,<sup>10</sup>  $\text{FoxWeb}_j$  is an indicator variable equal to 1 if  $j$  is the Fox News mobile website, and  $\text{time}_t$  is an indicator variable equal to 1 if  $t$  equals to the second period and 0 if other. The coefficient  $\beta_1$  captures the effect of Fox News app on the average likelihood of visiting all mobile websites,  $\beta_2$  measures the time trend for Fox mobile news website, and  $\beta_3$  measures the effect of the Fox News app on visits to the Fox News mobile website, our focal mobile website. If  $\beta_3$  is positive, the Fox News app causes higher media consumption at the Fox News mobile website.  $X_{dt}$  is a vector of individual-level control variables that could vary over time. The term  $\mu_{dj}$  is an individual-website fixed effect that captures individual-level preferences for news in general ( $\mu_d$  in our earlier notation) as well as individual preferences for particular news sources that may vary with income and education; for example, a recent report showed that 38% of New

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<sup>10</sup> Because the Fox News app did not exist in 2009, its adoption rate in 2009 is 0.

York Times readers had a household income of \$75,000 or more while only 23% of the Fox News audience had household incomes in this range (Pew Research Center for The People & The Press 2012). In a nutshell, our approach measures changes in the visits to the mobile Fox News website (Foxnews.com) from Fox app adoption compared to changes in the visits to other mobile news websites (e.g., CNN.com, news.google.com, news.yahoo.com) after Fox News app adoption.

While our difference-in-difference estimation model is formulated at the individual level, as noted earlier, we do not observe the same individual over time in our MobiLens data. Therefore, we follow Deaton (1985) in estimating a pseudo panel model in which we compute and use cohort-level averages of Fox app adoption, Fox web adoption, and our control variables to estimate the following model:

$$(2) \quad y_{ijt} = \alpha + \beta_1 \text{FoxApp}_i \times \text{time}_t + \beta_2 \text{FoxWeb}_j \times \text{time}_t + \beta_3 \text{FoxApp}_i \times \text{FoxWeb}_j \times \text{time}_t + \gamma \text{time}_t + \theta X_{it} + \mu_{ij} + \varepsilon_{ijt},$$

where  $i$  indexes cohort,  $y_{ijt}$  indicates cohort-level average value of Fox website visits, and other variables are corresponding cohort-level averages and computed comparably. Under a set of conditions established by Deaton (1985) and described further in the Appendix A, estimation of the model in Equation (2) will deliver consistent estimates of the individual-level parameters in Equation (1). We use heteroskedasticity-robust standard errors for  $\varepsilon_{ijt}$  since there may be heterogeneity in the distribution of unobservables across cohort-websites.

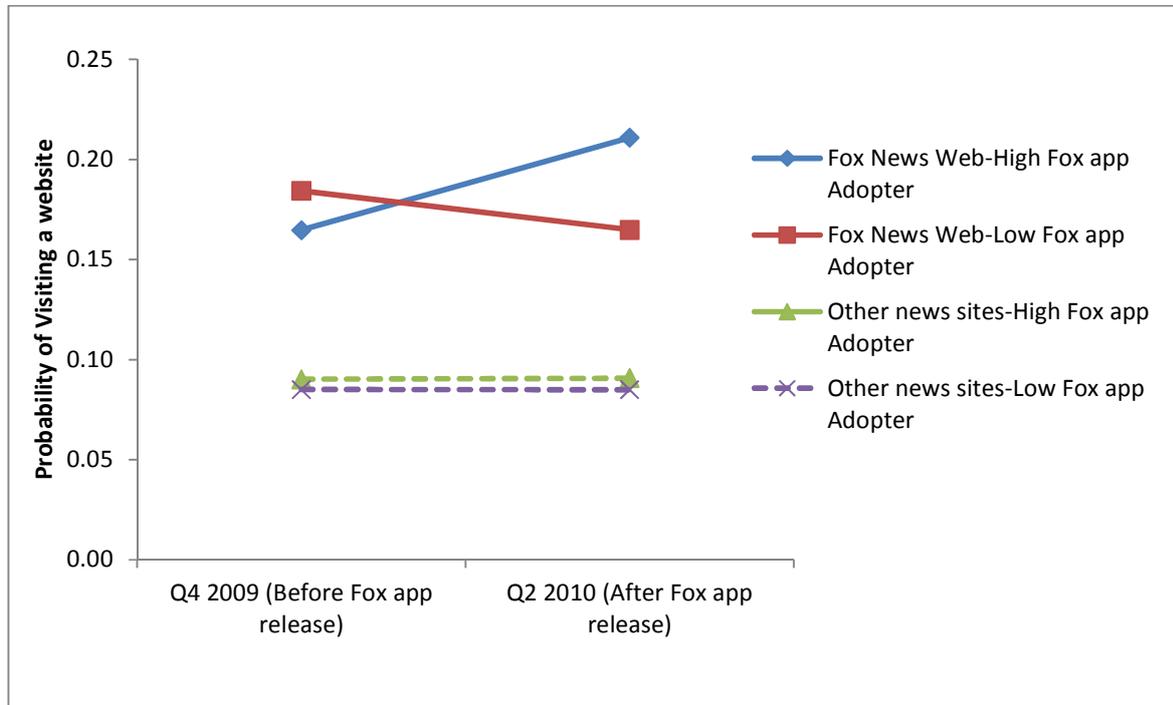
Our identification strategy requires the assumption that, along with the adoption of the Fox News app, there are no coinciding time-varying changes in unobserved factors that materially affect the probability of visiting the Fox News mobile website relative to other websites. These unobservables could be changes in preferences for Fox News or changes in

measurement error as described before. To be clear, to bias our results these time-varying unobservables would need to influence the probability of visiting the Fox News mobile website but have no effect on the probability of visiting other websites. However, in a series of robustness checks (discussed subsequently in the following section), we probe the validity of our core identification assumption.

### **2.5.2 Results**

Before discussing the results of our empirical analysis, we first demonstrate how the variance in the data identifies the core relationship of interest without imposing functional form restrictions. To that purpose, we conduct a nonparametric difference-in-differences analysis of the probability of visiting Fox mobile news websites between Q4 2009 and Q2 2010. We use a median-split strategy; if the cohort's average adoption rate of the Fox News app during the second quarter of 2010 is greater than the median adoption rate across all cohorts during the same quarter, we define the cohort as the treated group, or "High Fox News app adopter." If not, we define the cohort as the control group, or "Low Fox News app adopter." We study changes in the average probability of the cohort visiting the Fox mobile news website for these two groups. Figure 2.3 shows that while high Fox News app adopters increase their probability of visiting the Fox News website by 4.62 percentage points, low Fox News app adopters decrease their probability of visiting by 1.94 percentage points. The change in high Fox app adopter's probability of visiting the mobile news website is a statistically significant (at the one percent level) 6.56 percentage points (or 40.02%) higher than that of low Fox app adopters. This provides preliminary evidence in support of potential complementarities between consumption of the app and website. We next explore this in further detail using the regression model described in Equation (2).

### A. Difference-in-Differences Analysis of the Probability of Visiting News Websites



### B. Difference Calculations

Probability of visiting Fox News mobile website	Before Fox app introduction (Q4 2009)	After Fox app introduction (Q2 2010)	First Difference (row)
High Fox News app adopter	.1647	.2109	.0462 ***
Low Fox News app adopter	.1843	.1649	-.0194 ***
<b>First Difference (col)</b>	<b>-.0196 ***</b>	<b>.0460 ***</b>	<b>.0656 ***</b>
Average probability of visiting other mobile news websites	Before Fox app introduction (Q4 2009)	After Fox app introduction (Q2 2010)	First Difference (row)
High Fox News app adopter	.0902	.0907	.0005
Low Fox News app adopter	.0851	.0850	-.0001
<b>First Difference (col)</b>	<b>.0051</b>	<b>.0057</b>	<b>.0006</b>
<b>Difference between Fox and others</b>	<b>-.0248 ***</b>	<b>.0403***</b>	<b>0.0650 ***</b>

**Figure 2.3: Probability of Visiting News Websites by Year and Extent of Fox News App Adoption**

Table 2.2 shows the coefficient estimates of Equation (2). Columns 1 and 2 show the estimated coefficients of the main models. We focus on the results in column 1 which includes the complete set of controls. The coefficient of  $FoxApp_i \times FoxWeb_j \times time_t$  in Column 1 is 0.2936, meaning that the probability of visiting the Fox News mobile website (vs. other mobile news websites) increases by 29.36 percentage points for a cohort in which 100% of users adopt the app compared to an equivalent cohort where no users adopt. Given that the average probability of visiting the Fox News mobile website is 0.1813 in our sample prior to the introduction of the Fox app (Figure 2.2), this coefficient translates into a 61.94% increase. From this finding, we show that adoption of the mobile Fox News app stimulates the visits to the Fox News mobile website. Note that the positive and statistically significant coefficient (0.0403) on  $FoxApp_i \times time_t$  suggests that cohorts who adopted the Fox News app also visited other mobile websites more than those who did not, but far less than the Fox News website. On the other hand, the coefficient for  $FoxWeb_j \times time_t$  (-0.0538) is significantly negative, suggesting that in our data, there was a systematic decline in visits to the Fox News mobile website compared to other mobile news websites during our testing period. In short, our analysis strongly supports that the adoption of the mobile news app complements visits to the mobile news website in our empirical setting. Column 2 includes a model without controls to address the potential concern that changes in these controls could be correlated with other unobserved factors influencing Fox News mobile website visits, and so might be endogenous. Our results are robust to this change.

**Table 2.2: The Probability of Visiting the Fox News Mobile Website Increases with Fox News App Adoption**

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Baseline Results	Baseline Results: No Controls	Bootstrap Sampling (Bootstrap SD)	Smaller Cohort Size	Smaller Cohort Size: No Controls
<i>Time dummy of 2010</i>	-.0046 (.0049)	-.0043 (.0046)	-.0042** (.0062)	-.0079* (.0045)	-.0083* (.0044)
<i>FoxApp × time</i>	.0403** (.0200)	.0315** (.0196)	.0170** (.0126)	.0244 (.0204)	.0276 (.0200)
<i>FoxWeb × time</i>	-.0538* (.0302)	-.0538* (.0301)	-.0197* (.0213)	.0019 (.0284)	.0019 (.0284)
<i>FoxApp × FoxWeb × time</i>	.2936** (.1371)	.2936** (.1347)	.1824*** (.0304)	.2746** (.1248)	.2746** (.1221)
<i>Controls</i>	Yes	No	Yes	Yes	No
<i>Constant</i>	.1371** (.0651)	.0941*** (.0022)		.0281 (.0487)	.0964*** (.0020)
Observations	6,644	6,644		10,208	10,208
R <sup>2</sup>	.6159	.6141		.6161	.6073
Number of cohorts	151	151		232	232

\*Significant at 10%; \*\*Significant at 5%; \*\*\*Significant at 1%.

Notes: Controls: the number of people in the household, the length of the mobile service usage, the monthly cost of the mobile service, and variables measuring users' technological sophistication. R-square includes the explanatory power of the fixed effects in the R-square computation. Heteroskedasticity-robust standard errors appear in parentheses.

### 2.5.3 Robustness Checks

Since we use a pseudo-panel data set for our empirical analysis, a potential concern exists that our results may not be robust to various sampling strategies from the cross-sectional data, cohort size, and cohort composition. Although the theoretical literature supports the large sample properties of the pseudo-panel analysis (e.g., Verbeek and Vella

2005; Cuesta, Nopo, and Pizzolitto 2011), we conduct various checks to ensure that our results are robust in the presence of potential errors in our raw data sampling as well as our cohort composition in the pseudo-panel.

First, we investigate the sampling robustness of our model. One potential concern is that comScore data may be subject to macro-sampling errors such as over-sampling Fox app or website users among the smart phone users. This in turn can bias our coefficient estimates. To that end, we conduct a bootstrap test by resampling from the data. The resampling probability of an individual from the cross-sectional data is assigned by the individual's representative weight used by comScore: each individual is separately weighted and projected to appropriately reflect independent census estimates of the U.S. population's demographic profiles by comScore. We replicate the process of resampling individuals, grouping them into cohorts to form a pseudo-panel, and for each replication, we repeat the same regression analysis. Column 3 of Table 2.2 presents the bootstrap regression results from 500 replications. In this column, the coefficient of interest is positive and significant, suggesting that our complementarity findings in the preceding section are not caused by potential macro sampling errors by comScore.

Second, we conduct a set of robustness checks on cohort composition, similar to prior studies (Cuesta, Nopo, and Pizzolitto 2011). That is, we construct our pseudo-panels by grouping individuals into cohorts on a different set of observable demographics (e.g., Verbeek and Vella 2005; Prince and Greenstein 2014). Under the current composition strategy, our pseudo-panel results in 151 cohorts with an average of 44 individuals per cohort in our main analysis. In an alternative cohort composition strategy, we include additional demographic variables, such as employment status. Under this alternative definition, we have 232 cohorts

and an average 25 observations per cohort. Columns 4 and 5 of Table 2.2 present the regression results for this alternative cohort strategy. From the results in the table we conclude that our estimates are robust to different cohort composition plans.

Lastly, we provide evidence for one of our key identification assumptions that there was no change in unobservable cohort characteristics before and after the introduction of the Fox News app that could systematically affect the demand of the Fox News mobile website relative to other news websites. This is an important assumption to validate since the positive effect of Fox app adoption on the probability of visiting the Fox mobile news website may be attributed to time-varying factors that were not captured in the analysis. We probe the salience of this assumption through a series of falsification analyses. To that end, we examine the impact of Fox News app adoption on visits to *other* Fox websites such as Fox Financial and Fox Weather mobile websites. We reason that, since the Fox News app does not have a separate financial news category, the adoption of the Fox News app should not increase visits to the Fox Financial News mobile website, because adoption of the Fox News app does not allow consumers to sample Fox Financial News. Similarly, the adoption of the Fox News app should not stimulate visits to the Fox Weather News mobile website, because the weather content is usually similar across the two platforms.

**Table 2.3: The Probability of Visiting the Fox News Mobile Website for Weather and Financial News Does Not Increase with Fox News App Adoption**

	(1)	(2)
VARIABLES	Weather	Financial
<i>Time dummy of 2010</i>	.0011 (.0065)	-.0052*** (.0017)
<i>FoxApp × time</i>	.0316* (.0206)	.0204*** (.0052)
<i>FoxWeatherWeb × time</i>	.0128 (.0123)	
<i>FoxApp × FoxWeatherWeb × time</i>	.0282 (.0896)	
<i>FoxFinancialWeb × time</i>		.0012 (.0048)
<i>FoxApp × FoxFinancialWeb × time</i>		.0243 (.0196)
<i>Constant</i>	.0067 (.0815)	-.0055 (.0280)
Observations	4,832	6,040
R <sup>2</sup>	.6589	.6581
Number of cohorts	151	151

\*Significant at 10%; \*\*Significant at 5%; \*\*\*Significant at 1%.

Notes: All regressions include the following controls: the number of people in the household, the length of the mobile service usage, the monthly cost of the mobile service, and variables measuring users' technological sophistication. R-square includes the explanatory power of the fixed effects in the R-squared computation. Heteroskedasticity-robust standard errors appear in parentheses. The list of financial news websites in our sample is: ABC, AOL, AP, Bloomberg, Business Week, CBS, CNBC, CNN, Economist, Fox News, Google, Marker Watch, MSNBC, MSN, New York Times, Reuters, USA Today, The Wall Street Journal, Yahoo, and NBC. The list of weather news websites in our sample is: ABC, Accuweather, AOL, CBS, CNBC, CNN, Fox News, Google, MSNBC, National Weather, USA Today, Weather Channel, Weather Underground, WeatherBug, Yahoo, and NBC.

In Table 2.3, we show the results of falsification tests based on Fox Financial and Weather mobile websites. In our regression model we use a specification similar to Equation (2) but one that differs in a couple of ways. First, the dependent variable in these analyses is the probability of visiting financial or weather news websites, instead of the probability of

visiting news websites. Second, and similarly, since we are interested in knowing whether the introduction of the Fox News app gives rise to increases or decreases in the probability of visiting the Fox Financial or Weather websites, the coefficients of interest are  $FoxApp_i \times FoxWeatherWeb_j \times time_i$  and  $FoxApp_i \times FoxFinancialWeb_j \times time_i$ . Table 2.3 shows that both coefficients are statistically insignificant. That is, we do not find any evidence to support the view that Fox News app adoption increases the demand for the Fox Financial or Weather mobile websites, relative to other mobile websites. This finding is consistent with the theoretical mechanism described above that might give rise to complementarity, and is less consistent with an alternative hypothesis that the presence of unobserved cohort-level characteristics (or measurement error) might be correlated both with Fox app and Fox mobile news adoption. For this alternative hypothesis to be true, it would need to be the case that these unobservables would influence visits to the Fox News mobile website but not visits to the Fox Weather or Fox Financial News websites, which we believe is less tenable.

In summary, our various robustness checks for sampling and cohort composition provide evidence in support of our conclusions. While we cannot completely rule out a role for omitted variable bias, our falsification analyses lend additional support to the notion that adoption of the Fox News app results in complementary visits to the corresponding mobile news website.

#### **2.5.4 Consumer Characteristics for Complementarity**

We have reported that the adoption of the Fox News app triggers complementary consumer demand at the Fox News mobile website. We next consider what types of consumers exhibit stronger or weaker complementarity between the two channels conditional on Fox News app adoption. Motivated by recent research in audience fragmentation and

ideological segregation in online media consumption, we examine customer segmentation using two variables, media consumption diversity and political propensity.

Prior research shows that the average consumer uses a diverse range of materials for news consumption (Webster and Ksiazek, 2012; Iyengar and Hahn, 2009). To measure an individual's preference for diversity in news content, we use the number of different news websites that she visits across different news categories in the second quarter of 2009 (prior to the start of our sample). We measure diversity using pre-sample behavior since the number of news websites visited in our estimation sample may be correlated with our dependent variable in the regression model. By using pre-sample behavior, we avoid a potential endogeneity issue. The set of news categories that we use include general news (e.g., world, national or local news), entertainment news, technology news, and sports news.

Since we do not observe the same individuals but the same cohorts over time, we need to construct a cohort-level measure of diversity. Motivated by prior literature (e.g., Verbeek and Vella 2005; Prince and Greenstein 2014), we compute measures of diversity for each individual in the pre-sample period, and then compute cohort-level averages. In particular, we first use a median-split strategy to create a dummy variable for individuals in Q2 2009. The dummy variable is equal to 1 if the individual visits a greater number of websites than the median value across all individuals in Q2 2009 (4.4), and is 0 otherwise.<sup>11</sup> For a cohort  $i$ , we then create a diversity measure ( $Diversity_i$ ), which is equal to the average across these individual-level dummy variables within the cohort.

To capture consumer political propensity, we first classify the 22 general news websites in our sample into three categories—right-leaning, left-leaning, and neutral—based on prior research (Gentzkow and Shapiro 2011). Two websites are classified as right-leaning

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<sup>11</sup> The results are similar if we define the dummy using the sample mean rather than the median.

(Fox News and Wall Street Journal), five are classified as left-leaning (BBC, Boston Globe, New York Times, Washington Post, and MSNBC), and the rest are neutral. As we did for Diversity, we first compute the shares of right-leaning or left-leaning news website visits for each individual in Q2 2009 as a proxy for consumer political propensity (Gentzkow and Shapiro 2011). We then define two individual-level binary variables using a median split strategy. The first variable that is equal to 1 if the individual's share of right-leaning news websites visits is greater than the median right-leaning share across all individuals in Q2 2009 (.13) and 0 otherwise; the other is equal to 1 if the individual's share of left-leaning news websites visits is greater than the median left-leaning share across all individuals in Q2 2009 (.17) and 0 otherwise. For each cohort  $i$ , we create a variable  $Right_i$  that takes the average value across all of the individual right-leaning dummies within the cohort. Similarly, we create a variable  $Left_i$  that takes the average value across all of the individual left-leaning dummies within the cohort. Note that 51 out of 151 cohorts are neither right-leaning nor left-leaning.

To capture consumer time constraints, we use a demographic variable in the comScore survey that indicates the consumer's employment status, coded categorically as full-time employed, part-time employed, not-employed, full-time student, full-time student employed, or retired. We define  $TimeConstraint_i$  as cohort  $i$ 's full-time employment share in Q2 2009.

Because some of our key moderators may be correlated with one another, we focus our analysis on the full regression model that includes all three intermediate variables:

$$(3) \quad y_{ijt} = \alpha + \beta_1 \text{FoxApp}_i \times \text{time}_t + \beta_2 \text{FoxWeb}_j \times \text{time}_t + \beta_3 \text{FoxApp}_i \times \text{FoxWeb}_j \times \text{time}_t + \delta_0 \text{Diversity}_i \times \text{time}_t + \delta_1 \text{FoxApp}_i \times \text{time}_t \times \text{Diversity}_i + \delta_2 \text{FoxWeb}_j \times \text{time}_t \times \text{Diversity}_i + \delta_3 \text{FoxApp}_i \times \text{FoxWeb}_j \times \text{time}_t \times \text{Diversity}_i + \lambda_0 \text{Right}_i \times \text{time}_t + \lambda_1 \text{FoxApp}_i \times \text{time}_t \times \text{Right}_i +$$

$$\lambda_2 \text{FoxWeb}_j \times \text{time}_t \times \text{Right}_i + \lambda_3 \text{FoxApp}_i \times \text{FoxWeb}_j \times \text{time}_t \times \text{Right}_i + \rho_0 \text{Left}_i \times \text{time}_t + \rho_1 \text{FoxApp}_i \times \text{time}_t \times \text{Left}_i + \rho_2 \text{FoxWeb}_j \times \text{time}_t \times \text{Left}_i + \rho_3 \text{FoxApp}_i \times \text{FoxWeb}_j \times \text{time}_t \times \text{Left}_i + \sigma_1 \text{FoxApp}_i \times \text{time}_t \times \text{TimeConstraint}_i + \sigma_2 \text{FoxWeb}_j \times \text{time}_t \times \text{TimeConstraint}_i + \sigma_3 \text{FoxApp}_i \times \text{FoxWeb}_j \times \text{time}_t \times \text{TimeConstraint}_i + \gamma \text{time}_t + \theta X_{it} + \mu_{ij} + \varepsilon_{ijt}.$$

Empirically, our strategy is to hold the effects of demographic characteristics across segments constant but to allow for heterogeneity in the probability of visiting the Fox News mobile website and in the effects of adopting the Fox app. The coefficients of interest show how the effects of the Fox app on the Fox News website are moderated by diversity, right- and left-leaning political preferences, and time constraints; i.e., coefficients  $\beta_3$ ,  $\delta_3$ ,  $\lambda_3$ ,  $\rho_3$  and  $\sigma_3$ . As a robustness check, we also estimate models that show the effects of each moderating variable separately.

The estimated coefficients of Equation (3) are shown in Column 1 of Table 4. First, we note that the mean effect of Fox app adoption estimated from coefficients  $\beta_3$ ,  $\delta_3$ ,  $\lambda_3$ ,  $\rho_3$  and  $\sigma_3$  is  $.1333 (\beta_3 + \delta_3 \times \text{meanDiversity} + \lambda_3 \times \text{meanRight} + \rho_3 \times \text{meanLeft} + \sigma_3 \times \text{meanTimeConstraint} = .3873 + (-.2861 \times .3412) + (.1154 \times .4057) + (-.4513 \times .3782) + (-.0928 \times .3503) = .1333$ ) which is positive, supporting our conclusion in the previous sub section. We next discuss the moderating effects of media diversity, political propensity, and time constraint on Fox News mobile website consumption conditional on Fox app adoption. The coefficient of  $\text{FoxApp}_i \times \text{FoxWeb}_j \times \text{time}_t \times \text{Diversity}_i$  is negative (-0.2861) and statistically significant. This means that, conditional on Fox News app adoption, more media-diverse cohorts visit the Fox News mobile website less frequently compared to less media-diverse cohorts. These results suggest that media diversity in a consumer's news consumption weakens the complementary effect between a provider's mobile news app and mobile news website.

**Table 2.4: Complementarity Is Stronger for Cohorts with a Lower Diversity of News Consumption, with a Right-leaning Propensity of News Media, and with a Lower Percentage of Users Who Are Employed Full-Time**

	(1)	(2)	(3)	(4)
	All Interactions	News Diversity	Right/Left	Full-Time Employment
<i>FoxApp × FoxWeb × time</i>	.3873** (.2059)	.2872** (.1201)	.4252** (.1871)	.2986** (.1098)
<i>FoxApp × FoxWeb × time × diversity</i>	-.2861** (.1254)	-.3235** (.1752)		
<i>FoxApp × FoxWeb × time × right</i>	.1154* (.0990)		.1824* (.0981)	
<i>FoxApp × FoxWeb × time × left</i>	-.4513** (.2009)		-.4968** (.2211)	
<i>FoxApp × FoxWeb × time × TimeConstraint</i>	-.0928* (.0590)			-.0981* (.0531)
<i>Constant</i>	.1064** (.0654)	.1269** (.0653)	.1037** (.0655)	.1360** (.0653)
Observations	6,644	6,644	6,644	6,644
R <sup>2</sup>	.6312	.6182	.6315	.6128
Number of cohort	151	151	151	151

\*Significant at 10%; \*\*Significant at 5%; \*\*\*Significant at 1%.

Notes: Key coefficients are shown in Table 4. All regressions include the following controls: the number of people in the household, the length of the mobile service usage, the monthly cost of the mobile service, and variables measuring users' technological sophistication. R-square includes the explanatory power of the fixed effects in the R-square computation. Heteroskedasticity-robust standard errors appear in parentheses. The full table is available upon request because of space limitation.

The same column also contains the coefficient that shows how political propensity influences the effects of Fox mobile app adoption on Fox mobile news website visits. Our parameter estimates show that the complementary effect of Fox News app on the probability of visiting the Fox News mobile website (a right-leaning news provider) is stronger among cohorts with “right-leaning” political preferences. The coefficient for  $FoxApp_i \times FoxWeb_j \times$

$time_t \times Right_t$  is positive (0.1154) and statistically significant. In contrast, the coefficient of  $FoxApp_i \times FoxWeb_j \times time_t \times Left_t$  is -0.4513. To put these results in perspective, cohorts without left- or right-leaning preferences and with mean levels of Fox app adoption will be 1.98 percentage points more likely to visit the mobile website than those with no Fox app adoption; in contrast, those with right-leaning preferences will be 2.12 percentage points more likely to visit, while those with left-leaning preferences will be 1.26 percentage points less likely to visit. That is, while Fox app adopters with right-leaning preferences will exhibit stronger complementarity, those with left-leaning preferences will exhibit substitution between the app and mobile website. This has important implications for audience targeting, which we discuss in detail in the following section.

Lastly, we discuss the effect of a consumer's temporal budget on Fox mobile news website consumption conditional on Fox News app adoption. Our results show that complementarity is stronger among less time-constrained cohorts since the coefficient of  $FoxApp_i \times FoxWeb_j \times time_t \times TimeConstraint_t$  is -.0928. The results suggest that customers' time constraints weaken the complementary effects between a provider's mobile news app and website. In columns 2 through 4, we present results showing the effects of each of the moderators separately. The sign of the coefficients and their significance is the same as in the baseline specification. The magnitudes are also quite similar across specifications.

We also examined how cohort demographic variables (including income, age, education and urban/rural that we used to construct our cohorts) may influence the complementary effect between the mobile news app and website. We did not find any evidence that the complementary effect varies significantly among consumers with different age levels, education levels or locations (urban vs rural). This may be because, as has been

found in previous studies (e.g., Van den Poel and Buckinx 2005), there may be little association between behavioral heterogeneity and observable demographic characteristics in our empirical setting. Alternatively, our data may also lack the statistical power to identify the behavioral heterogeneity from consumer characteristics. However, we do find that complementarity is systematically weaker for higher income cohorts. This is consistent with research reports that have shown that higher income individuals are less likely to visit Fox News (e.g., Pew Research Center 2012), and so these results could reflect differences in tastes for conservative news.<sup>12</sup>

## **2.6 Discussion and Conclusion**

### **2.6.1 Summary**

In this research, we analyzed the impact of mobile news apps on consumer demand at the corresponding mobile news websites. We believe this is an important topic for marketers to understand in order to achieve better advertising policies across mobile news distribution channels. Using large scale survey data, we find robust empirical evidence that the adoption of a mobile news app significantly increases the probability of visiting the provider's corresponding mobile website. In doing so, we overcome data limitations by adopting a pseudo-panel technique in which we transform our repeated cross-sectional data into a panel of cohorts. In addition, we find that the complementarity is stronger for consumers who favor less diverse news content, whose political propensity is aligned to that of the news provider, and who are less time-constrained. Building upon recent theoretical and empirical findings, our findings support the view that ideological segregation makes it easier for advertisers to segment and target audiences in a multi-channel environment.

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<sup>12</sup> We thank an anonymous reviewer for encouraging this exploration. Due to space constraints, these results are available from the authors upon request.

## **2.6.2 Managerial Implications**

Our findings have several important managerial implications for content providers and advertisers on their mobile advertising decisions across multiple channels. They also hold insights for policy makers on current media “silo” effects among online consumers. We start by discussing the implications of our findings on various aspects of advertising such as spillover, reach, and frequency on the mobile platform. Given the rapid growth of mobile advertising (International Data Corporation 2013) and the challenges mobile advertisers face (Lohr 2013), our findings offer valuable insights. First, our analysis shows that there is positive traffic spillover from the Fox News app to its mobile news website. Our analysis suggests that the app may be an effective channel for media companies to sustain their traffic levels in the ever-crowded mobile web landscape.

Second, because our analysis shows that Fox News app adopters are more likely to visit the Fox News websites and consume content on both channels, the app may contribute more to “frequency” than “reach” in mobile advertising metrics. That is, advertisements placed across channels are more likely to have repeated impressions on the same audience than a single impression on a broader set of audiences. Consequently, media planners who pursue frequency more than reach should consider placing ads on both apps and mobile websites. Advertising on multiple platforms substantially increases consumers’ ability to remember an advertising campaign compared with when the advertisement is viewed on, for example, television alone (Nielsen 2011). In contrast, it may be more cost efficient for media planners who pursue “reach” to consider placing ads only on the mobile website to minimize duplicated impressions.

Third, our analysis shows that among Fox News app adopters, right-leaning news readers typically consume more content at the Fox News mobile news website. This has two important implications. From the media planners' perspective, they can expect ads placed on both channels to repeatedly reach consumers with ideological propensity aligned to that of the news provider, in our case, a conservative audience. Therefore, our results suggest that ideological segregation will aid advertisers who wish to target segmented consumers on multiple mobile channels.

From the policy maker's perspective, our result suggests that an additional channel on mobile devices contributes to a higher degree of segregation or media "silo" among online audiences with similar political propensity. In our empirical setting of Fox news, the right-leaning audience exhibits a stronger channel complementary while in contrast the left-leaning audience exhibits the opposite and shows substitution between the two mobile channels. The contrast with recent research is informative. Recent theoretical models have shown that increases in media competition—as has been enabled by the digitization of news content—might lead consumers self-segregate ideologically (e.g., Mullainathan and Shleifer 2005). However, Gentzkow and Shapiro (2011) found no evidence that the Internet is becoming more ideologically segregated over time, in part because a significant share of consumers get news from multiple outlets. Our findings suggest that the introduction of new channels may increase some consumers' visits to their preferred news channels.

Finally, we suggest that the best strategy for news providers to attract more traffic on mobile devices is to manage the two distribution channels differently—that is, to offer more news stories on the mobile website than the app rather than simply devoting most of their resources to developing apps. Marketers may gain significant benefits from having different

digital media strategies across the two platforms, even though the cost might be high. A company could, for example, have different types of advertisements on the two platforms (i.e., simple banner advertisements on apps and more detailed advertisements on mobile websites) and, consistent with our findings, rely on complementarities to encourage consumers to visit both platforms.

### **2.6.3 Further Research**

Our findings of complementarity offer several directions for future research. First, further study of the existence of complementarity or substitution across news media channels is needed. Our study, like some prior work in this literature (e.g., Gentzkow 2007) has focused on a small number of providers in a specific market. Given findings of both complementarity and substitution in different contexts, more research is needed to identify when complementarity is most likely to be most prevalent. This call echoes that in other areas of the marketing literature on channels to identify whether and when one channel complements or substitutes another (e.g., Avery et al. 2012).

Related, researchers can extend the current study by investigating the mechanism behind the source of complementarity between two channels. Although we discuss similarities and dissimilarities between two mobile channels and report the extent of complementarity in our empirical analysis, the MobiLens data do not allow us to study in detail the mechanism responsible for the reported complementarity. If future researchers have access to panel data as well as the data on articles that are consumed on the two different channels, they will be able to study consumer behavior in greater detail. For instance, future work can identify the different news consumption patterns on two different channels, which may evolve differently over time as consumers become more familiar with the particular app or the mobile website.

Findings in this area may help news providers with their content management decisions between different channels.

Lastly, future research could take a similar approach to examine the interrelationships across different content providers or different channels that are associated with social networking sites.

## **CHAPTER 3**

# **BATTLE OF THE INTERNET CHANNELS: HOW DOES MOBILE AND FIXED-LINE QUALITY DRIVE INTERNET USE?**

### **3.1 Introduction**

According to estimates by the International Telecommunication Union (2013), the 2.1 billion active mobile Internet users in the world at the end of 2013 represented 29.5% of the global population. Mobile Internet subscriptions grew 40% annually between 2010 and 2013, roughly three times the growth rate for fixed broadband subscriptions (International Telecommunication Union 2013). This rapid growth has been accompanied by increasing research interest in how consumers use the mobile Internet (e.g., Bang et al. 2013; Ghose and Han 2011; Ghose, Han and Xu 2013; Xu et al. 2014a; Xu et al. 2014b), though we still know relatively little about the competition among different Internet channels and their effects on consumption. On the one hand, fixed-line and mobile networks provide many of the same basic functionalities, so consumers may use one channel to perform all online activities. On the other hand, important differences demarcate the two Internet platforms, such that mobile service enables ubiquitous access, whereas fixed-line service boasts superior service quality and reliability. Ghose, Goldfarb and Han (2013) show that that consumers behave differently when using mobile versus fixed-line Internet connections. Therefore, do mobile Internet networks compete with traditional fixed-line Internet networks? If they do, how and where can mobile Internet providers win this battle with fixed-line Internet providers?

Our research fits nicely into the literature on channel competition. In general, changing the utility consumers gain from one channel will influence how consumers adopt and use

another competing channel to access information. One stream of prior work specifically focus on the competition between offline and online channels in commodity markets by modeling a trade-off between a set of fixed disutility costs and the lower search and transportation costs of buying online, in addition to any price differences across the two channels (e.g. Balasubramanian 1998; Brynjolfsson, Hu and Rahman 2009; Forman, Ghose and Goldfarb 2009). Surprisingly few studies have explicitly examined the effect of the quality of service delivered through multiple channels as a determinant of customer channel choice (Sousa and Voss 2012). Customer adoption and use of new channels can be influenced by the level of service quality provided by the benchmark alternative channels. This has been documented in the competition between online and offline channel (Montoya-Weiss, Voss and Grewal 2003; Falk et al. 2007). However, consumer behavior is increasingly occurring through different emerging online channels. Our paper extends this to the competition between mobile Internet and fixed-line Internet channels. The trade-off for consumers to choose between different online channels is different than the trade-off between offline and online channels. We offer a framework and analyze relevant data to understand how the quality of the fixed-line Internet influences the adoption and use of the mobile Internet. We further study how the level of competition between fixed-line and mobile Internet services varies across different types of mobile activities, and varies across different consumer segments.

In turn, how the quality of fixed-line Internet service influences the adoption and usage of mobile services has significant policy implications for the market structure of mobile service provision. Telecommunication policy makers worry about a lack of competition in the mobile service market, where service providers often operate with few competitors. The U.S. Department of Justice thus sought to block a proposed purchase of T-Mobile USA by AT&T,

ultimately leading AT&T to abandon its bid (AT&T, 2011). However, if mobile service providers need to compete with the fixed-line service providers to offer Internet services, it actually alleviates many competitive concerns in the Internet service market.

For this investigation, we employ a novel survey data set of 28,117 U.S.-based mobile phone users in the second quarter of 2011, combined with local Internet coverage data from the National Broadband Map (NBM). We estimate probit models with our cross-sectional data, such that consumers choose whether to adopt a mobile data plan, and choose whether to conduct certain categories of activities on their mobile phones. Our primary interest is in determining whether the speed offered by local fixed-line and mobile service providers influences mobile Internet adoption and usage, so we adopt two approaches to assess whether the relationships are causal. First, we include area demographic variables as controls, because a plausible alternative explanation of the causal effect of Internet speed on mobile Internet adoption is that higher-density, higher-income, or higher-education areas encourage both Internet service quality and Internet adoption (e.g., Greenstein and Mazzeo 2006; Kolko 2012; Prieger 2003). Second, to investigate whether Internet speed influences mobile Internet adoption and usage through other omitted variables, we employ two instruments in our probit models: the proxy costs of providing local wire service and historical mobile coverage information in adjacent areas.

Although better local mobile Internet speed can increase the likelihood of adopting mobile Internet plans, the impact of local fixed-line Internet speed on mobile Internet adoption is negative. Thus, fixed-line and mobile Internet appear to be competitors. Considering the usage of different mobile activities, for mobile online activities, similar to the mobile Internet adoption, local mobile Internet speed is positively associated with the use of

mobile online activities, while local fixed-line Internet speed is negatively associated with the use of mobile online activities. However, we do not find significant impacts of fixed-line or mobile Internet speed on the consumption of mobile-specific offline activities that do not require an Internet connection. The average effect also masks significant heterogeneity in consumer responses. In particular, younger consumers view the fixed-line and mobile Internet as stronger competitors. Because fixed-line and mobile Internet speeds are more comparable in areas with relatively low fixed-line Internet speeds, consumers living in such areas also exhibit stronger competitive cross-channel effects.

Overall, this study explicates cross-channel Internet consumption behavior on mobile devices. Such understanding is increasingly important as online search, browsing, and purchase behavior move more to mobile devices (comScore 2012), and it offers several substantive contributions to extant literature. There are many recent studies on the competition between digital and non-digital channels (e.g., Avery et al. 2012; Bang et al. 2013; Brynjolfsson, Hu and Rahman 2009; Gentzkow 2007; Forman, Ghose, and Goldfarb 2009). However, we do not know much about how consumers choose across different digital channels. In this paper, we seek to investigate the competition between different digital channels by studying how the quality of an incumbent online channel influences the adoption and use of an emerging online channel. Building on several recent works on how consumer behavior might be different on the fixed-line and mobile Internet (e.g., Ghose and Han 2011; Ghose, Goldfarb and Han 2013), we seek to refine implications of how fixed-line and mobile Internet are different. Service quality is one of the most important factor that distinguishes fixed-line and mobile Internet. We specifically show that how the change in fixed-line Internet service quality influences the adoption and usage of the mobile Internet. Finally, by

demonstrating the level of competition between the fixed-line and mobile Internet and identifying consumer segments for which competition is greater, we provide insights for policy makers and practitioners about how and where mobile Internet providers can compete with fixed-line Internet providers, potential infrastructure investment strategies for mobile Internet providers, and appropriate targeting.

### **3.2 Theoretical Framework**

Different factors influence the utility of adopting any general purpose technology (Bresnahan and Trajtenberg 1995). According to a standard probit model of diffusion (e.g., David 1969; Karshenas and Stoneman 1993), consumers adopt a technology if the utility of doing so is greater than zero, i.e. benefits of doing so exceed its adoption costs. As the utility (i.e., benefits minus costs) on adopting increases, the likelihood of adoption increases too. Post-adoption usage then determines how much value consumers derive from the technology (Fichman and Kemerer 1997). Similar to the adoption decision, consumers use the technology more if the utility from usage is higher.

Our framework builds on existing theoretical models that examine consumer substitution between online and offline channels. Prior literature that studies the competition between offline and online channels in commodity markets suggests that changes in distance to offline store influences disutility of visiting offline store by increasing transportation costs, and thus influences the likelihood consumers will visit the online channel (e.g. Balasubramanian 1998; Forman, Ghose and Goldfarb 2009). However, when we consider Internet channels only, distance does not matter. Generally speaking, the traditional Internet service via a fixed-line Internet network has superior service quality and reliability. The

quality of a mobile Internet service is not as good as a fixed-line Internet network because of technology limitations. However, one disadvantage of using the fixed-line Internet are strict limitations on geographical mobility and access of a fixed-line network, while the mobile Internet has fewer of the constraints related to time and space, because consumers can use their portable mobile phones to access the mobile Internet at any time and at any place.

Channel-specific service quality is one important category of factors affecting customer multi-channel behavior (Balasubramanian, Raghunathan and Mahajan 2005; Sousa and Voss 2012; Verhoef, Neslin and Vroomen 2007). We investigate whether mobile Internet networks compete with traditional fixed-line Internet networks by examining how fixed-line Internet quality affects the probability of mobile Internet adoption and usage of the mobile Internet. Changes in the quality of fixed-line Internet channel directly change the utility consumers gain from that channel, and as a result affect how consumers adopt and use the mobile Internet channel.

For both fixed-line and mobile Internet services, Internet connection speed is one of the most important determinants of service quality (Limayem, Khalifa, and Frini 2000; Yoo and Donthu 2001). We first discuss how mobile Internet and fixed-line Internet speed affects the utility to mobile Internet adoption, and then focus on how mobile Internet and fixed-line Internet speed affects the utility to mobile Internet usage.

### ***3.2.1. Probability of Adoption***

As a benchmark analysis, we first study how the mobile Internet speed influences the mobile Internet adoption decision. Consumers obtain more benefits if they adopt a faster Internet service, so mobile Internet connection speeds should have a positive impact on the

utility of adopting the mobile Internet service. Mobile Internet connection speed should be positively associated with the likelihood of mobile Internet adoption.

If there are two competitive channels available, consumers may take the quality of one channel into consideration for the adoption and use decision of the other competitive channel. Consistent with channel choice literature that lower perceptions of alternative channel service quality leads to more adoption of the focal channel (e.g., Balasubramanian, Raghunathan and Mahajan 2005; Sousa and Voss 2012; Montoya-Weiss, Voss and Grewal 2003; Verhoef, Neslin and Vroomen 2007), all else equal, decrease in the local fixed-line Internet speed directly decrease the utility of fixed-line Internet adoption, and thus increase the likelihood of mobile Internet adoption. Therefore, the fixed-line Internet connection speed would be negatively associated with the likelihood of mobile Internet adoption.

### ***3.2.2. Usage across Different Mobile Activities***

We then seek to identify the conditions under which the mobile Internet is a better or worse competitor for the fixed-line Internet by examining how the competitive effect varies across the use of different types of mobile activities. We focus on two types of mobile activities. That is, consumers use mobile phones to perform online activities that correspond with activities performed through the fixed-line Internet (e.g., check e-mail, search for information, social networking, read news, online banking, share photo/video) but also perform mobile-specific offline activities without corresponding activities through fixed-line Internet connections (e.g., take photos, make videos). We primarily investigate the effects of local fixed-line and mobile Internet speeds on the use of mobile online activities, and then show that the effects do not appear for the use of mobile offline activities.

For the usage of mobile online activities, similar to our predictions for probability of adoption, we anticipate that mobile Internet speed may be positively associated with usage intensity, because the utility that consumers achieve from consuming more data increases more with faster mobile Internet connection speeds. And we predict that the lower quality of local fixed-line Internet service will lead to higher use of the mobile Internet to perform online activities.

We then consider the use of mobile-specific offline activities, for which mobile Internet speed should not correlate with usage intensity, because mobile-specific offline activities do not require any Internet connection, and as a result greater mobile Internet speed does not affect their utilities. Similarly, the fixed-line and mobile Internet should not be competitors for such activities, because they can only be performed on mobile phones and do not have direct competitive activities available through fixed-line networks.

### **3.3 Empirical Analysis**

#### ***3.3.1 Model***

To investigate empirically how the local speed of mobile and fixed-line Internet services influences consumers' probability of mobile Internet adoption, we apply a linear probability model,<sup>13</sup> in which consumers choose whether to adopt a mobile data plan or not.

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<sup>13</sup> We choose the linear probability model because instrumental variables can be easily used in linear models, and interaction results are easier to interpret. Our main interest is to estimate the marginal effect of the independent variable on the response probability, then the fact of a linear probability model that some predicted values are outside the unit interval may not be very important (Wooldridge, 2010). The probit or logit model with instrumental variables or control function approach requires specific distribution assumptions (Wooldridge, 2010). The results remain robust to probit IV model and logit model with control function approach.

The likelihood of adopting a mobile data plan for individual  $i$  living in zip code  $z$  is assumed to be

$$(1) Y_{iz}^{Adoption} = \alpha^{Adoption} + \beta^{Adoption} X_i + \delta^{Adoption} D_z + \gamma^{Adoption} Fixed_z + \theta^{Adoption} Mobile_z + \sum_{j=1}^7 m_j^{Adoption} MoCarrier_{jz} + \sum_{l=1}^7 \rho_l^{Adoption} FixCarrier_{lz} + \sum_{k=1}^{50} d_k^{Adoption} S_{ik} + \varepsilon_{iz}^{Adoption},$$

where  $Fixed_z$  is the average fixed-line Internet download speed in  $z$  across all available carriers;  $Mobile_z$  is the average mobile Internet download speed available in  $z$  across all available carriers.<sup>14</sup> The fixed-line and mobile Internet speeds in different places within the same zip code are highly correlated, because there is a high spatial correlation in installation and maintenance costs to provide mobile and fixed-line Internet services (Boer and Evans 1996; Czernich et al. 2011; Dai 2008). Most prior literature that studies the effect of Internet speed on Internet diffusion is conducted at the zip code level or even at the county level (i.e. Dai 2008; Greenstein and Mazzeo 2006; Kolko 2012; Prieger 2003). Thus, zip code-level average speed information is sufficient to study how the quality of local fixed-line Internet service influences consumer's mobile Internet and usage decision.

$\gamma^{Adoption}$  and  $\theta^{Adoption}$  measure the sensitivity of mobile Internet adoption to local fixed-line and mobile Internet speed. If mobile Internet speed has a positive impact on mobile Internet adoption,  $\theta^{Adoption}$  should be significantly positive. If the decrease in the local fixed-line Internet speed increases the likelihood of mobile Internet adoption, the effect of the fixed-line speed on mobile Internet adoption should be negative,  $\gamma^{Adoption} < 0$ .

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<sup>14</sup> The results remain consistent if we use the average of download and upload speeds for fixed-line and mobile Internet.

Many other factors may influence the utility of adopting a mobile data plan too.  $X_i$  are individual-level control variables, such as age, gender, income, area, the number of people in the household, and the length of the mobile service usage.<sup>15</sup>  $D_z$  are the zip code-level demographic control variables, including median income, population, and percentage of the population with a bachelor's degree.<sup>16</sup>  $MoCarrier_{jz}$  is a list of dummy variables indicating whether a mobile carrier  $j$  is available in zip code  $z$ , and  $FixCarrier_{lz}$  is a list of dummy variables indicating whether a fixed-line Internet provider  $l$  is available in zip code  $z$ , to control for different service plans offered by different active carriers in the local market. The two sets of dummy variables can be viewed as proxies for the overall level of service provided across the two platforms. They can also be used to control for any carrier specific characteristics.<sup>17</sup> We also include a series of state dummies indicating whether individual  $i$  lives in state  $k$ ,  $S_{ik}$ .

An important omitted variable in our model is price. After careful and extensive searching, we are not able to find price data for either fixed-line Internet or mobile Internet services in our sample period. To identify the relationship between two goods, one natural

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<sup>15</sup> Age, gender, education, income and area are coded as categorical variables in our data. For example, the categories for the age group variable are 2=18–24, 3=25–34, 4=35–44, 5=45–54, 6=55–64, and 7=65 and over; the categories for gender are 0=Female, 1=male; the categories for the income-level variable are 1=<\$25,000, 2=\$25,000–\$50,000, 3=\$50,000–\$75,000, 4= \$75,000–\$100,000, and 5=greater than \$100,000; the categories for education level are 1=grammar school or less, 2=some high school, 3=high school completed, 4=some college, 5=associate degree, 6=bachelor's degree, and 7=postgraduate degree; the categories for area are 0=Rural, 1=Urban.

<sup>16</sup> We obtain the zip code-level demographic data from the 2010 U.S. Census.

<sup>17</sup> There are seven active mobile carriers in the zip codes we have in our comScore data: AT&T, Verizon, T-Mobile, Sprint, U.S. Cellular, Leap Wireless, MetroPCS. We choose MetroPCS as the baseline carrier (i.e. the omitted category), because the number of MetroPCS subscribers is the lowest (<5%) in our data. And there are ten active fixed-line Internet carriers in our data: AT&T, Verizon, Comcast, CenturyLink, Time Warner Cable, Cox, Charter, Frontier, Suddenlink, Cablevision. We include the dummy variables for the top six fixed-line Internet providers (AT&T, Verizon, Comcast, CenturyLink, Time Warner Cable, Cox), and one dummy variable for the rest of fixed-line Internet providers. We choose the rest of fixed-line Internet providers as the baseline carrier, because the total number of subscribers for those providers is very low (<5%) in our data.

source of information is variables that can be excluded a priori from the utility of one or more goods. In many settings, price is the obvious candidate. The identification argument is also valid for non-price variables, however, and so can be applied where prices do not vary (Gentzkow 2007). In the Internet service market, given that a mobile or a fixed-line Internet carrier is active in some local markets, the type and price of service plans offered by that carrier do not vary across different local markets (German 2013). However, the Internet service quality in terms of the connection speed does vary a lot across local markets. Therefore, when we study how the competition between the fixed-line and mobile Internet, we focus on the variations in the Internet speeds.

Another set of omitted variables are local telecommunications regulatory rules, which could influence mobile service decisions, because of different firms' unique reactions to similar regulatory incentives (Greenstein and Mazzeo 2006). Because regulatory rules are normally applied at the state level, we use the state dummies in the model to control for any specific local telecommunications regulatory rules. As we note in detail subsequently, the state dummies also control for potential differences in the way we collected service data across states.

Similar to the adoption decision, consumers can choose whether to use certain mobile activities more intensively or not. Specifically, the likelihood of choosing to perform mobile activities more intensively, by individual  $i$  at zip code  $z$ , is assumed to be

$$(2) \quad Y_{iz}^{Use} = \alpha^{Use} + \beta^{Use} X_i + \delta^{Use} D_z + \gamma^{Use} Fixed_z + \theta^{Use} Mobile_z + \sum_{j=1}^7 m_j^{Use} MoCarrier_{jz} + \sum_{l=1}^7 \rho_l^{Use} FixCarrier_{lz} + \sum_{k=1}^{50} d_k^{Use} S_{ik} + \varepsilon_{iz}^{Use},$$

where  $Y_{iz}^{Use}$  is binary variable indicating whether individual  $i$  at zip code  $z$  uses different categories of mobile activities more frequently. By aggregating the usage across different categories of activities, we use cluster analysis to classify consumers into two clusters, according to whether they perform mobile activities frequently or not. Detailed explanations are provided in the Data section.  $\gamma^{Use}$  and  $\theta^{Use}$  measure the sensitivity of mobile usage to local fixed-line and mobile Internet speed. If mobile Internet speed has a positive impact on usage of mobile activities,  $\theta^{Use}$  should be significantly positive. If the decrease in the local fixed-line Internet speed increases the likelihood of using mobile online activities, the effect of the fixed-line speed on usage of mobile online activities should be negative,  $\gamma^{Use} < 0$ . We include the same control variables from the Equation (1).

We conduct separate analyses of the uses of mobile online activities and mobile-specific offline activities using the model represented by Equation (2). We first examine the effects of fixed-line and mobile Internet speeds on the use of mobile online activities, and then show that there are no effects of fixed-line and mobile Internet speeds on the use of mobile-specific offline activities.

### **3.3.2 Data**

To estimate our empirical models, we use data from the second quarter of 2011, obtained from comScore MobiLens. The MobiLens data are constructed from detailed, quarterly surveys of the mobile activities of a nationally representative sample of U.S. mobile subscribers, who have been recruited from a large, demographically diverse population through a variety of recruitment methods. Each quarterly sample includes responses from more than 20,000 individual mobile subscribers. The survey asks mobile phone users about

their consumption behaviors across a wide variety of mobile activities, including whether they adopted a mobile data plan and usage frequencies for different mobile online and mobile-specific offline activities.

We combine the MobiLens data with local Internet coverage data (fixed-line and mobile Internet) obtained from the National Broadband Map (NBM). The National Broadband Map data (NBM) are generated and managed by the U.S. National Telecommunications and Information Administration, with assistance from the Federal Communications Commission (FCC). These data were first released in June 2010. NBM data have been used to compare broadband availability across geographic areas and demographic groups, which can inform policies to support private sector investments in deploying broadband (National Telecommunications and Information Administration, 2011). Because the NBM data are collected by individual states independently, the speed and availability measures in the NBM data could vary by collection methods and procedures across states. We can use the state fixed effects in our model to control for any differences in data collection processes.

The finest geographic level in the comScore MobiLens data is a consumer zip code; in contrast, the NBM data are reported at the census block level. We match zip codes with census blocks using the point-in-polygon method by determining if the centroid of a block fell within a polygon of a zip code (Gordon-Larsen et al. 2006; Henry and Boscoe 2008). We also conduct robustness checks with other criteria, including whether the centroid of a block was within a certain radius range (20 miles, 30 miles, 50 miles) of the centroid of a zip code. The results remained consistent. Summary statistics are shown in Table 3.1.

**Table 3.1 Summary Statistics**

Variable	Mean	SD	Min	Max
Adopt a mobile data plan	0.35	0.48	0.00	1.00
Fixed-line speed (mbps/Zip)	26.12	32.87	0.42	126.26
Mobile speed (mbps/Zip)	2.11	0.59	0.52	4.59
Log median income (\$/Zip)	10.88	0.36	5.80	12.32
Log population (Zip)	9.93	0.92	3.69	11.62
Percent bachelor's degree (Zip)	28.09	15.50	0.00	91.40
Number of mobile carriers (Zip)	4.37	0.87	1.00	7.00
Number of fixed-line Internet providers (Zip)	4.82	3.40	1.00	14.00
Number of household members	2.75	1.43	1.00	8.00
Length of mobile phone use (year)	3.73	0.63	1.00	4.00
Number of observations	28,117			

Notes: Summary statistics for Age, Gender, Education, Income, and Area are available on request.

We observe the usage frequency for many categories of mobile activities in our data, but we do not know actual number of minutes or actual amount of data consumption for each activity. We would like to examine the usage intensity across multiple categories of mobile online activities, rather than any particular category of activity. To do this, we apply cluster analysis and classify consumers into two clusters, according to whether they perform mobile online activities intensively. We aggregate usage frequency variables for a list of different categories of mobile online activities in our data (e.g., e-mail, search for information, social networking, read news, online banking, share photo/video etc.) using a k-medians clustering algorithm.<sup>18</sup> Specifically, on the basis of the usage frequencies of  $n$  categories of mobile

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<sup>18</sup> The results remain consistent with other clustering algorithms, such as k-means clustering or hierarchical clustering algorithms with different linkage criteria.

online activities, we partition all consumers into two clusters, such that each consumer belongs to the cluster with the nearest median vector.<sup>19</sup> Thus, one cluster of consumers frequently use all categories of mobile online activities, and the other use all categories of mobile online activities much less frequently.

Similarly, to classify consumers on the basis of whether they perform mobile-specific offline activities frequently, we use usage frequency variables for different mobile-specific offline activities (e.g., take photos, make videos) and conducted the cluster analysis according to the k-medians algorithm.<sup>20</sup> The cluster of consumers who perform mobile online activities more frequently did not correlate perfectly with the cluster of consumers who perform mobile-specific offline activities more frequently, so a consumer might engage in neither mobile online activities nor mobile-specific offline activities

### ***3.3.3 Identification Strategy***

A relationship between Internet speed and mobile Internet adoption and usage does not, in itself, mean that speed causes adoption and usage. For example, service providers might choose to improve service because mobile Internet adoption and usage is growing faster in a particular location. More importantly, there may be omitted variables that could be correlated with both Internet speed and mobile service adoption and usage, such as advertising expenditures by service providers. We apply instrumental variables in our linear probability model to address endogeneity concerns.

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<sup>19</sup> We also cluster the consumers into multiple groups as a robustness check. But the Calinski–Harabasz pseudo-F statistics show that this two-group clustering (more vs. less frequent) is more effective than using more than two groups to explain consumer’s heterogeneity, which suggests that it is very rare to have consumers who only use few online or offline categories very frequently while use other online or offline categories much less frequently.

<sup>20</sup> In our main analysis, we use take photos and take videos as mobile-specific offline activities. As a robustness check, we also include more mobile offline activities in our data, like play offline games and listen to offline music on mobile phones. The results remain very consistent.

The costs of delivering Internet service differ in ways that do not correlate with consumers' adoption and usage behavior (Kolko 2012). We use this fact to identify the effect of mobile and fixed-line Internet quality on mobile Internet adoption and usage. We instrument local mobile Internet speed by using historical coverage information in adjacent areas, namely, the number of mobile carriers that offered the service six years ago in areas adjacent to the focal zip code (Dai 2008).<sup>21</sup> An adjacent area is a zip code within the same Census city. We also conduct robustness checks with different definitions of adjacent areas—such as zip codes in the same county or within a certain radius range (50 miles, 30 miles)—and found consistent results. Because of the economies of scale or scope associated with providing mobile service in a focal area (Boer and Evans 1996), there is a high spatial correlation in installation and maintenance costs for mobile services across adjacent locations. Moreover, preexisting service by a carrier influences its current service plan, because of the sunk costs of its investment (Czernich et al. 2011). Therefore, the number of carriers offering service in adjacent areas six years prior should be closely associated with the quality of mobile service offered in the focal area, but the available mobile service offered six years ago in adjacent areas should not correlate with consumers' adoption or usage decisions in our sample period.

Next, we instrument for fixed-line Internet speed with a proxy of the engineering cost of wire service in the local exchange area, calculated according to the FCC's Hybrid Cost Proxy Model (HCPM) as of January 2000.<sup>22</sup> The HCPM is an economic engineering model

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<sup>21</sup> Mian Dai from Drexel University for provided us with historical data on mobile carrier service, collected in December 2005 from letstalk.com, a leading online wireless service retailer. Our choice of using a six year lag for our instrument is because of the time period when these data were collected and our sample year (2011).

<sup>22</sup> James E. Prieger from Pepperdine University provided us these proxy cost data for wire services in the local exchange area.

that calculates the cost of providing local wire service using efficient technology, given an area's geographic terrain and subscriber density (Prieger 2003). Proxy costs are not available for approximately one-third of the wire centers (mostly smaller carriers), so in these cases, we use the cost for the nearest wire center available (Prieger 2003). Wire center boundaries are matched to zip code areas. The costs of providing local wire service correlate strongly with the quality of the provider's fixed-line Internet services but are unlikely to correlate with consumers' mobile Internet adoption or usage decisions.

To further verify that our findings are not driven by potential endogeneity concerns, we examine how the local fixed-line and mobile Internet speeds influenced the usage of mobile-specific offline activities. Mobile Internet speed should have little impact on the usage of mobile-specific offline activities, because their consumption does not require a mobile Internet connection. Similarly, fixed-line Internet speed should not affect a consumer's use of mobile-specific offline activities because mobile-specific offline activities cannot easily be performed on the fixed-line Internet.

A potential concern associated with our Internet speed data is that the fixed-line Internet and mobile Internet speeds might vary consistently across different locations. If they are perfectly correlated, we can identify only the net effects, not the distinct effects of fixed-line and mobile Internet speed. However, the Spearman rank correlation between the fixed-line Internet and mobile Internet speeds across different U.S. locations in our data is 0.32, which indicates that these speeds did not correlate strongly.

## **3.4 Results**

### ***3.4.1 Main Results***

We present the estimated coefficients from the models as represented by Equation (1) and (2) in Table 3.2 both without and with instrumental variables. The coefficients of the number of carriers offering service in adjacent areas six years prior and the proxy costs to provide wire line service are significant (at 1%) when we instrument them on the fixed-line Internet speed and mobile Internet speed, suggesting they are strong instruments.<sup>23</sup> A comparison of the models with and without the use of instrumental variables reveal that the parameters of interest—the positive coefficient of *Mobile Speed* and the negative coefficient of *Fixed-line Speed*—become less positive when instrumental variables are used, consistent with the anticipated omitted variable bias. Locations with high quality Internet service likely differ in unobserved ways that correlate positively with Internet adoption and usage, which in turn should cause a positive coefficient bias. In Columns 1 and 2 of Table 3.2, the positive coefficient of *Mobile Speed* suggests that better local mobile Internet coverage increases the likelihood of adopting mobile data plans; the negative coefficient of *Fixed-line Speed* suggests that if the local fixed-line connection is insufficient, consumers get online through their mobile phones as a substitute. Specifically, with the use of instrumental variables in Column 2, one unit (1mbps) increase in mobile Internet speed leads to a 10.11 percentage point increase in the probability of choosing a mobile data plan, on average. The overall average probability of adopting a mobile data plan is 0.35, so this increase represents a 28.89% increase. In contrast, one unit (1mbps) increase in the fixed-line Internet speed decreases the probability of choosing a mobile data plan by 5.23 percentage points, equivalent to a 14.94% drop.

In Columns 3 and 4 of Table 3.2, the significantly positive coefficient of *Mobile Speed* and significantly negative coefficient of *Fixed-line Speed* also affirm that mobile Internet

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<sup>23</sup> The estimation results of the first stage in the 2SLS estimation for the endogenous variables are in Table B1 in the Appendix B.

speed is positively associated with usage intensity of mobile online activities, but fixed-line Internet speed is negatively associated with this intensity. If mobile Internet speed increased by one unit (1 mbps), consumers are more likely, by 12.63 percentage points, to conduct their mobile online activities more frequently. The overall probability of performing mobile online activities more frequently in our data is 0.28, so this increase was equivalent to 45.11%. If the fixed-line Internet speed increases by one unit (1mbps), consumers are 5.97 percentage points (21.32%) less likely to conduct frequent mobile online activities though.

**Table 3.2 Mobile/Fixed-Line Internet Speed and Mobile Internet Adoption and Usage**

	Mobile Internet Adoption		Mobile Online Usage		Mobile Offline Usage	
	LPM	LPM IV	LPM	LPM IV	LPM	LPM IV
<b>VARIABLES</b>	<b>(1)</b>	<b>(2)</b>	<b>(3)</b>	<b>(4)</b>	<b>(5)</b>	<b>(6)</b>
<i>Fixed-line Speed</i>	-0.0428** (0.0195)	-0.0523** (0.0248)	-0.0445** (0.0211)	-0.0597** (0.0269)	-0.0086 (0.0096)	-0.0098 (0.0102)
<i>Mobile Speed</i>	0.1847*** (0.0462)	0.1011*** (0.0251)	0.2034*** (0.0375)	0.1263*** (0.0235)	0.0153 (0.0173)	0.0163 (0.0187)
<i>Log Median Income (Zip)</i>	0.1335*** (0.0131)	0.1406** (0.0548)	0.1730** (0.0131)	0.1625** (0.0548)	0.1484** (0.0621)	0.1853* (0.0945)
<i>Log Population (Zip)</i>	0.0625* (0.0356)	0.0553** (0.0250)	0.0527* (0.0249)	0.0392* (0.0230)	0.0928* (0.0467)	0.0834* (0.0413)
<i>Percent Bachelor's Degree (Zip)</i>	0.0008 (0.0005)	0.0073* (0.0035)	0.0018* (0.0009)	0.0084* (0.0041)	0.0010 (0.0006)	0.0023 (0.0026)
<i>Individual Controls</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Mobile &amp; Fixed-line Carrier Dummies</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Constants</i>	1.3285* (0.6372)	1.1006* (0.5230)	0.8325*** (0.2146)	0.7009*** (0.1983)	0.8127*** (0.2048)	0.7687*** (0.2334)
Observations	28,117	28,117	28,117	28,117	28,117	28,117

\*Significant at 10%; \*\*Significant at 5%; \*\*\*Significant at 1%.

Notes: The individual controls are age, gender, income, area, education, number of people in the household, length of mobile service usage, and state dummies. Heteroskedasticity-robust standard errors appear in parentheses.

Columns 5 and 6 of Table 3.2 include the estimation results for the impacts of fixed-line and mobile Internet speeds on mobile data plan adoption and mobile-specific offline usage. As we expect, the insignificant coefficient of Mobile Speed in Columns 5 and 6 suggests that mobile Internet speed does not significantly affect usage of mobile-specific offline activities. The insignificant coefficient of Fixed-line Speed in Columns 5 and 6 also confirms that fixed-line Internet speed does not affect usage of mobile-specific offline activities. The fixed-line Internet platform is not a good substitute for mobile-specific offline activities. These results are consistent with the predictions of our theoretical framework but not with an explanation based on the effects of the omitted variables correlated with speed.

### ***3.4.2 Robustness Checks***

We conduct different analyses to test the robustness of our main findings. First, to further probe the effects of omitted variable bias on our results, we add more area demographic control variables (percentage of men in a zip code, percentage of people younger than 45 years in a zip code, percentage of homeownership in a zip code, percentage of full employment in a zip code, average travel time to work in a county). As we show in Table 3.3, adding these controls does not change the estimates much; the impact of unobservable variables would have to be great, relative to the impact of the observable variables, if omitted variables were to influence the results (Altonji, Elder, and Taber 2005).

**Table 3.3 Mobile/Fixed-Line Internet Speed and Mobile Internet Adoption and Usage:  
Additional Area Level Controls**

	<b>Mobile Internet Adoption</b>	<b>Mobile Online Usage</b>	<b>Mobile Offline Usage</b>
<b>VARIABLES</b>	<b>(1)</b>	<b>(2)</b>	<b>(3)</b>
<i>Fixed-line Speed</i>	-0.0511** (0.0240)	-0.0573** (0.0257)	-0.0078 (0.0086)
<i>Mobile Speed</i>	0.0968*** (0.0246)	0.1124*** (0.0229)	0.0139 (0.0166)
<i>Log Median Income (Zip)</i>	0.0867** (0.0393)	0.0936** (0.0415)	0.0822** (0.0386)
<i>Log Population (Zip)</i>	0.0496*** (0.0136)	0.0425*** (0.0114)	0.0654*** (0.0153)
<i>Percent Bachelor's Degree (Zip)</i>	0.0151* (0.0076)	0.0162* (0.0083)	0.0147* (0.0075)
<i>Percent Male (Zip)</i>	0.0036 (0.0041)	-0.0046 (0.0074)	0.0024 (0.0045)
<i>Percent Age &lt; 45 (Zip)</i>	0.0285 (0.0263)	0.0337 (0.0318)	0.0284 (0.0248)
<i>Percent Homeownership (Zip)</i>	0.0172 (0.0136)	0.0171 (0.0135)	0.0153 (0.0183)
<i>Percent Employment (Zip)</i>	0.0316 (0.0385)	0.0275 (0.0286)	0.0357 (0.0375)
<i>Average travel time to work (County)</i>	0.0573 (0.0426)	0.0449 (0.0424)	0.0396 (0.0401)
<i>Individual Controls</i>	Yes	Yes	Yes
<i>Mobile &amp; Fixed-line Carrier Dummies</i>	Yes	Yes	Yes
<i>Constants</i>	2.2898*** (0.3182)	2.2281*** (0.3918)	2.3890*** (0.3846)
Observations	28,117	28,117	28,117

\*Significant at 10%; \*\*Significant at 5%; \*\*\*Significant at 1%.

Notes: The individual controls are age, gender, income, area, education, number of people in the household, length of mobile service usage, and state dummies. Heteroskedasticity-robust standard errors appear in parentheses. We use the linear probability model with instrumental variables.

Although we cannot completely eliminate potential omitted variable bias, it is worth noting that many sources of potential omitted variables would tend to bias the coefficients of

the fixed-line Internet speed positively. That is, places where fixed-line Internet speed is high likely are places where mobile Internet adoption and usage are high, for other unobserved reasons. For example, if more intense regional Internet adoption leads to both local Internet service improvements and more mobile Internet adoption and usage (Belo and Ferreira 2012), the fixed-line Internet speed would be positively associated with mobile Internet adoption and usage. Therefore, the negative impacts of fixed-line Internet speed on mobile Internet adoption and usage even might be underestimated due to the potential omitted variable bias.

Second, the estimates from a linear probability model can be biased and inconsistent if predicted values from a linear probability model are outside the unit interval. We apply the probit model with instrumental variables to test the robustness of our linear probability model. Table 3.4, Panel A, includes the estimation results for the impacts of fixed-line and mobile Internet speeds on mobile data plan adoption and usage of mobile online activities and mobile-specific offline activities, with and without instrumental variables. Because the estimated coefficients reflect a non-linear logit model, in Panel B of Table 3.4 we report the corresponding average marginal effect of a one unit change in the variable of interest on the probability of choice across all observations in the sample, computing the average marginal effects across all covariate values in the distribution. The significant positive marginal effect of Mobile Speed and the significant negative marginal effect of Fixed-line Speed are consistent with our findings using a linear probability model.<sup>24</sup>

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<sup>24</sup> To further test the robustness of our model, we apply a two-stage logit model using a control function approach with instrumental variables, in which consumers first choose whether to adopt a mobile data plan, and then choose whether to perform mobile activities more intensively or not. We find similar results. The estimation results are reported in Table C1 and C2 in the Appendix C.

**Table 3.4. Mobile/Fixed-Line Internet Speed and Mobile Internet Adoption and Usage: Probit Model**

**A. Coefficient Estimates**

	Mobile Internet Adoption		Mobile Online Usage		Mobile Offline Usage	
	Probit	Probit IV	Probit	Probit IV	Probit	Probit IV
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
<i>Fixed-line Speed</i>	-0.0003 (0.0002)	-0.0007* (0.0003)	-0.0004 (0.0003)	-0.0010* (0.0005)	-0.0003 (0.0002)	-0.0004 (0.0003)
<i>Mobile Speed</i>	0.0868*** (0.0174)	0.0638** (0.0283)	0.0927** (0.0401)	0.0712** (0.0313)	0.0652 (0.0571)	0.0452 (0.0326)
<i>Log Median Income (Zip)</i>	0.1274** (0.0573)	0.1062** (0.0416)	0.2002*** (0.0321)	0.1773** (0.0703)	0.2011*** (0.0327)	0.1471** (0.0733)
<i>Log Population (Zip)</i>	0.0474** (0.0202)	0.0410** (0.0184)	0.0628*** (0.0076)	0.0458* (0.0225)	0.0656*** (0.0089)	0.0376* (0.0227)
<i>Percent Bachelor's Degree (Zip)</i>	0.0033* (0.0015)	0.0030* (0.0014)	0.0024** (0.0008)	0.0016* (0.0007)	0.0021** (0.0007)	0.0022 (0.0014)
<i>Individual Controls</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Mobile &amp; Fixed-line Carrier Dummies</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Constants</i>	2.4989*** (0.8313)	1.9545*** (0.7324)	2.1974*** (0.7729)	2.2810*** (0.8694)	2.1781*** (0.6826)	2.1665*** (0.7347)
Observations	28,117	28,117	28,117	28,117	28,117	28,117

**B. Average Marginal Effects**

	Mobile Internet Adoption		Mobile Online Usage		Mobile Offline Usage	
	Probit	Probit IV	Probit	Probit IV	Probit	Probit IV
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
<i>Fixed-line Speed</i>	-0.0125* (0.0063)	-0.0178* (0.0089)	-0.0136* (0.0068)	-0.0195* (0.0098)	-0.0034 (0.0044)	-0.0053 (0.0068)
<i>Mobile Speed</i>	0.2017** (0.0822)	0.1577** (0.0685)	0.2175** (0.0878)	0.1762** (0.0739)	0.0947 (0.0938)	0.0812 (0.0759)

\*Significant at 10%; \*\*Significant at 5%; \*\*\*Significant at 1%.

Notes: The individual controls are age, gender, income, area, education, number of people in the household, length of mobile service usage, and state dummies. Heteroskedasticity-robust standard errors appear in parentheses. In Panel B, we present the marginal effect of a one unit change (1mbps) in each variable on the probability of the outcome, computed according to the average marginal effects across all covariate values in the distribution. The effects are calculated for each individual, and then averaged across individuals in the sample. The results remain robust to marginal effects at the mean values of the covariates.

Third, to address the concern that usage frequency of mobile activities might not be highly correlated with the actual amount of consumption, we use monthly mobile service cost as an alternative dependent variable to examine whether and how the local fixed-line and mobile Internet speeds are associated with monthly mobile service costs. Although we do not know which specific mobile plan a consumer adopts and a consumer's actual mobile service consumption volume in our data, we do observe consumers' monthly mobile service costs. Monthly mobile service costs vary mostly because of the mobile data consumption, while the cost of voice and text does not vary much across different mobile service plans and different usage patterns. Therefore, monthly mobile service costs should be highly correlated with consumers' data plan choice and data usage volume. Because the monthly mobile service cost is coded as a categorical variable in our data,<sup>25</sup> we utilize the ordered probit model using control function with instrumental variables (Imbens and Wooldridge 2007; Wooldridge 2014). In Column 1 of Table 3.5, the coefficient estimate of the local fixed-line Internet speed is significantly negative, and the coefficient estimate of the local mobile fixed-line Internet speed is significantly positive, consistent with our main findings.

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<sup>25</sup> Categories for monthly mobile service cost are: less than \$20, \$20-\$40, \$41-\$60, \$61-\$80, \$81-\$100, \$101-\$120, \$121-\$140, \$141-\$160, \$161-\$180, \$181-\$200, more than \$200.

**Table 3.5. The Effect of Mobile/Fixed-Line Internet Speed on Mobile Service Cost and Usage of Different Categories of Activities**

	Monthly Mobile Service Cost	Mobile Online Usage				Mobile Offline Usage			
		Email	Social Networking	News	Search	Take Photos	Take Videos	Play Games	Listen to Music
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
<i>Fixed-line Speed</i>	-0.0006* (0.0003)	-0.0008* (0.0004)	-0.0021** (0.0008)	-0.0006* (0.0003)	-0.0014* (0.0006)	-0.0004 (0.0004)	-0.0005 (0.0004)	-0.0004 (0.0003)	-0.0003 (0.0002)
<i>Mobile Speed</i>	0.0586*** (0.0202)	0.0837*** (0.0236)	0.0669** (0.0263)	0.0437** (0.0165)	0.0501** (0.0217)	0.0384 (0.0387)	0.0529 (0.0426)	0.0398 (0.0373)	0.0455 (0.0426)
<i>Individual and Area Controls</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Mobile &amp; Fixed-line Carrier Dummies</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,117	28,117	28,117	28,117	28,117	28,117	28,117	28,117	28,117

\*Significant at 10%; \*\*Significant at 5%; \*\*\*Significant at 1%.

Notes: We use the ordered probit model with instrumental variables. Monthly mobile service cost is coded as a categorical variable in our data: less than \$20, \$20-\$40, \$41-\$60, \$61-\$80, \$81-\$100, \$101-\$120, \$121-\$140, \$141-\$160, \$161-\$180, \$181-\$200, more than \$200. Usage frequency is coded as a categorical variable in our data: never used this service; used it before but not in the previous month; used it once to three times in the previous month; used it at least once each week in the previous month; or used it almost every day in the previous month. The individual and area controls are age, gender, income, area, education, number of people in the household, length of mobile service usage, state dummies, log median income (Zip), log population (Zip) and percent bachelor's degree (Zip). Heteroskedasticity-robust standard errors appear in parentheses.

Fourth, classifying consumers into two clusters according to whether they perform all categories of mobile online or mobile-specific offline activities frequently may not be able to fully capture consumers' different possible mobile usage patterns. For example, consumers may use only few categories of online activities very frequently while use other online activities much less frequently. To further explore the correlations among different categories of mobile online and

offline activities, we examine how the local fixed-line and mobile Internet speeds influence the usage of each category of mobile activities. Consumers choose how much they would like to consume for a specific category of mobile activities (i.e. emails, social networking, news, search information, take photos, take videos, play offline games, listen to offline music). We apply the ordered probit model using control function with instrumental variables. We use the usage frequency of one category of mobile activities as the dependent variable, because usage frequency is coded as a categorical variable in our data. As shown in Column 2 to 9 of Table 3.5, we find very consistent results for different categories of mobile online activities that the impact of the fixed-line Internet speed is significantly negative, and the impact of the mobile Internet speed is significantly positive. We also find the fixed-line and mobile Internet speed are not correlated with different categories of mobile offline activities. The findings further support our clustering results that consumers' online and offline mobile usage are very consistent across different categories of activities.

Last, to further address the concern that our results might be driven by omitted individual or zip code-level variables, instead of using our cross-sectional data in one time period, we construct a pseudo-panel across two time periods (Q2 2010 and Q2 2011) by grouping individuals into cohorts based on zip codes. Pseudo panel analysis is undertaken by aggregating the observational units in the cross-sectional data into "cohorts", matching cohorts, and running panel analysis on the synthesized cohorts (Browning, Deaton and Irish 1985; Deaton 1985; Verbeek and Vella 2005). There are 2,638 matching cohorts (or zip codes) across the two time periods from around 11,000 zip codes in one time period, with an average of 2.91 individuals per cohort. We use the first differenced fixed-effects model, and instrument the differences in fixed-line and mobile internet speed between the two periods

using our instrumental variables. As shown in Table 3.6, the fixed-line Internet speed is significantly negatively associated with the likelihood of mobile Internet adoption and usage of mobile online activities, and the mobile Internet speed is significantly positively associated with the likelihood of mobile Internet adoption and usage of mobile online activities, while fixed-line and mobile Internet speed do not have significant impact on the usage of mobile-specific offline activities, consistent with our main results from cross-sectional analysis.

**Table 6. Mobile/Fixed-Line Internet Speed and Mobile Internet Adoption and Usage: Pseudo-Panel Zip Code Fixed-Effects (Q2 2010, Q2 2011)**

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Mobile Internet Adoption	Mobile Internet Adoption - IV	Mobile Online Usage	Mobile Online Usage - IV	Mobile Offline Usage	Mobile Offline Usage - IV
<i>ΔFixed-line Speed</i>	-0.0187* (0.0094)	-0.0217* (0.0109)	-0.0204* (0.0102)	-0.0231* (0.0116)	-0.0196 (0.0184)	-0.0228 (0.0114)
<i>ΔMobile Speed</i>	0.0714** (0.0331)	0.0564** (0.0252)	0.0763** (0.0342)	0.0625** (0.0280)	0.0328 (0.0316)	0.0312 (0.0304)
<i>Individual Controls</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Mobile &amp; Fixed-line Carrier Dummies</i>	No	No	No	No	No	No
<i>Constants</i>	0.0215** (0.0086)	0.0183* (0.0092)	0.0207** (0.0080)	0.0179* (0.0090)	0.0194* (0.0097)	0.0142* (0.0071)
R <sup>2</sup>	0.6123	0.6289	0.6101	0.6281	0.6048	0.6216
Number of cohorts	2,638	2,638	2,638	2,638	2,638	2,638

\*Significant at 10%; \*\*Significant at 5%; \*\*\*Significant at 1%.

Notes: We construct a pseudo-panel across two time periods (Q2 2010 and Q2 2011) by grouping individuals into cohorts based on zip code. There are 2,638 matching cohorts (or zip codes) across the two time periods from about 11,000 zip codes in one time period, with an average of 2.91 individuals per cohort. For about 11,000 zip codes in one time period, around 80% of them are from a MSA, and about 50% of zip codes have more than one individual. Among 2,638 matching cohorts (or zip codes), 84.6% of them are from a MSA. Fixed-line and

mobile Internet speeds are the average download speeds at the zip code level. Other variables are corresponding cohort-level averages. We use the first differenced model, and instrument the differences in fixed-line and mobile Internet speed between the two periods using our instrumental variables. The individual time-varying controls are age, gender, income, area, education, number of people in the household, length of mobile service usage. Heteroskedasticity-robust standard errors appear in parentheses.

### ***3.4.3 Interaction Effects***

#### ***3.4.3.1 Local and Consumer Characteristics with Substitution***

We report that the speed of the fixed-line Internet has a negative impact on mobile Internet adoption and usage. We next identify how the competitive effect between the mobile Internet and the fixed-line Internet varies across different consumer segments, if any.

On average, the fixed-line Internet offers higher speeds than the mobile Internet (FCC 2013). In the NBM data for example, the average fixed-line Internet speed is 25.34 mbps, and the average mobile Internet speed is 1.87 mbps in the second quarter of 2011. But in areas with relatively low fixed-line Internet speeds, these speeds are more comparable, which may make the fixed-line and mobile Internet closer substitutes for consumers when they perform online activities. For instance, in Atlanta, Georgia, the average fixed-line Internet speed is 45.72 mbps, and the average mobile Internet speed is 3.68 mbps, but in Valdosta, a small town in South Georgia, the average fixed-line Internet speed is 8.23 mbps, and the average mobile Internet speed is 2.21 mbps. The fixed-line and mobile Internet speeds are much more comparable in Valdosta than that in Atlanta. The utility of adopting and using the mobile Internet for consumers in areas with relatively lower fixed-line Internet speeds increase, and they are more likely to rely on the mobile Internet to perform online activities, because the connection speed is similar to that offered by the poor fixed-line Internet. In short, the fixed-line and mobile Internet are closer competitors when fixed-line speeds are low.

We next consider the effects of a consumer's age on the degree of competitive effect. Younger users exhibit a stronger substitution effect between the mobile and fixed-line Internet. Although the mobile Internet generally is slower than the fixed-line Internet, younger consumers might be less sensitive to this slower speed, because their opportunity cost for time is lower than that for older people (Goldfarb and Prince 2008; Krantz-Kent and Stewart 2007; Posner 1995). Moreover, younger consumers likely use the features of a mobile phone more effectively and can compensate for the smaller screen when conducting online activities. Therefore, younger consumers may view the mobile Internet as a closer competitor for the fixed-line Internet than relatively older consumers.

To capture the relative quality of the local fixed-line Internet, we create a dummy variable for each zip code,  $LowFixedSpeed_z$ , which is equal to 1 if the fixed-line Internet connection speed is lower than the 25th percentile of the fixed-line Internet speed across all zip codes in the sample (7.7 mbps), and 0 otherwise. To capture consumers' ages, we create another dummy variable for each individual,  $Young_i$ , equal to 1 if the consumer's age category is either 18–24 or 25–34, as 25–34 represents the 25th percentile of the age categories across the entire sample, and 0 otherwise. Because some of the key moderators may correlate, we focus on the full model including both interaction variables for both adoption and usage. Specifically, the likelihood of individual  $i$  in zip code  $z$  of adopting a mobile data plan is:

$$(3)$$

$$Y_{iz}^{Adoption} = \alpha^{Adoption} + \beta^{Adoption} X_i + \delta^{Adoption} D_z + \gamma^{Adoption} Fixed_z + \theta^{Adoption} Mobile_z + \pi_1^{Adoption} LowFixedSpeedArea_z + \pi_2^{Adoption} Fixed_z \times LowFixedSpeedArea_z + \pi_3^{Adoption} Mobile_z \times LowFixedSpeedArea_z + \sigma_1^{Adoption} Young_i + \sigma_2^{Adoption} Fixed_z \times Young_i + \sigma_3^{Adoption} Mobile_z \times Young_i + \sum_{j=1}^7 m_j^{Adoption} MoCarrier_{jz} + \sum_{l=1}^7 \rho_l^{Adoption} FixCarrier_{lz} + \sum_{k=1}^{50} d_k^{Adoption} S_{ik} + \varepsilon_{iz}^{Adoption},$$

and the model for usage intensity is similar.

The estimated coefficients of the model represented by Equation (3) for mobile Internet adoption and usage appear in Table 3.7. We use the number of carriers offering service in adjacent areas six years prior, proxy costs to provide wire line service, and their interactions with  $Young_i$  and  $LowFixedSpeed_z$  as instruments for *Fixed-line Speed*, *Mobile Speed*, *Fixed-line Speed × Young*, *Mobile Speed × Young*, *Fixed-line Speed × Low Fixed-line Speed Area*, and *Mobile Speed × Low Fixed-line Speed Area*. The coefficient estimates reveal that the effects of the fixed-line Internet speed on mobile Internet adoption and usage are moderated by variation in both fixed-line Internet speed and consumer age.

The coefficients of *Fixed-line Speed × Young* are negative and statistically significant in both Column 1 and 2 of Table 3.7. These results suggest that younger consumers will display stronger substitution between the mobile and fixed-line Internet. Specifically, given the same one unit decrease (1 mbps) in the fixed-line Internet speed, the increase in the probability that younger consumers choose a mobile data plan is 2.73 percentage points (7.80%) greater than the probability that other consumers do so. The increase in the probability of performing mobile online activities more frequently is 2.94 percentage points (10.50%) higher for younger, compared with older consumers.

**Table 3.7. Mobile/Fixed-Line Internet Speed and Mobile Internet Adoption and Usage: Age and Fixed-Line Internet Speed Interaction Effects**

	<b>Mobile Internet Adoption</b>	<b>Mobile Online Usage</b>	<b>Mobile Offline Usage</b>
<b>VARIABLES</b>	<b>(1)</b>	<b>(2)</b>	<b>(3)</b>
<i>Fixed-line Speed</i>	-0.0349* (0.0175)	-0.0395* (0.0196)	-0.0128 (0.0163)
<i>Mobile Speed</i>	0.1011*** (0.0251)	0.1263*** (0.0135)	0.0158 (0.0147)
<i>Young</i>	0.0314** (0.0129)	0.0321** (0.0136)	0.0267** (0.0128)
<i>Fixed-line Speed × Young</i>	-0.0273** (0.0130)	-0.0294** (0.0142)	0.0102 (0.0099)
<i>Mobile Speed × Young</i>	-0.0319 (0.0367)	-0.0438 (0.0392)	-0.0381 (0.0474)
<i>Low Fixed-line Speed Area</i>	-0.0097* (0.0048)	-0.0102* (0.0051)	0.0205 (0.0272)
<i>Fixed-line Speed × Low Fixed-line Speed Area</i>	-0.0256** (0.0124)	-0.0286** (0.0137)	-0.0143 (0.0158)
<i>Mobile Speed × Low Fixed-line Speed Area</i>	0.0236 (0.0215)	0.0204 (0.0219)	0.0376 (0.0318)
<i>Log Median Income (Zip)</i>	0.0612*** (0.0211)	0.0683** (0.0295)	0.0815** (0.0326)
<i>Log Population (Zip)</i>	0.0664*** (0.0098)	0.0390* (0.0236)	0.0276 (0.0247)
<i>Percent Bachelor's Degree (Zip)</i>	0.0037*** (0.0007)	0.0031** (0.0013)	0.0022 (0.0014)
<i>Individual Controls</i>	Yes	Yes	Yes
<i>Mobile &amp; Fixed-line Carrier Dummies</i>	Yes	Yes	Yes
<i>Constants</i>	2.1987*** (0.3917)	2.5234*** (0.4875)	2.1298*** (0.3903)
Observations	28,117	28,117	28,117

\*Significant at 10%; \*\*Significant at 5%; \*\*\*Significant at 1%.

Notes: The individual controls are age, gender, income, area, education, number of people in the household, length of mobile service usage, and state dummies. Heteroskedasticity-robust standard errors appear in parentheses. We use the linear probability model with instrumental variables.

The coefficients of *Fixed-line Speed × Low Fixed-line Speed Area* also are negative and statistically significant in both Columns 1 and 2 of Table 3.7, suggesting that that in areas with lower fixed-line Internet speeds, consumers are more likely to adopt the mobile Internet and perform mobile online activities, substituting for the slow fixed-line Internet connection. We find that the same one unit increase (1mbps) in fixed-line Internet speed decreased the probability of choosing a mobile data plan among consumers in areas with higher average fixed-line Internet speed by 2.56 percentage points (7.31%) less than it does among consumers in areas with lower fixed-line Internet speeds. The decrease in the probability of performing mobile online activities more frequently is 2.86 percentage points (10.21%) less for consumers in areas with higher, rather than lower, fixed-line Internet speeds.

In contrast, the estimated coefficients of *Mobile Speed × Low Fixed-line Speed Area* in both Columns 1 and 2 are insignificant in Table 3.7. The impact of mobile Internet speed on mobile internet adoption and usage does not depend on different local fixed-line Internet speeds, as we expect. Furthermore, the estimated coefficients of *Mobile Speed × Young* are insignificantly negative, which offers an interesting result. Although young consumers appear more sensitive than older consumer to changes in fixed-line speed, mobile Internet speed has equivalently positive impacts on mobile Internet adoption and usage by consumers of all ages. One possible explanation for this result is that younger consumers' preferences for mobile Internet access make their behavior less sensitive to changes in mobile service quality. In support of this view, Table 3.7 indicates that younger consumers are more likely to adopt and use all aspects of the mobile Internet, all else being equal. However, more investigation into

this question is needed. Finally, we find no significant interaction effects for mobile-specific offline usage in Column 3 of Table 3.7, as we expect.

### ***3.4.3.2 Robustness Checks for Interaction Effects***

To determine age and area effects separately, instead of using dummy variables in a full model, we apply the linear probability model with instrumental variables to the subpopulations of our sample. Columns 1 and 2 of Table 3.8 show the estimation results for younger consumers (<35), and the estimation results for consumers older than 35 are listed in Column 3 and 4. Column 5 and 6 include the estimation results for areas with lower fixed-line Internet speeds (<7.7 mbps), and Column 7 and 8 show the results for areas with higher fixed-line Internet speeds. The coefficients of *Fixed-line Speed* for younger consumers are more negative than those for older consumers. Similarly, the coefficients of *Fixed-line Speed* for areas with lower fixed-line Internet speeds are more negative than those in areas with higher fixed-line Internet speeds. That is, younger consumers and consumers in areas with lower fixed-line Internet speeds exhibit stronger substitution effect between the fixed-line and mobile Internet, consistent with the results in Table 3.7.

We examine the robustness of our results to different cutoff points to define the dummy variables for younger consumers and lower fixed-line Internet speed areas. To do this, we conduct another analysis based on a spline model for each variable, namely, with interactions for all the fixed-line Internet speed percentile dummies (10%, 25%, 50%, 75%, 90%) and interactions for all age categories (18–24, 25–34, 35–44, 45–54, 55–64, 65+ years). The estimated coefficients for the interactions between fixed-line speed and the percentile dummies of fixed-line Internet speed are significantly negative (i.e., stronger substitution) at

10% and 25% but insignificant for other percentiles. The estimated coefficients for the interactions between fixed-line speed and the age categories are significantly negative (i.e., stronger substitution) for 18–24 and 24–35 years but insignificant for the other age categories.<sup>26</sup> Thus, consumers younger than 35 years and those living in areas with a fixed-line Internet speed lower than the 25th percentile exhibit stronger substitution between the two Internet platforms.

**Table 3.8. Mobile/Fixed-Line Internet Speed and Mobile Internet Adoption and Usage: Age and Fixed-Line Internet Speed Split Samples**

	Split Samples, Young		Split Samples, Old		Split Samples, Low Speed		Split Samples, High Speed	
	Mobile Internet Adoption	Mobile Online Usage	Mobile Internet Adoption	Mobile Online Usage	Mobile Internet Adoption	Mobile Online Usage	Mobile Internet Adoption	Mobile Online Usage
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Fixed-line Speed</i>	-0.0662** (0.0323)	-0.0798** (0.0372)	-0.0416** (0.0200)	-0.0493** (0.0235)	-0.0648** (0.0309)	-0.0741** (0.0336)	-0.0439** (0.0205)	-0.0516** (0.0248)
<i>Mobile Speed</i>	0.0947*** (0.0315)	0.1128** (0.0384)	0.1135*** (0.0391)	0.1314*** (0.0412)	0.1108*** (0.0372)	0.1294*** (0.0399)	0.0985*** (0.0316)	0.1247*** (0.0379)
<i>Log Median Income (Zip)</i>	0.1705** (0.0823)	0.1676** (0.0794)	0.2106** (0.0923)	0.2215** (0.1006)	0.1984** (0.0868)	0.2149** (0.0984)	0.1605** (0.0784)	0.1576** (0.0737)
<i>Log Population (Zip)</i>	0.0571*** (0.0162)	0.0487*** (0.0104)	0.0632*** (0.0179)	0.0621** (0.0297)	0.0591*** (0.0117)	0.0525*** (0.0121)	0.0648*** (0.0183)	0.0672** (0.0313)
<i>Percent Bachelor's Degree (Zip)</i>	0.0033* (0.0017)	0.0027* (0.0014)	0.0021** (0.0008)	0.0018** (0.0007)	0.0045** (0.0020)	0.0022* (0.0011)	0.0037** (0.0014)	0.0031** (0.0013)
<i>Individual Controls</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Mobile &amp; Fixed-line Carrier Dummies</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

<sup>26</sup> These detailed results are available on request.

<i>Constants</i>	2.2898*** (0.3182)	2.3890*** (0.3846)	2.2281*** (0.3918)	2.2814*** (0.3163)	3.1038*** (0.3918)	3.2814*** (0.4163)	2.6298*** (0.3257)	2.7190*** (0.3592)
Observations	9,483	9,483	18,634	18,634	7,029	7,029	21,088	21,088

\*Significant at 10%; \*\*Significant at 5%; \*\*\*Significant at 1%.

Notes: The individual controls are age, gender, income, area, education, number of people in the household, length of mobile service usage, and state dummies. Heteroskedasticity-robust standard errors appear in parentheses. We use the linear probability model with instrumental variables.

### 3.5 Discussion and Conclusion

#### 3.5.1 Summary

With this study, we seek to investigate how the quality of a possible substitute influences the adoption and usage of the mobile Internet. Prior research on channel competition has focused on the competition between online and offline channels (e.g., e.g. Balasubramanian 1998; Brynjolfsson, Hu and Rahman 2009; Forman, Ghose and Goldfarb 2009), but we know less about consumers' decisions across different online channels. Such an understanding is very important as with various emerging online channels, consumers rely more and more on online channels to perform different categories, like purchasing, social networking and searching information.

Considering the potential for channel competition and multichannel consumption behavior, we the conditions that mobile Internet providers can compete with fixed-line Internet providers. We find, using large-scale survey data and public Internet speed data, robust empirical evidence of a negative impact of local fixed-line Internet speed on mobile Internet adoption and usage. Thus, we offer evidence of substitution between the fixed-line and mobile Internet. This substitution effect is stronger among younger consumers, likely because these consumers are less sensitive to slower mobile Internet speeds and more

accepting of the features of mobile devices. Because fixed-line and mobile Internet speeds are comparable in areas with relatively low fixed-line Internet speeds, we also show that consumers living in such areas exhibit stronger substitution between the fixed-line and mobile Internet. Better local mobile Internet coverage also could lead to a higher likelihood of adopting and using mobile Internet services.

### ***3.5.2 Managerial and Policy Implications***

The question of whether and how fixed-line and mobile Internet compete with each other has important implications for public policy. Telecommunication policy makers worry that market structures for mobile service provision are very concentrated. Most large mobile service providers face minimal competition from just a few other large mobile carriers. In introducing its National Broadband Plan to improve Internet access, the FCC (2010) shows that 98% of the U.S. population lived in census tracts with at least one 3G mobile provider, of which 77% live in tracts with three providers, 12% have two, and 9% have one. Similarly, a lack of competition characterizes the fixed-line Internet market. According to the National Broadband Plan, most households can obtain fixed-line service from only one of two large firms in their area: 78% can choose between two providers, 13% have access to one, and 5% have none. Only 4% of the U.S. population lives in a location with three or more suppliers (FCC 2010). However, we find robust evidence that the mobile Internet serves as a substitute for the fixed-line Internet, and consumers switch channels if they do not receive sufficiently fast data delivery. The resulting competition between mobile carriers and fixed-line Internet providers should alleviate some concerns in both the mobile and the Internet markets.

Our findings also have important implications for mobile service providers. Carrier infrastructure investments are among the largest cost outlays for mobile providers; investments in mobile infrastructure, though costly, improve service quality, encourage consumer adoption of mobile services, and enhance post-adoption usage. Therefore, if a mobile service provider invests more to achieve better connection speed, more consumers likely adopt its Internet service. Our finding that fixed-line and mobile Internet are stronger substitutes in areas where the fixed-line Internet speed is low indicates that it will be more valuable for mobile carriers to provide higher mobile Internet speeds in these areas, to attract more consumers. These insights should inform telecommunication carriers' strategic mobile infrastructure investments.

With the emergence of a potentially disruptive platform, marketers must monitor changes in consumer behavior to understand their implications for marketing strategy (Ahonen 2011). For example, advertisers may need to adjust their cross-platform advertising strategies to reach their target audience more effectively. We find that consumers go online through the mobile Internet if the fixed-line Internet is not satisfactory. This finding suggests that it will be harder for advertisers to reach their target audience, which likely is more dispersed across platforms. Advertisements placed across channels likely produce a single impression on a broader audience, rather than repeated impressions on the same audience.

### ***3.5.3 Limitations and Further Research***

Several important data and econometric limitations arise in this study. First, because we do not observe individual behaviors on the fixed-line Internet, we investigate how fixed-line Internet speed influences mobile Internet adoption and usage; we cannot examine how

mobile Internet speed influences consumer behavior on the fixed-line Internet. Second, we know whether a consumer has adopted a mobile data plan and monthly mobile service costs, but we cannot observe the particular type of mobile data plan each consumer adopts. Although consumers' choices of data plans and monthly mobile service costs likely influence the extent of their usage, we expect that consumers who frequently engage in mobile online activities adopt mobile data plans with higher bandwidth caps with high costs. Third, we observe consumers' usage frequencies across different mobile online activities but do not know whether they use their mobile data plans or Wi-Fi to perform online activities. However, if consumers use their mobile phones to get online through available Wi-Fi, rather than a mobile data plan, fixed-line Internet speeds may be positively associated with usage of mobile online activities, because the speed of the Wi-Fi connection at home or at work depends on the speed of the associated fixed-line network. The possibility that consumers perform mobile online activities through Wi-Fi could bias the substitution effect between the fixed-line and mobile Internet toward greater complementarity. Therefore, the substitution we find might be underestimated.

Our competition finding also offers several directions for research. Additional studies are needed to address usage of the fixed-line and mobile Internet to perform different online activities. If researchers could access data about Internet consumption behavior for both mobile and fixed-line settings, they could identify when substitution or complementarity was likely to prevail for the usage of different types of online activities. For example, consumers might use both Internet platforms as substitutes to check and sent e-mail, because e-mails generally are not data intensive, and either platform is sufficient. However, they might read online news on both platforms as complements, in that they prefer to check timely headlines

with a mobile app on their smaller mobile screen but then further explore interesting news stories in-depth on their personal computers using a fixed-line Internet.

Researchers also might extend the current study by investigating the mechanism or source of substitution. We note some similarities and dissimilarities between the two Internet channels, but the MobiLens data cannot reveal the mechanisms responsible for the substitution we find. If researchers could access Internet consumption data together with data about the specific contents consumed on each platform, they could provide more detailed insights into consumer behavior. The different consumption patterns on the two Internet channels also might evolve differently over time, as consumers become more familiar with using mobile devices to conduct online activities. Findings along these lines could help Internet content providers make more informed content management decisions across different Internet platforms.

## **CHAPTER 4**

### **LITERATURE REVIEW AND FUTURE RESEARCH ON CONSUMER ADOPTION AND USAGE BEHAVIOR ON THE MOBILE INTERNET**

#### **4.1 Introduction**

There is no doubt that the use of wireless and mobile networks and devices is growing. More and more people rely on their mobile phones to do various activities, like online communicating, searching, browsing, and purchasing behavior. The number of worldwide mobile Internet-enabled users passed the one billion mark in 2011 (Gerpott and Thomas 2014). According to Cisco (2012), global mobile Internet data traffic has again more than doubled in 2011, compared to 2010, and is expected to increase 18-fold between 2011 and 2016. As consumers increasingly move to mobile devices to perform online activities, it triggers a substantial body of research on consumers' behavior on the mobile Internet. This chapter reviews the literature on consumers' adoption and usage behavior on the mobile Internet to identify gaps in the prior literature and future research directions.

First, I discuss how the mobile Internet might be different from the traditional fixed-line Internet in general, and whether and how the differences might influence consumer online behavior. Second, I review literature that particularly examines consumers' cross-channel consumption behavior on the mobile Internet. The primary motivation of this stream of literature is to identify the substitution and complementarity effects among different online channels. Third, I review research that focuses on other emerging mobile

Internet behavior, like mobile social media and mobile technologies in marketing, and identify areas for future research.

#### **4.2 How the Mobile Internet is Different**

Consumer adoption and usage of mobile Internet service has been growing steadily over the past few years. According to estimates by the International Telecommunication Union (2013), the 2.1 billion active mobile Internet users in the world at the end of 2013 represented 29.5% of the global population. Mobile Internet subscriptions grew 40% annually between 2010 and 2013, roughly three times the growth rate for fixed broadband subscriptions (International Telecommunication Union 2013). As consumers increasingly use mobile phones to access the Internet, it is important to understand whether and how mobile Internet user behavior matches online behavior on personal computers (PCs).

For general Internet browsing, there are both similarities and differences between the mobile devices and PCs. 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 three main reasons. First, mobile phones typically have smaller screens than do PCs. Second, mobile phones are, by definition, portable and not fixed to a location. Third, because of the portability, mobile users have access to timely information (Ghose, Goldfarb and Han 2013). Among the few studies that investigate how Internet behavior varies between mobile devices and PCs because of the differences of browsing behavior between the two platforms, Ghose, Goldfarb and Han (2013) show that ranking effects are higher on mobile phones suggesting higher search costs: links that appear at the top of the screen are especially likely to be clicked on mobile phones and the benefit of browsing for geographically close matches is higher on mobile phones. Although

information technology and Internet markets have allowed people to consume niche products, thereby creating longer tails for internet businesses in terms of sales distribution, Ghose and Park (2013) find that smartphone users' product sales are more concentrated than those of users with PCs or tablets because of the advent of small size mobile devices with higher search costs. Their results suggest that mobile commerce markets do not follow long tail phenomenon, but follow "Pareto Principle" in terms of sales divers it because smart phone users have less willingness to purchase unpopular products than tablet users. Bang, Lee and Han (2014) analyze the changes in purchase time dispersion of e-marketplace users after their adoption of mobile channel, and they find that a user's purchase time becomes more dispersed throughout a day after the mobile channel adoption. These findings present strong empirical evidences of access affordance of the mobile channel and how the affordance is realized across e-market users.

Regarding to the pricing structure, mobile Internet has another unique characteristic that some users incur explicit expenses (for example, by paying usage-based data transmission charges) during their mobile Internet usage. These are based on the number of bytes uploaded or downloaded. Although many mobile providers recently introduced additional mobile Internet price schemes (e.g., various "bucket pricing plans" with different capped mobile Internet traffic allowances, device type specific prices), over-usage might incur additional costs.

Somewhat related to mobile Internet adoption and usage behavior, there exists a stream of research studying Internet adoption and usage behavior via PCs or laptops at individual levels (e.g. Goldfarb 2006; Goldfarb and Prince 2008; Lambrecht 2006). However, prior work examining traditional Internet adoption and usage cannot be simply extended to

the mobile setting because of significant differences between the two different Internet platforms. Although researchers have recently started to focus on how different features of the mobile Internet can change consumer online behavior, there are still many open questions that remain poorly understood and need to be addressed in the future research.

As a specific example for future research, there is a well-documented “digital divide” in the Internet and online service adoption and usage (e.g. Lambrecht and Seim 2006; Goldfarb and Prince 2008). It would be interesting to study whether similar divides exist for mobile Internet adoption and usage. For instance, Goldfarb and Prince (2008) find that high-income, educated people were more likely to adopt the Internet, but they also spend considerably less time online, conditional on adoption. Internet adoption and usage patterns via PCs or laptops differ in terms of income and education, because traditional Internet via PCs or laptops has both fixed connection fees and near-zero usage fees, and PCs or laptops render stricter limitations on geographical mobility and access, typically constraining it to office or home or locations where there is access in place. However, for a mobile Internet plan, there might be explicit over-usage expenses. Therefore, conditional on adoption, the existence of caps and incremental fees of mobile Internet services may change the relationship between income and mobile Internet usage for mobile users.

Prior literature has suggested that the smaller screen size of mobile devices can lead to variations in mobile browsing behavior as compared to browsing behavior on PCs and laptops (Ghose, Goldfarb and Han 2013). The screen size of smartphones has experienced dramatic changes over time, while tablets stay within a predefined range of 7 to 12 inches (IDC 2010). The first iPhone launched by Apple in 2007 was 3.5 inches. Later models of iPhones (2G to 5C) are either 3.5 or 4 inches, and in September of 2014 Apple introduced

the 4.7-inch iPhone 6 and the 5.5-inch iPhone 6 Plus. In 2011, Samsung launched the Galaxy Note with a 5.3-inch screen and has since then introduced even bigger phones with screens of 6 inches or more (Ma and Chen 2015). One recent paper, Ma and Chen 2015, examines the relationship between screen size and cellular data consumption for a large number of phone and tablet users. They do not find a significant relationship between screen size and cellular data consumption measured by either the time spent on the mobile network or the amount of data transmitted for smartphones with screens 3.5 inches or higher, and for tablet users, they find evidence that suggests that people spend less time on tablets with bigger screens, which could potentially be due to the reduced portability of large tablets. However, how the screen size of smartphones and tablets influence the usage of different categories of mobile usage has not been studied yet in the literature, although it is likely that the effect of the mobile device's screen size varies across different types of mobile activities. For instance, the screen size should not affect the use of voice calls, texting messages, or emails that much, because those activities usually do not need to show the user a large amount of information on one page. However, the screen size should have a significant impact on the use of activities which require a larger screen to show a greater amount of information, such as searching information, reading news and watching streaming video/TV. Understanding how the mobile device's screen size influences the use of different categories of mobile activities is critical for mobile device manufacturers and mobile carriers to set optimal screen sizes and offer different mobile Internet services to users with different sizes of mobile devices.

How would the increasing use of location-based service on the mobile Internet change consumers' online behavior? Consumers may tend to rely on the mobile Internet

network to consume locally-targeted online content more, while they may use the traditional fixed-line Internet to search information in general. Moreover, will the mobile Internet behave more as a substitute or complement for cities given easy access to location-based services on mobile devices? Sinai and Waldfogel (2004) document that larger markets have more locally-targeted online content and that individuals are more likely to connect in markets with more local online content, suggesting the Internet is a complement to cities. Yet, holding local online content constant, people are less likely to connect in larger markets, indicating that the Internet is also a substitute for cities. In a mobile setting, it is not clear whether urban consumers are more likely to use location-based applications. On the one hand, urban markets have locally-targeted online content. On the other hand, urban people have more channels to consume locally-targeted online content other than the mobile channel, like a high-speed fixed-line Internet network. Therefore, how urban and rural users consume location-based mobile applications differently is an empirical question that needs to be addressed in the future.

Considering the pricing structure of mobile Internet services and mobile Internet consumption, Xu et al. 2014b develop a dynamic structural model in which an individual user's daily data usage is derived from a utility-maximization model considering the intertemporal trade-off between current and future consumption, and they find that a large percentage of users appear to dynamically optimize their daily data consumption. Further investigations need to be conducted on associations between different mobile Internet price schemes and mobile Internet consumption. For instance, it would be interesting to examine what kinds of consumers would benefit the most from certain type of mobile data plans by quantifying the consumer surplus from adopting a specific mobile data plan. They are likely

to provide insights for mobile providers to design service and tariff packages for different types of consumers.

### **4.3 Multi-Channel Consumption on the Mobile Internet**

#### ***4.3.1 Multi-Channel Consumption on Mobile Devices***

A long stream of literature has examined the interdependence among different channels to access information. Extant findings about how one channel affects the consumption of other, similar channels are by no means conclusive; some prior research offers evidence that different channels can be substitutes (e.g. Brynjolfsson , Hu and Rahman 2009; Gentzkow 2007; Forman, Ghose, and Goldfarb 2009), but other recent literature reports complementarity across digital channels (e.g., Chiou and Tucker 2011; Smith and Telang 2009). Given the rapid growth of usage on mobile devices, there is an emerging stream of literature particularly focusing on users' multichannel consumption behavior on mobile devices (e.g. Bang et al. 2013; Ghose, Han and Xu 2013; Kim et al. 2010; Xu et al. 2014a). With the emergence of various mobile channels, it is imperative for researchers and practitioners to monitor changes in consumer behavior and to understand their implications for the market. Regarding to non-mobile Internet services, prior work has examined the interaction between voice and SMS services. The impact of SMS on voice (and vice versa) is ambiguous. On the one hand, SMS can be a close substitute for voice if it is perceived to serve the same purpose. However, SMS and voice may serve possibly different purposes, and at best they are weak substitutes. Andersson, Foros and Steen (2009) analyze the relationship of the two services in the context of network size. They estimated the cross-price elasticity of voice and SMS and showed that, depending on the network size, the relationship could be either substitutive or complementary. Grzybowski and Periera

(2008) show that SMS and voice have a complementary relationship. Although their data were at the individual level, they did not observe the user's plan choice, and hence did not observe the marginal prices paid by the user. Kim et al. (2010) has access to individual-level consumption data for SMS and voice services, which allows them to build a richer model to measure the own- and cross-price elasticity of these services, and they find that SMS and voice service are small substitutes.

The mobile data has become a key revenue source for mobile providers. Most mobile providers are betting on an increasing uptake of mobile data services and investing billions in infrastructure. Despite tremendous growth in mobile data services, quite a few prior works examine the interaction among the emerging mobile Internet and other existing digital channels. Bang et al. 2013 develops a theoretical framework for understanding the interactions between mobile and traditional online channels for products with different characteristics, and their results suggest that for products with high time criticality and low information intensity, the mobile channel substitutes for the online channel significantly, but regarding products with high time criticality and high information intensity, there is a strong synergy between the online and mobile channels. Ghose, Han and Xu 2013 quantifies the economic impact of tablets in ecommerce and m-commerce markets by examining its complementary and substitution effects with two other channels – PCs and smartphones, and finds that the tablet channel acts as a substitute for the PC channel and a complement for the smartphone channel, suggesting that tablets are in many ways performing like PCs when it comes to shopping.

### ***4.3.2 Future Research***

There is lack of empirical work that seeks to understand about the multi-channel consumption behavior of consumers in the emerging area of mobile channels. As consumers increasingly rely on apps, accessed through their mobile phones, to communicate with others (e.g., WhatsApp, Facebook, Gmail), more studies are needed to examine consumption behaviors across different communication apps and SMS. Some recent studies suggest a relationship between uses of mobile voice services and SMS, but despite the tremendous growth in the uses of mobile communication apps, our understanding of how users consume these services remains limited. Specifically, researchers can study the interaction of different categories of communication app services (e.g., e-mails, social networking apps, text messaging apps, SMS). Text messaging apps may be closer substitutes for SMS, because they are both designed mainly for one-to-one (or small group) communication. In contrast, social networking apps generally are used to broadcast messages to a large community, so they may not be strong substitutes for, or even could complement, SMS. Understanding how consumers use e-mail, social networking apps, text messaging apps, and SMS interchangeably on a mobile platform is extremely important for mobile carriers. If they can predict user responses in multichannel communication environments, as well as how different communication apps and SMS interact, they can set pricing and promotion strategies more effectively for different services, along with appropriate marketing strategies.

### **4.4 Other Mobile Usage Behavior**

As consumers increasingly use their web-enabled mobile devices to perform various online activities, such as online communications, search, browsing, and purchasing, more and

more recent studies examines various aspects of mobile behavior. This review specifically focuses on two mostly studied mobile behaviors in the economics of Information System literature: mobile social media and mobile marketing.

#### ***4.4.1 Mobile Social Media***

The increasing ubiquity and easy access of social media has dramatically increased user engagement with new media platforms for content creation and consumption. While the medium via which users accessed the Internet in the past was mostly computers, increasingly web-enabled mobile devices have become a more popular device to access online social media (Ghose, Han and Iyengar 2012). Grappling with this social phenomenon, scholars have started to investigate and analyze how people consume social media activities on mobile devices from different angles and dimensions to better understand the phenomenon and its consequences.

One broad area of research on mobile social media specifically studies the content generated and consumed through mobile social media. For instance, as consumers are increasingly engaged in not only content usage but also content generation using their mobile phones, Ghose and Han (2011) find that there is a negative and statistically significant temporal interdependence between content generation and usage on the mobile Internet. This is because, on the mobile Internet, users not only invest time, but also incur transmission charges to generate and use content in certain countries. Burch and Hong (2014) broadly explore the implications for review characteristics from offering a mobile online review channel to consumers by examining different aspects of online reviews across mobile and desktop reviews. They find that mobile reviews are more likely to be extreme, more likely to contain indications of recent consumption, more likely to contain concrete

information; mobile reviews are shorter in length, lower in valence; and mobile reviews receive more helpful votes from other consumers.

Another stream of related literature focuses on the relationship between mobile social media consumption and traditional social media consumption via PCs or laptops. Jung et al. (2014) examine how a mobile social media application influences consumer online social behavior by investigating a causal impact of the adoption of a mobile app on user behavior in the context of online dating, and show that mobile app adopters send more messages and get more matches, and also achieve higher efficiency of matching per every initiated conversation. Ghose, Han and Iyengar (2012) study how consumer's online social networking behavior affects their mobile Internet consumption. They model the impact of two characteristics of personal social networks relevant for information sharing (tie strength and network density) and social contagion on the usage of mobile Internet. Their results show that both tie strength and network density significantly impact individual usage of mobile Internet service after controlling for the other. What is more interesting is that tie strength has a positive impact on individual usage while density has a negative impact. There is also evidence of positive social contagion but its impact on users is moderated by their tie strength with others and density of their personal social networks. Bapna, Gupta and Sen (2014) design a randomized field experiment to study how providing online incentives (i.e., rewards offered within the game to players) can generate offline diffusion of a mobile social game which can only be played in a group of co-located friends.

One of the challenges of studying mobile social media is access to users and content. Despite the prevalence of mobile devices in the world, recruitment of mobile social media consumption data can be difficult. Privacy concerns may lead many users to close off public

access to their mobile social media use (Humphreys 2013). As Boase (2013) points out, how we collect this data and define the analytical tools for studying mobile social media content are not yet readily determined.

#### ***4.4.2 Mobile Marketing***

Mobile devices and mobile applications offer retailers more than just the opportunity to exploit a new channel to reach customers (Strom, Vendel and Bredican 2014). A mobile device is a constant companion to the consumer, a gateway to a relationship between the consumer and the retailer, making it an ideal supplementary channel for distance selling and physical retailing (Shankar et al. 2010). Mobile devices are different from PCs and laptops due to a limited keyboard and screen size (Ghose, Goldfarb, and Han 2012), and offer functions such as a camera and a Global Positioning System (GPS). This makes mobile marketing potentially different from PC Internet and traditional marketing. The Mobile Marketing Association's definition of mobile marketing is "a set of practices that enable organizations to communicate and engage with their audience in an interactive and relevant manner through any mobile device or network technologies in marketing."

The explosive growth of Smartphone and location-based services has contributed to the rise of mobile advertising. Location-based services and mobile advertising can enable retailers to deliver information to mobile phone users in real time about offers in geographical proximity to them (Li, Liu and Ghose 2014). Previous studies have mainly examined consumer perceptions and attitudes towards mobile location-based advertising (Brunner and Kumar 2007; Xu, Oh and Teo 2009). Recently, mobile couponing and location-based advertising have gained increasing interest as a marketing tool. Molitor, Reichhart and Spann (2012) show that the higher the discount from mobile coupons and the

closer the consumers are to the physical store offering the coupon, the more likely they are to download the mobile coupons. The research on location-based advertising is still in its nascent stage. Luo et al. (2013) examines both the short-term and long-term sales effects of location-based advertising. Li, Liu and Ghose (2014) propose a new mobile advertising strategy that leverages full information on consumers' offline moving trajectories from four different mobility dimensions (i.e., semantic, temporal, spatial and velocity). To examine the effectiveness of this new mobile trajectory-based advertising strategy, they design a large-scale randomized field experiment.

#### ***4.4.3 Future Research***

Despite that online activities such as social networking and purchasing increasingly move to mobile devices, many issues in consumers' usage behavior across different categories of activities on the mobile Internet have not been investigated thoroughly. I propose some interesting open questions for future research.

Consumer's social networking behavior on PCs or laptops has been widely studied in the literature recently. However, as more and more people conduct online social networking activities on their mobile devices today, there are more and more social networking applications that are mobile devices specific, like WeChat, the most popular social networking app in China that can only be used on mobile devices. Therefore, whether and how is a person's mobile social networking behavior different from his or her social networking activities via PCs or laptops? How different types of consumers behave differently across social networking activities on different platforms? Some consumers might be more likely to communicate with people with strong ties on a mobile social network, but if they want to contact people with weak ties, they might rely on social

networking activities via PCs or laptops, while some consumers may behave the other way around. If researchers could collect individuals' daily activities on a mobile social networking app and their activities on a social platform through PCs, an interesting research question would be to compare mobile social networking behavior with traditional online social networking behavior. It is important for developers of social networking applications to consider whether and how they should develop their applications differently for mobile devices and for PCs to attract more mobile users.

One of the most common forms of using mobile and social media technologies is the use of micro-blogging such as Twitter on mobile devices. Choi, Im and Yoo (2013) develop a theoretical framework that can effectively predict or interpret the changes in the way people communicate in a mobile social network. They posit that micro-blogging on a mobile device brings higher levels of the communication liquidity in three dimensions – temporal, spatial, and conversational. Future empirical investigation is needed to study how the micro-blogging behavior via mobile devices is different from that via PCs or laptops. Researcher can collect the posts on a micro-blogging platform (such as Twitter), and compare different aspects of micro-blogging behavior across mobile and desktop posts. As predicted in the theoretical framework, mobile micro-blogging posts should be more likely to contain more timely information; they might be more likely to be extreme, consistent with the idea that mobile users partake in “rants and raves” (Burtch and Hong 2014); and they might be more likely to be re-tweeted or liked by other users.

Because location-based services and mobile advertising can enable retailers to trace consumers in real time, an important issue in the mobile marketing that needs to be examined in the future research is the consumer's response to different instant sales offers

provided by retailers through the mobile medium. How much of push and pull marketing activities should a retailer undertake through the mobile medium? What kinds of sales offer will a consumer take when he/she is in a mall that houses one of that retailer's stores? For example, if the consumer is closer to a retailer's shoe department, how likely he/she will prefer to redeem an instant mobile discount offer from another competitive retailer's shoe department? By the same token, if the consumer is at another store buying an item that is not sold by the retailer, how likely he/she will redeem an instant mobile discount offer from the retailer if the retailer prompts the consumer with an offer on a related item?

One of the biggest venues for online advertising is through users' searches. Recently, mobile search has become larger than search on PCs or laptops, according to Google search queries. By 2018, 85.9% of the US digital search advertising market will be mobile search spending (eMarketer, 2014). For monetization of search, it is critical for marketers to understand how consumer mobile search behavior is different from their desktop search behavior. Regarding to search via search engines, because links that appear at the top of the screen are especially more likely to be clicked on mobile phones (Ghose, Goldfarb and Han 2013), advertisements that show up at the top of the page would be much more valuable for mobile searchers as compared to desktop searchers. Moreover, "call extensions" that display a phone number directly in the search ad might become an attractive feature for mobile search ads, because mobile searchers can simply tap the number in the ad to call. Search engines are not necessarily the first place smartphone and tablet consumers use. The explosion of mobile app usage means mobile users have more and more specialized alternatives for finding information. Google still dominates browser-based searches on mobile devices, but niche search apps are also becoming much more prevalent (eMarketer

2014). Future research could examine whether mobile searchers use search apps to substitute or complement for search engines. For advertisers, such a study can help them appropriately target consumers in a multichannel mobile search environment.

There are other emerging mobile behaviors that are rarely studied in the literature. For instance, mobile devices can be used in a variety of payment scenarios, such as payment for digital content (e.g., music or games), tickets, parking fees, bills and invoices (Dahlberg et. al. 2008) and the most recent mobile payment and digital wallet service Apple Pay, which lets Apple mobile devices make payments at retail and online checkout by replacing the credit or debit magnetic stripe card transaction at credit card terminals. Considering the rapid development of mobile technologies to support various types of mobile payment services, if there are multiple payment methods available, what factors would drive a consumer to use a mobile payment rather than other payment methods? Moreover, how should merchants redesign their business processes to realize potential value from various mobile payment services? Future research needs to explore how merchants can best attract customers and other merchants to an existing mobile payment services network.

Another example of emerging mobile behaviors is mobile health. Mobile technologies are being used to deliver health information and health behavior interventions. Researchers should assess the effectiveness of mobile health technologies to improve health care service delivery, including which functions are most effective (SMS, video, oral instruction, application software), which behavior change techniques are effective, and whether the effectiveness of interventions is influenced by setting or participant demographics.

## 4.5 Conclusion

The rapid growth of the mobile Internet has attracted the attention of both practitioners and academics. In particular, research activities on consumers' behavior on the mobile Internet have increased significantly recently. This chapter reviews an extensive amount of existing studies related to consumers' technology adoption and usage behavior on the mobile Internet, and identifies several directions for future research. Although this review does not claim to be exhaustive, it does provide a reasonable amount of insight into the state of the art in this stream of research.

The results presented in this chapter have several important implications. First, there is no doubt that mobile Internet research will burgeon in the future. The key question remains poorly studied in the literature is how consumer online behavior changes relative to the different comparative advantages or disadvantages of mobile devices, such as easier to use location-based applications, but harder to manipulate large quantities of information. Second, I expect more empirical research to be conducted on consumers' actual usage activities on the mobile Internet using individual-level consumption data in the future as more mobile consumption data become available. Third, currently, it seems that most existing research studies the mobile Internet service adoption and usage in general, but not the consumption on a specific category of mobile activities. It is surprising not to see many articles focusing specifically on any popular categories of mobile Internet applications, like mobile texting applications and mobile social networking applications. Additional research is also required in other emerging categories of mobile Internet applications, such as mobile health, mobile payments and so forth.

## APPENDIX A

### FOR CHAPTER 2: PSEUDO-PANEL DATA ANALYSIS

#### Overview

The advantages of panel data vs. cross-sectional data are well documented in standard econometric literature. Using panel data, researchers have greater flexibility in modeling differences in behavior across individuals (Greene 2003). From an econometric perspective, panel analysis allows a researcher to control for individual-specific, time-invariant, unobserved heterogeneity, which can become the source of bias in cross-sectional data. However, in many marketing research settings, researchers may have little or no access to panel data and instead will use various kinds of cross-sectional data.<sup>27</sup> Many economics researchers also face similar issues. For instance, many labor and macro economists often have access to repeated cross-sectional data (e.g., U.S. Current Population Survey) and lack access to true panel data. As a result, the pseudo-panel analysis approach first developed by Deaton (1985) has seen wide use in many research areas including applied micro econometrics (e.g., Browning et al. 1985) and monetary economics (e.g., Campbell et al. 2007), to name a few. In its essence, the pseudo-panel method aggregates the observational units in the cross-sectional data into “cohorts”, matches them across time, and synthesizes a panel-type data structure from the repeated cross-sectional data. To be more precise, a “cohort” is defined as a group with a fixed membership (Deaton 1985). For large enough cohorts, or large enough samples, successive surveys will generate successive random samples of individuals from each of the cohorts. The core idea is that the summary statistics from these

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<sup>27</sup> By one measure, about 30% empirical research published between 1996 and 2005 in *Journal of Marketing* and *Journal of Marketing Research* are based on survey data (Rindfleisch et al. 2008).

random samples generate a time series that can be used to infer behavioral relationships for the cohort as a whole just as if panel data were available (Deaton 1985). Procedures for constructing cohorts and for estimation using the resulting data are discussed next.

As an illustration, consider the following individual-level, linear fixed-effects model,

$$(W1) \quad y_{dt} = \alpha_d + \beta X_{dt} + \varepsilon_{dt}$$

where  $y_{dt}$  is the response variable for individual  $d$  at time  $t$ ,  $X_{dt}$  is a vector of covariates and  $\beta$  is a row vector of the parameters of interest. Deaton (1985) suggests the use of cohorts to obtain consistent estimates for  $\beta$  in (W1) when repeated cross-sections are available, even if individual effect  $\alpha_d$  is correlated with one or more of the explanatory variables (Verbeek 2008). In general, constructing a pseudo-panel involves identifying a set of time-invariant criteria with which to construct data groupings so that the same individual remains in the same cohort over time (Prince and Greenstein 2014). For instance, observable demographic characteristics that are stable over the sample period are commonly used in the literature to group individuals into cohorts (e.g. Browning et al. 1985; Cuesta, Nopo, and Pizzolitto 2011). Once these cohorts are formed, the corresponding linear regression equation in the synthetic panel is

$$(W2) \quad \bar{y}_{it} = \alpha_i + \beta \bar{X}_{it} + \varepsilon_{it} .$$

where the subscript  $i$  denotes cohorts and the subscript  $t$  denotes time periods as before. We replace individual-level measures in the cross-sectional data with cohort-level measures in the pseudo-panel, by replacing  $y_{dt}$  and  $X_{dt}$  with  $\bar{y}_{it}$  and  $\bar{X}_{it}$ , respectively. The latter two variables are the averages for  $y_{dt}$  and  $X_{dt}$  in cohort  $c$  at time  $t$ . The slope  $\beta$  is the parameter of interest.

The literature has explored the conditions under which the parameters can be consistently estimated, given the data limitations imposed by a set of repeated cross-sections (Cuesta et al. 2011). If the true population cohort means would be observable, (W2) could be used to estimate  $\beta$  using standard procedures for a panel consisting of cohorts (Verbeek 1992). However, we can regard the observed cohort averages  $\bar{y}_{it}$  and  $\bar{X}_{it}$  as error-ridden measurements of the true population cohort means. If we have sufficient observations per cohort, we can get an asymptotically consistent estimator of  $\beta$  using cohort averages in a pseudo-panel model. Deaton (1985), Verbeek (2008), and Imbens and Wooldridge (2007) have provided detailed proofs that interested readers may explore.

Due to the aggregation involved in the pseudo-panel analysis, researchers typically conduct various robustness checks. One such analysis is to investigate the effect of different cohort definitions on the estimation results (Cuesta, Nopo, and Pizzolitto 2011). That is, the boundaries for the cohorts and the tradeoff between the number of cohorts and the number of observations in each cohort can affect the statistical inference. As we draw tighter boundaries among cohorts, we can obtain a larger number of cohorts but at the same time will have a smaller number of observations per cohort. A larger number of cohorts in pseudo-panel analysis is equivalent to a larger number of observations in panel analysis and helps achieve greater identification power. However, the tradeoff is that fewer units in a cohort implies that the cohort mean may be a poor estimate of the true population mean for that cohort, which can lead to loss of efficiency (Prince and Greenstein 2014). Therefore, in our main empirical analysis, we conduct various robustness checks on different cohort compositions.

#### Application to our empirical analysis

We begin the description of our empirical specification by constructing an individual-level model. Let  $\text{webvisit}_{djt}$  be a variable that measures individual  $d$ 's visitation of news website  $j$  at time  $t$ ,

$$(W3) \text{webvisit}_{djt} = \alpha + \gamma \text{time}_t + \beta_1 \text{FoxApp}_d \times \text{time}_t + \beta_2 \text{FoxWeb}_j \times \text{time}_t + \beta_3 \text{FoxApp}_d \times \text{FoxWeb}_j \times \text{time}_t + \theta X_{dt} + \mu_{dj} + \varepsilon_{djt},$$

where  $\text{FoxApp}_d$  is a binary variable that is equal to one if individual  $d$  adopts the Fox News app at time  $t$ ,<sup>28</sup>  $\text{FoxWeb}_j$  is an indicator variable equal to 1 if the mobile news website  $j$  is the Fox News mobile website, and  $\text{time}_t$  is an indicator variable equal to 1 for the second period.  $X_{dt}$  is a vector of individual-level control variables that may vary over time.

Corresponding to individual behavior, we consider the sample cohort-level equation by replacing  $\text{webvisit}_{djt}$ ,  $\text{FoxApp}_d$ , and  $X_{dt}$  with  $\text{webvisit}_{ijt}$ ,  $\text{FoxApp}_i$ , and  $X_{it}$ , respectively. The last three variables are cohort  $i$ 's average values computed by taking the average of  $\text{webvisit}_{djt}$ ,  $\text{FoxApp}_d$ , and  $X_{dt}$  across individuals in cohort  $i$ . For instance, the average for  $\text{FoxApp}_i$  measures cohort  $i$ 's average adoption rate of the Fox News app in the second period, i.e. the percentage of individuals who adopt the Fox News app in cohort  $i$ . We reformulate equation (W3):

$$(W4) \text{webvisit}_{ijt} = \alpha + \gamma \text{time}_t + \beta_1 \text{FoxApp}_i \times \text{time}_t + \beta_2 \text{FoxWeb}_j \times \text{time}_t + \beta_3 \text{FoxApp}_i \times \text{FoxWeb}_j \times \text{time}_t + \theta X_{it} + \mu_{ij} + \varepsilon_{ijt},$$

In this paper, the cohort selection criteria consist of observable demographic characteristics that we believe are stable over a short period of time (one year), which is a

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<sup>28</sup> Because the Fox News app did not exist in 2009, this variable is, by definition, equal to zero in the first period.

typical strategy adopted in previous research (e.g., Verbeek and Vella, 2005; Prince and Greenstein 2014). These include age group, income, education, and location (urban vs. rural), which have been adopted in prior literature. As an example, a cohort can comprise a group of consumers who range in age from 25 to 34, have an income of \$50,000–\$75,000, have a bachelor's degree, and live in an urban area.

## APPENDIX B

### FOR CHAPTER 3: REGRESSIONS FOR THE ENDOGENOUS VARIABLES

**Table B1. Linear Regressions for the Endogenous Variables on Instruments**

	Fixed-Line Internet Speed	Mobile Internet Speed
VARIABLES	(1)	(2)
<i>Number of Mobile Carriers</i>	0.7726*** (0.1279)	1.7945** (0.7746)
<i>Proxy Cost</i>	-1.0028*** (0.0056)	-0.2116*** (0.0815)
<i>Log Median Income (Zip)</i>	0.7892*** (0.1647)	0.0859*** (0.1048)
<i>Log Population (Zip)</i>	1.0123*** (0.2635)	0.0456*** (0.0127)
<i>Percent Bachelor's Degree (Zip)</i>	0.0461*** (0.0176)	0.0060** (0.0019)
<i>Individual Controls</i>	Yes	Yes
<i>Mobile &amp; Fixed-line Carrier Dummies</i>	Yes	Yes
<i>Constants</i>	8.5112*** (0.7980)	0.8369*** (0.2433)
Observations	28,117	28,117

\*Significant at 10%; \*\*Significant at 5%; \*\*\*Significant at 1%.

Notes: The individual controls are age, gender, income, area, education, number of people in the household, length of mobile service usage, and state dummies. Heteroskedasticity-robust standard errors appear in parentheses. The instruments pass the weak identification test indicating they are strong instruments.

## APPENDIX C

### FOR CHAPTER 3: TWO-STAGE LOGIT MODEL

**Table C1. Mobile/Fixed-Line Internet Speed and Mobile Internet Adoption and Usage:  
Two Stage Logit Model**

	Two-Stage Model for Online Usage (No Control Function)		Two-Stage Model for Online Usage (With Control Function)		Two-Stage Model for Offline Usage (With Control Function)	
	Mobile Data Plan Adoption	Mobile Online Usage	Mobile Data Plan Adoption	Mobile Online Usage	Mobile Data Plan Adoption	Mobile- Specific Offline Usage
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
<i>Fixed-line Speed</i>	-0.0002 (0.0002)	-0.0004 (0.0003)	-0.0005* (0.0003)	-0.0009** (0.0004)	-0.0005* (0.0003)	-0.0003 (0.0002)
<i>Mobile Speed</i>	0.0927** (0.0401)	0.0838** (0.0323)	0.0868*** (0.0174)	0.0652** (0.0313)	0.0822*** (0.0171)	0.0452 (0.0326)
<i>Log Median Income (Zip)</i>	0.1328** (0.0573)	0.1062** (0.0416)	0.2002*** (0.0321)	0.1373** (0.0574)	0.1984*** (0.0327)	0.1529** (0.0613)
<i>Log Population (Zip)</i>	0.0474** (0.0202)	0.0410** (0.0184)	0.0664*** (0.0098)	0.0390* (0.0236)	0.0656*** (0.0089)	0.0376 (0.0247)
<i>Percent Bachelor's Degree (Zip)</i>	0.0033* (0.0015)	0.0030* (0.0014)	0.0024** (0.0008)	0.0016* (0.0007)	0.0021** (0.0007)	0.0022 (0.0014)
<i>Individual Controls</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Mobile &amp; Fixed-line Carrier Dummies</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Residual for Fixed- Line Speed</i>			0.0499** (0.0231)	0.0372* (0.0165)	0.0519** (0.0247)	0.0484* (0.0226)
<i>Residual for Mobile Speed</i>			0.0298** (0.0100)	0.0302** (0.0115)	0.0310** (0.0118)	0.0249** (0.0092)
<i>Inclusive Value</i>	0.3817 (0.2750)		0.3952 (0.3074)		0.4013 (0.3238)	
<i>Constants</i>	4.4989*** (0.8313)	0.7545* (0.4324)	3.1974*** (0.5729)	0.5810* (0.2694)	3.1781*** (0.6826)	0.4665* (0.2347)
Observations	28,117	28,117	28,117	28,117	28,117	28,117

**Table C2. Two Stage Logit Model: Average Marginal Effects**

	Two-Stage Model for Online Usage		Two-Stage Model for Offline Usage	
	Mobile Data Plan Adoption	Mobile Online Usage (Conditional on Adoption)	Mobile Data Plan Adoption	Mobile-Specific Offline Usage (Conditional on Adoption)
<b>VARIABLES</b>	<b>(1)</b>	<b>(2)</b>	<b>(3)</b>	<b>(4)</b>
<i>Fixed-line Speed</i>	-0.0205** (0.0090)	-0.0229** (0.0115)	-0.0211** (0.0096)	-0.0329 (0.0314)
<i>Mobile Speed</i>	0.2008*** (0.0428)	0.1176** (0.0494)	0.2010*** (0.0459)	0.1229 (0.1183)

\*Significant at 10%; \*\*Significant at 5%; \*\*\*Significant at 1%.

Notes: The individual controls are age, gender, income, area, education, number of people in the household, length of mobile service usage, and state dummies. Heteroskedasticity-robust standard errors appear in parentheses. In Table C1, the control functions with instrumental variables are in Column 3–6. A positive residual suggests that the mobile Internet possesses desirable attributes that are not controlled for by observable variables. Table C2 presents the marginal effect of a one unit change in each variable on the probability of the outcome, according to the average marginal effects across all covariate values in the distribution. The marginal effects for models with control functions are reported. Columns 1–4 in C2 correspond to columns 3–6 in C1. The results remain robust to the marginal effects at the mean values of the covariates.

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