EXAMINING THE CAUSAL RELATIONSHIP BETWEEN SCREEN SIZE AND CELLULAR DATA CONSUMPTION

Baojun Ma, School of Economics and Management, Beijing University of Posts and Telecommunications, Beijing, China, mabaojun@bupt.edu.cn

Hailiang Chen, Department of Information Systems, College of Business, City University of Hong Kong, Hong Kong, hailchen@cityu.edu.hk

Abstract

This study utilizes a terabyte dataset from a telecommunications company to examine the relationship between screen size and cellular data consumption for a large number of phone and tablet users. We find the relationship exhibits a different pattern within the two device categories of phones and tablets. For phone users, there is an overall positive and significant relationship over the range of screen size from 1 inch to below 7 inches, which is, however, mainly driven by the dramatic decrease in usage on traditional phones with screens less than 3 inches. Particularly for smartphones with screens 3.5 inches or higher, we 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 tablet users, we 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. Our findings can provide important implications for mobile network operators in promoting data plans to users with different devices.

Keywords: big data, telecommunications, screen size, data usage, smartphone, tablet.

1 INTRODUCTION

The use of mobile devices such as tablets and smartphones is continuously increasing over the past few years. Together with that, we also see a rapid growth in the mobile data traffic, which reached 18 exabytes (i.e., 18 million terabytes) in 2013, according to the Cisco Visual Networking Index 2014. Although the mobile data market generated more than US$100 billion of revenues in 2011, it is still in the early stage of development. It is important for operators to understand different aspects of customer behavior in order to further grow this market (Informa Telecoms & Media 2012). There have been a few industry initiatives that examine how screen size may affect people's mobile data consumption on phones. One study by The NPD Group reports that monthly Wi-Fi and cellular data consumption on smartphones with screens 4.5 inches and larger is significantly higher than on smartphones with screens below 4.5 inches (The NPD Group 2013). Another report published by OpenSignal suggests that data usage over Wi-Fi networks increases with screen size but there is only a weak correlation between screen size and data usage over cellular networks, based on data collected from Android phones (OpenSignal 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 "only" 3.5 inches, which at that time was considered to be much bigger than the average size (Barredo 2014; Taylor 2014). Later models of iPhones (2G to 5C) are either 3.5 or 4 inches, and in September 2014 Apple introduced the 4.7-inch iPhone 6 and the 5.5-inch iPhone 6 Plus. In 2011, Samsung created the "Phablet" market by launching the Galaxy Note with a 5.3-inch screen (Paczkowski 2011) and has since then introduced even bigger phones with screens of 6 inches or more.

Since the screen size of smartphones is increasing simultaneously with mobile data usage over time, it is unclear whether and how much the increase in the screen size contributes to the increase of people's mobile data usage. From a theoretical point of view, a mobile device with a bigger screen could better accommodate tasks such as writing a document, watching videos, and playing games; prior studies in the information systems literature suggest that the utilization level of an information system can be higher if the technology fits the requirements of a task (e.g., Davis 1989; Goodhue and Thompson 1995; Hartwick and Barki 1994; Thompson et al. 1991). Should mobile network operators promote a larger data plan to people having larger devices? To answer this question, we conduct a large-scale study involving over 1 million cellular data users with a telecommunications company. We obtain a terabyte dataset from the company that includes detailed records of the cellular data usage for all subscribers in a large city in China. Besides the information about every user's data streaming activities at the transaction level (i.e., every data connection with the cellular network), the company also keeps track of the devices used by subscribers to connect to the network. Both phone and tablet users are represented in the dataset. We manually collect the public information on the screen sizes of 2,979 devices produced by 109 manufacturers appearing in our dataset from the Internet. We observe a wide range of screen sizes, ranging from 1 inch for feature phones up to 12.2 inches for tablets.

We first conduct regression analyses at the device level and the individual level to explore the relationship between screen size and monthly cellular data usage. We construct two measures to assess the intensity level of cellular data usage behavior in a month: total number of hours spent on streaming and total amount of data transmitted in megabytes (MBs). For analyses at the device level, we aggregate the two usage measures across all users with the same device and regress each of these measures on the screen size of the device and manufacturer fixed effects. For analyses at the individual level, we further control for individual characteristics such as gender, age, and membership tier (Basic, Silver, Gold, or Diamond) and the amount of data included in the subscribed service plan. Considering that people may use phones and tablets for different purposes, we run regressions on four different sets of observations: (1) phones only; (2) phones with screen sizes 3 inches or larger; (3)

phones with screen sizes below 3 inches; and (4) tablets only. We select 3 inches as the split point because most smartphones nowadays have a screen of at least 3 inches (Barredo 2014; Taylor 2014).

We obtain largely consistent results from analyses at these two levels. Overall, the regression analyses at the device and individual levels seem to suggest that screen size is positively associated with cellular data usage on phones but negatively associated with cellular data usage on tablets. The positive association for the phone category is in line with the industry reports based on correlation analysis. We suspect the negative relationship between screen size and cellular data usage on tablets is due to the decreased portability of large tablets.

The exploratory regression analyses provide some interesting insights. However, the regression analyses may suffer from problems such as omitted variable bias or selection bias and thus produce misleading results. In an attempt to infer a causal relationship between screen size and cellular data usage, we utilize the quasi-experimental design to conduct two additional analyses. First, we employ propensity score matching (Rosenbaum and Rubin 1983) to address selection bias that may lead to the potentially overestimated effects in the regression analyses. We conduct the analyses for both phones and tablets. For phones, we randomly select four groups of users whose phones have the screen size of 4 inches, 5 inches, 3.5 inches and 3.2 inches, respectively. We select the 4-inch phone users as the control group, as 4 inches is the most popular screen size in our dataset. The other three groups serve as the treatment groups that receive different treatments of one inch more, half inch less, and 0.8 inch less, respectively. We use observed individual characteristics (gender, age, membership tier) and the characteristics of the service plan subscribed by each individual (number of text messages, number of voice call minutes, amount of data in MBs, and the data plan cost), to find matched groups of treated and untreated users who have the similar tendencies to join the treatment group. We obtain consistent results using any of the four matching methods (Becker and Ichino 2002): Nearest Neighbor, Kernel, Stratification, and Radius. We find that a bigger screen does not lead to more cellular data usage for mainstream smartphones, but cellular data usage on low-end smartphones or feature phones that have much smaller screens is significantly less than usage on mainstream smartphones. For tablets, we randomly select two groups of users whose tablets have the screen size of 7.9 inches (control group) and 9.7 inches (treatment group). Our propensity score matching analyses show that screen size is negatively associated with the number of hours spent on streaming, but screen size does not have an effect on the amount of data transmitted on tablets.

Second, we adopt the difference-in-difference approach to implement a pre-post test design to compare the differences in cellular data usage before and after switching phones for two groups of users over a study period of six months. The control group of users sticks to the same screen size even after switching phones, while the treatment group of users switches to phones with screen sizes different from before. We run fixed effects models to test the effect of screen size on the total time spent on data streaming and the amount of data transmitted. Within each of the two categories, mainstream smartphones (screen sizes 3 inches or larger) and traditional phones (screen sizes below 3 inches), we do not find support that a bigger screen would lead to more cellular data usage after switching phones. However, if a user switches from a traditional phone to a smartphone, both the number of hours spent on streaming and the amount of data transmitted increase significantly. This result confirms that there is a significant difference in cellular data usage between phones with screen sizes 3 inches or larger and phones with screen sizes below 3 inches.

As the first academic study that aims to infer a causal relationship between screen size and cellular data usage based on the behavior of a large number of users, this paper serves as an initial attempt of utilizing big data to generate insights to support decision making in the telecommunications industry. Our study provides important practical implications for network operators, as we confirm the belief that the screen size of the device connected to the mobile network is a determinant of a user's cellular data usage. First, our analyses suggest that the relationship between screen size and cellular data usage depends on the type of devices. Although there is a disproportionate drop in cellular data usage on small-screen phones compared to mainstream smartphones with screens 3.5 inches or larger, screen size does not affect cellular data usage on mainstream smartphones. For tablets, users spend much less time on larger tablets, but the amount of data transmitted is not affected by screen size. Second, we also find that tablet users are in general heavy users of data services; they tend to consume more data than phone users. Based on this, network operators could offer larger data plans to tablet users.

2 LITERATURE REVIEW

This study builds upon the literature of studying consumer behavior and pricing strategies in the telecommunications industry. Text messages, voice call, and data services are three main revenue streams for network operators. How to design various pricing models to optimize the revenue or profit is a central question for service providers. One stream of studies focuses on examining the profit optimization and welfare implications of pricing models for one type of service. For instance, the three-part tariff plan or "fixed-up-to" plan is increasingly becoming a popular pricing strategy. This pricing plan requires a basic access fee, a free usage allowance, and a variable charge for usage beyond the free allowance. Masuda and Whang (2006), Lambrecht et al. (2007), and Iyengar et al. (2008), to name a few, have studied this multi-part tariff plan for voice call or internet access service under different contexts. Another stream of studies attempts to investigate the consumer demand and pricing strategies of multiple services at the same time. For instance, Kim et al. (2010) proposes a structural model to empirically evaluate the own- and cross-price elasticity demand of short message service (SMS) and voice calls; Niculescu and Whang (2012) proposes a model to examine the adoption of voice and data services for different types of consumers and applies it to the Japanese wireless services market; Lahiri et al. (2013) compares the profit and social welfare of two different pricing schemes for wireless services: one is based on service type (e.g., voice, text messaging, data, etc.) and the other is based on traffic (e.g., bytes) regardless of service type.

While there is no academic study that directly analyzes how different screen sizes would influence mobile data usage to the best of our knowledge, a few recent studies have investigated the differences between mobile Internet and desktop Internet that arise due to the smaller screen size of mobile devices than that of personal computers. Ghose et al. (2013) explores how Internet browsing behavior differs on mobile phones and personal computers. The authors show that search costs are higher on mobile phones because the screen is smaller, so links at the top of the screen are more likely to be clicked. Adipat et al. (2011) adopts the design science research framework and proposes an approach to adapt the presentation of web pages for mobile handheld devices; one of the important considerations in the study is the small screen size. The authors also evaluate the effects of the proposed presentation adaptation approach and find that it improves user performance and perception of mobile Web browsing.

This paper is also related to the growing literature of studies that examine various kinds of consumer behavior, such as adoption of mobile services and content generation/consumption, in the mobile era. For example, Hong and Tam (2006) investigates the factors that determine the adoption of mobile data services in non-work settings; Venkatesh et al. (2012) extends the unified theory of acceptance and use of technology (UTAUT) to propose the UTAUT2 in a consumer context, and the authors conduct a two-stage online survey to explain the acceptance and use of mobile Internet technology; Ghose and Han (2011) empirically analyzes the interdependence between content generation and content consumption behavior on the mobile Internet; Xu et al. (2014) studies how the adoption of a mobile news app may affect the traffic to a corresponding mobile web site. Different from these prior studies that use either survey or sampling methodologies to collect data, this paper attempts to utilize big data to infer a causal relationship between screen size and cellular data usage.

3 DATA

This section describes our dataset and introduces the main variables of interest.

3.1 Cellular Data Usage

Our main dataset is obtained from a leading telecommunications company in China. We have access to information about usage behavior of all 3G data users in a large city in April 2014. All personally identifiable information is anonymized. The size of data stored in the database is more than 1 TB. The number of active 3G users is over 1 million. For each user, we observe each data transmission between the user and a base transceiver station, which is regarded as a transaction in this study. For each transaction, we have information on the duration of the data transmission in seconds and the amount of data transmitted in bytes.

We construct two measures for monthly cellular data usage at different levels depending on the unit of analysis. Hour is the total number of hours spent on streaming, and MB is the total amount of data transmitted in megabytes (MBs). For device level analyses, information about all users using the same device k are aggregated to generate the device-level usage measures, $Hour_k$ and MB_k; for individual level analyses, all transactions related to the user i are aggregated to create the user-level usage measures, $Hour_i$ and MB_i. Since users may run multiple applications that require data connections at the same time, the total time spent on streaming is an aggregation of all time needed for all data transmissions (i.e., multiple data transmissions may parallel and overlap with each other).

3.2 Screen Size

The company keeps track of the terminal models of phones and tablets that are connected to the network. In our dataset, there are 73 tablet models produced by 10 manufacturers and 2,906 phone models produced by 109 manufacturers. Apple, Huawei, Lenovo, Nokia, Samsung, and Xiaomi are the main manufacturers (or brands). We search on the Internet for the screen size information for all the brands and terminal models of phones and tablets in our dataset. Overall, this is a very labor-intensive data collection process. We define Screen as the variable that measures the diagonal screen size of a device in inches. The range of this variable is 1 to 12.2 in our sample. The range of screen sizes for phones is 1 to below 7 inches, while the range for tablets is 7 to 12.2 inches.

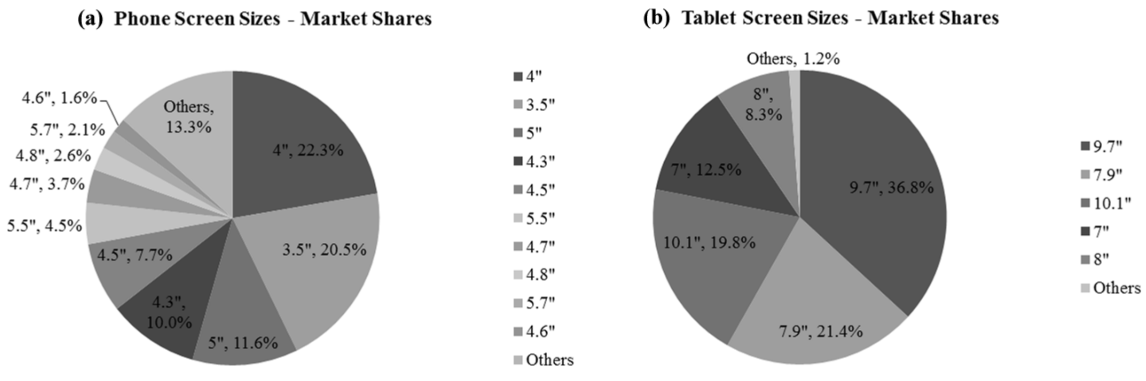

Figure 1. Market shares of different phone screen sizes (a) and different tablet screen sizes (b).

Figure 1 present the market shares of phones and tablets with different screen sizes measured by the total number of users, respectively. Many device models from different manufacturers may share the same screen size. For the phone market, major models include Apple iPhone 5 series (4 inches), iPhone 4 series (3.5 inches), Samsung Galaxy S4 (5 inches), Xiaomi's MI 2 and MI 2S (4.3 inches), MI 2A (4.5 inches), Huawei Ascend (4.5 inches), Samsung Galaxy Note 2 (5.5 inches), and so on. Apple's iPad (9.7 inches) and iPad Mini (7.9 inches) are the dominant tablets, accounting for almost 60% of the tablet market.

3.3 Individual Characteristics

We also observe some individual characteristics including gender, age, and membership tier. $Female_i$ is 1 if the gender of user i is female, and 0 otherwise. Age_i is user i's age as of 2014. The company offers four membership tiers: Basic, Silver, Gold, and Diamond. Non-Basic membership tiers enjoy different levels of benefits, e.g., free replacement SIM cards, exclusive shopping discounts, car rental discounts, a dedicated relationship manager, and so on. Most users are basic members. A non-basic membership tier can often be attained if a certain spending threshold is reached in the past few months. For each of the four membership tiers, we define a dummy variable to denote whether user i belongs to that tier. These four dummy variables are $Basic_i$, $Silver_i$, $Gold_i$, and $Diamond_i$. Membership tier information is available for all users, but gender and age information are missing for some users, which is assumed to be missing at random according to the company practice.

3.4 Service Plan Characteristics

We also obtain information on the service plan subscribed by each user, including the quota limits for text messages, voice call, and data services, and the cost of the service plan in Chinese Yuan (CNY). Msg_i is the number of free text messages included in user i's monthly plan. $Minute_i$ is the number of voice call minutes and $DataPlan_i$ is the number of MBs included in the monthly plan. $Cost_i$ is the price of the service plan for user i. The amount of free data included in a service plan should have a significant impact on the actual usage, although we do observe some users would go over the limit.

4 EXPLORATORY RESULTS

In this section, we report the main findings of our exploratory analyses.

4.1 Descriptive Statistics

To gain an overall idea about the bivariate relationship between screen size and monthly cellular data usage, we aggregate the monthly usage data for users whose devices share a similar screen size and compare the mean values of *Hour* and *MB* across different screen sizes. The results are presented in Figure 2. The screen size (x axis) is categorized in terms of 12 intervals, where only the beginning of each interval is labelled, i.e., the number 5 on the x axis denotes a range of screen sizes equal to or larger than 5 inches, but below 6 inches. The dark grey columns represent the average number of hours spent on streaming and the light grey columns represent the average amount of data transmitted in MBs.

The following observations can be made. First, both the number of hours and the amount of data are significantly smaller for devices with screen sizes below 3 inches than other devices. By examining the terminal models within this group, we find that most of these devices are feature phones, multimedia phones, or low-end smartphones. Second, for devices with screen sizes 3 inches or larger but below 7 inches (i.e., mainstream smartphones), the amount of data transmitted falls within a tight range from 300 to 400 MBs, and the number of hours spent on streaming follows a similar pattern except the number of hours on devices with screen sizes 6 inches or larger is much lower. Third, as the screen size increases from 7 to 12 inches for tablets, the number of hours spent on streaming gradually decreases from around 400 hours to below 200 hours. However, there are wide fluctuations in the amount of data transmitted from 300 to 600 MBs. Fourth, comparing between phones (below 7 inches) and tablets (7 inches and above), tablet users seem to consume more data than phone users on average. This is good news for mobile network operators, as tablet users have identified themselves as heavy users of data services, at least on average across the board. Overall, it is difficult to infer whether there is a significant difference in monthly cellular data usage among mainstream smartphones based on the results shown in this figure, especially for those above 3 and below 6 inches.

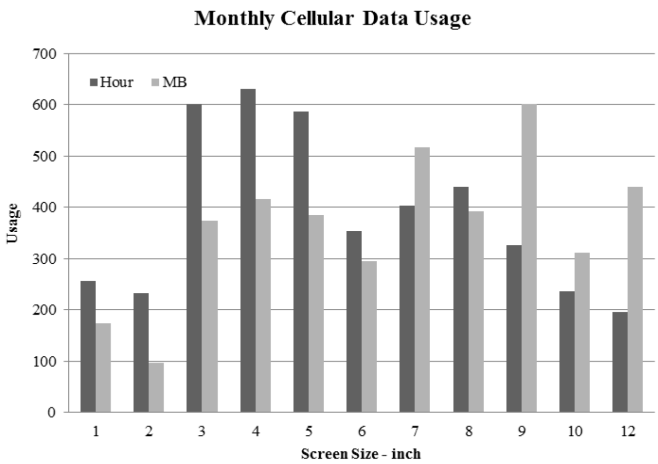

Figure 2. *Aggregate monthly usage across different screen sizes.*

4.2 Device-Level Regressions

To further investigate the effect of screen size on cellular data usage, we run cross-sectional regressions at the device-level to gain more insights. We specify the following OLS regression model:

$$DV = Screen_k + BrandDummies + \varepsilon \quad (1)$$

The dependent variable in Equation (1) can be either $Hour_k$ or MB_k, where k denotes a device. The main independent variable is $Screen_k$, which is the diagonal screen size of device k. Brand dummy variables are included to control for any manufacturer specific effects. For instance, certain design factors by popular brands such as Apple and Samsung may induce users to spend more time on their devices. Standard errors are clustered by brands to account for the residual correlation across devices produced by the same manufacturer. Given that people use phones and tablets for different purposes, e.g., people may use tablets to watch videos and use phones to check emails, we examine the relationship between screen size and cellular data usage separately for tablets and phones.

	Panel A: $Hour_k$				**Panel B: MB_k**			
	(1) Phone <7”	(2) Phone >=3”	(3) Phone <3”	(4) Tablet >=7”	(1) Phone <7”	(2) Phone >=3”	(3) Phone <3”	(4) Tablet >=7”
$Screen_k$	108.90*** (7.50)	64.54*** (15.01)	20.15 (22.32)	-53.78*** (14.56)	68.87*** (6.60)	82.08*** (12.33)	-38.04** (15.12)	21.15 (25.17)
#Brand	109	103	55	10	109	103	55	10
Obs	2,906	2,230	676	73	2,906	2,230	676	73
Adj. R^2	0.259	0.083	0.021	0.272	0.138	0.146	0.039	0.155

Note: * p-value<0.1, ** p-value<0.05, *** p-value<0.01.

Table 1. *Device-level Regressions Results.*

Table 1 presents the regression results on four different sets of observations. Panel A contains the results for regressions in which the dependent variable is $Hour_k$, and Panel B contains the results for regressions in which the dependent variable is MB_k. In Column (1) of both Panel A and Panel B, the regressions are on the sample of all phones. The coefficient estimates on $Screen_k$ are 108.90 and 68.87 in Column (1) of Panel A and Panel B, respectively; both are statistically significant at the 1% level. This indicates that a one-inch increase in a phone’s screen size is on average associated with an additional 108.90 hours spent on streaming and an additional 68.87 MBs in the amount of data transmitted in one month.

Similarly, in Column (2), where only phones with screen sizes 3 inches or larger are considered, the coefficient estimates on $Screen_k$ are both positive (64.54 and 82.08) and statistically significant at the 1% level. This seems to suggest that a bigger screen does lead to more cellular data usage on mainstream smartphones in terms of both the number of hours spent on streaming and the amount of data transmitted. Later, we will further investigate whether this result is robust in other analyses. In Column (3), when the regressions are on phones with screen sizes below 3 inches only, we do not find a significant positive relationship between screen size and the number of hours spent on streaming, but on the contrary a statistically negative relationship between screen size and the amount of data transmitted in MBs. The percentage of users associated with phones that are below 3 inches in screen sizes is only 2.8% in our dataset; the total amount of data consumed by these users accounts for even less (0.8% of all data). As the economic significance of this group of phones is small and also declining over time, we refrain from making them as our main focus.

When the regressions are on tablets only in Column (4), the coefficient estimate on $Screen_k$ in Panel A is negative (-53.78) and statistically significant at the 1% level, while the one in Panel B is positive but statistically insignificant at the 10% level. This result indicates that a one-inch increase in screen size among tablets is actually associated with a decrease in the number of hours spent on streaming. One possible explanation for this is that as the size of the tablet increases, its portability feature is diminished. A large-screen tablet also becomes similar as a laptop, so people may start to prefer using laptops instead because of their benefits in power and performance.

4.3 Individual-Level Regressions

In this subsection, we conduct regression analyses at the individual level to control for the effect of observed individual and service plan characteristics. We specify the following regression model:

$$DV = Screen_i + Female_i + Age_i + Diamond_i + Gold_i + Silver_i + DataPlan_i + BrandDummies + \varepsilon \quad (2)$$

	Panel A: *$Hour_i$*				Panel B: *MB_i*			
	(1) Phone <7”	(2) Phone >=3”	(3) Phone <3”	(4) Tablet >=7”	(1) Phone <7”	(2) Phone >=3”	(3) Phone <3”	(4) Tablet >=7”
$Screen_i$	49.94^{***} (18.56)	23.99 (17.00)	76.45^{***} (12.76)	-53.95^{***} (2.80)	77.69^{***} (10.34)	85.59^{***} (13.87)	-38.41^{***} (2.71)	-19.67^{**} (9.91)
$Female_i$	-46.50^{***} (13.68)	-46.87^{***} (13.98)	-28.30^{***} (3.78)	-31.30^{***} (10.48)	-52.68^{***} (3.60)	-53.67^{***} (3.74)	-14.97^{***} (3.40)	-6.01 (28.11)
Age_i	-6.96^{***} (0.60)	-6.83^{***} (0.58)	-5.71^{***} (0.34)	-3.60^{***} (1.34)	-8.08^{***} (0.81)	-8.28^{***} (0.79)	-2.88^{***} (0.14)	-6.80^{***} (0.18)
$Diamond_i$	-13.00 (77.38)	-7.72 (75.96)	-317.8^{***} (115.64)	198.38^{***} (64.66)	425.9^{***} (93.64)	429.9^{***} (92.26)	-243.2^{*} (125.14)	552.3^{**} (256.61)
$Gold_i$	8.01 (46.72)	12.66 (45.48)	-148.9^{**} (65.72)	201.52^{***} (47.19)	168.3^{***} (56.73)	170.4^{***} (56.03)	-51.08 (76.00)	-40.86 (43.58)
$Silver_i$	159.13^{***} (15.13)	163.0^{***} (16.31)	24.57 (19.89)	246.93^{***} (57.44)	177.2^{***} (8.34)	178.9^{***} (7.69)	46.42^{***} (10.87)	208.3^{***} (37.96)
$DataPlan_i$	0.35^{***} (0.10)	0.35^{***} (0.10)	0.43^{***} (0.02)	-0.06 (0.07)	0.41^{***} (0.03)	0.41^{***} (0.03)	0.43^{***} (0.02)	0.14 (0.14)
#Brand	109	103	55	10	109	103	55	10
Obs	1,095,197	1,067,842	27,355	18,134	1,095,197	1,067,842	27,355	18,134
Adj. R^2	0.101	0.091	0.111	0.066	0.162	0.156	0.123	0.025

Note: * p-value<0.1, ** p-value<0.05, *** p-value<0.01.

Table 2. Individual-Level Regressions.

Similar as the device-level regressions, the dependent variable in Equation (2) can also be either $Hour_i$ or MB_i, where i denotes a user. The main independent variable is $Screen_i$, which is the diagonal screen size of the device owned by user *i*. We also control for $Female_i$, Age_i, three membership-tier dummies ($Diamond_i$, $Gold_i$, and $Silver_i$), and the amount of data quota limit, which are all defined in the data section. The basic membership tier would serve as the benchmark case. Brand dummy variables are included to control for any manufacturer specific effects. Standard errors are clustered by brands to account for the residual correlation across devices produced by the same manufacturer.

The results of individual-level regressions are presented in Table 2. Panel A contains the results for regressions in which the dependent variable is $Hour_i$, and Panel B contains the results for regressions in which the dependent variable is MB_i. Our main findings related with $Screen_i$ are largely similar as that of device-level regressions, so we focus more on comparing the results of individual-level and device-level regressions and pointing out any differences in the coefficient estimates on the variable screen size in Table 2 as follows. In Column (2) of Table 2's Panel A, the coefficient estimate on $Screen_i$ is positive (23.99) but not significant at the 10% level, which implies that at the individual level screen size has no effect on the number of hours spent on streaming for mainstream smartphones. In Column (3) of Panel A, we find a positive and statistically significant relationship between screen size and the number of hours spent on streaming for phones with screen sizes below 3 inches. In Column (4) of Panel B, the coefficient estimate on $Screen_i$ is negative (-19.67) and statistically significant at the 1% level, indicating that screen size has a significant negative effect on the amount of data transmitted on tablets at the individual level.

5 QUASI-EXPERIMENTAL DESIGN

The exploratory regression analyses in the previous section can provide some interesting insights, but the corresponding results are sometimes not consistent, although the signs of the coefficient estimate on screen size are almost always consistent. In addition, these analyses may potentially suffer from omitted variable bias or selection bias. In the device-level regressions, if any omitted technical factors of a device are correlated with screen size, the coefficient estimate on screen size would be biased. In the individual-level regressions, we may have similar issues like omitted variable bias as we do not observe all individual characteristics, or more importantly, selection bias could potentially become a serious concern. For instance, heavy users of cellular data services may self-select to purchase newer smartphone models that have larger screens and are also faster, which could possibly result in an over-estimation of the effect of screen size on cellular data usage. In order to resolve any discrepancies in the exploratory results and infer a causal relationship, we report two additional analyses in this section to further examine the problem at hand following a quasi-experimental design.

5.1 Propensity Score Matching

To adjust for any potential selection bias, we first employ the Propensity Score Matching method (Rosenbaum and Rubin 1983) to find a matched control group that is observationally identical to a treatment group. For tablets, we select the two most popular screen sizes (9.7 and 7.9 inches) and examine whether cellular data usage on 9.7-inch tablets is less than that on 7.9-inch tablets. For phones, to cover small, medium, and large screen sizes, we select four different phone screen sizes (3.2, 3.5, 4, and 5 inches) to make comparisons and investigate whether there is a positive relationship between screen size and cellular data usage on phones. As shown in Figure 1, 4 inches is the most popular phone screen size in our dataset, so we choose it as the benchmark case. In general, 4 inches is considered as neither too big nor too small; it is also very close to the median screen size of all phones in our dataset, which is 4.3 inches. 3.5 and 5 inches are the second and third most popular screen sizes, respectively. We select 3.2 inches other than 3 inches because it is much more popular than 3 inches, even though 3.2 inches is already ranked 12th in terms of popularity among all phone screen sizes. We make the following three comparisons for phones: 4 inches vs. 5 inches, 4 inches vs. 3.5 inches, and 4 inches vs. 3.2 inches.

To illustrate the detailed steps of our analyses, we use the comparison between 4 inches and 3.5 inches as an example. We randomly select two groups of 1000 users whose phones have the screen size of 4 and 3.5 inches, respectively. Many phone manufacturers and models are represented in these random samples. We identify 122 phone models from 29 manufacturers in the random sample of 1000 users whose phones fall under the 4-inch category; there are 67 phone models from 26 manufacturers represented in the 3.5-inch category. Table 3 provides the list of top 5 phone models for each screen size based on the number of users in our random samples. Having a diverse mix of manufacturers and models helps alleviate confounding concerns related with manufacturer- or model-specific characteristics that would arise if the random sampling is based on phone models only, for example, Apple iPhone 5 (4 inches) and Samsung Galaxy Ace (3.5 inches). For 4-inch devices, the average number of hours spent on streaming among 1000 randomly selected users is 649.87 and the average amount of data transmitted in MBs is 455.55. For 3.5-inch devices, these two usage measures are 638.14 and 412.36. The 3.5-inch group serves as the treatment group. The purpose of the propensity score matching technique is to find matched users in the 4-inch group as the control group.

4-inch		**5-inch**		**3.5-inch**		**3.2-inch**	
Apple	iPhone 5	Samsung	Galaxy S4 I9500	Apple	iPhone 4S	Nokia	5230
Apple	iPhone 5S	Samsung	Galaxy S4 I9502	Apple	iPhone 4	Nokia	5235
Samsung	Galaxy Trend II Duos	Huawei	G610-U00	Samsung	Galaxy Ace S5830I	Nokia	5233
Samsung	Galaxy S Duos	Xiaomi	MI 3W	ZTE	Blade	Nokia	C5-03
Apple	iPhone 5C	Samsung	Galaxy Grand Duos I9082	Lenovo	A65	Samsung	Galaxy Gio

Table 3. Top 5 Phone Models with Different Screen Sizes.

We run a Probit regression to evaluate how different observed characteristics affect the user's probability of joining the treatment group. The dependent variable of this Probit regression is $Treatment_i$, which is 1 if the user is in the 3.5-inch group and 0 if the user is in the 4-inch group. The independent variables include individual characteristics and service plan characteristics. Table 4 presents the results of this regression. We find that age, attaining a Silver membership tier, number of free voice call minutes, amount of free data, and the cost of service plan are good predictors of a user's choice of phone screen size.

	Treatment
$Female_i$	0.08 (0.07)
Age_i	0.01*** (0.00)
$Diamond_i$	-0.76 (0.57)
$Gold_i$	-0.23 (0.24)
$Silver_i$	0.21** (0.09)
$Log(Msg_i)$	-0.01 (0.02)
$Log(Minute_i)$	0.29** (0.13)
$Log(DataPlan_i)$	0.19** (0.09)
$Log(Cost_i)$	-0.95*** (0.33)
Constant	1.44*** (0.48)
Obs	2,000
Likelihood Ratio	41.51

Note: * p-value<0.1, ** p-value<0.05, *** p-value<0.01.

Table 4. Propensity Score Matching.

After we calculate the propensity score for each user, we adopt four different matching methods (Nearest Neighbor, Kernel, Stratification, and Radius Matching) illustrated in Becker and Ichino (2002) to find matched users in the control group. Table 5 presents the testing results of these four matching methods on both outcome variables, *Hour* and *MB* in Panel A and B, respectively. All the t-stats of different matching methods in both panels of Table 5 suggest that there is no significant difference in cellular data usage between the control and treatment groups even at the 10% level.

	Panel A: ***Hour***					**Panel B:** ***MB***				
Matching Method	Treated	Controls	Diff.	Std.Err.	t-stat	Treated	Controls	Diff.	Std.Err.	t-stat
Nearest Neighbor	1,000	740	24.82	25.84	0.96	1,000	740	18.54	31.38	0.59
Kernel	1,000	999	7.57	22.14	0.34	1,000	999	6.63	23.72	0.28
Stratification	1,000	999	7.53	20.30	0.37	1,000	999	1.67	23.50	0.07
Radius (0.1)	1,000	999	7.36	22.09	0.33	1,000	999	9.94	26.37	0.38

Table 5. Comparison between 4-inch and 3.5-inch Phones.

It is possible that the difference between 4 inches and 3.5 inches is too small to significantly influence people's cellular data usage behavior. However, we obtain similar results in the comparison of 4-inch and 5-inch phones, which imply that an increase of one-inch in screen size from 4 inches does not lead to any significant change in cellular data usage.

However, when we make the comparison between 4-inch and 3.2-inch phones, we find a different pattern. Table 6 reports the propensity score matching results for these two groups. The mean differences of two outcome variables between the treated and matched controls are all negative and statistically significant at the 1% level, which indicate that cellular data usage on 3.2-inch phones (treatment group) is much less than usage on 4-inch phones (control group). As there is no difference in cellular data usage on 4-inch and 3.5-inch phones (reported in Table 5), it seems to suggest that cellular data usage would drop dramatically from 3.5 inches to 3.2 inches. This result is consistent with the fact that most mainstream smartphones have a screen size of 3.5 inches or larger, while low-end smartphones or feature phones tend to have a smaller screen size than 3.5 inches. Based on these results, we conclude that screen size does not affect the level of cellular data usage for mainstream smartphone users.

We can follow similar steps to make comparisons for 7.9-inch and 9.7-inch tablets. The tablet market is much more concentrated in a few manufacturers than the phone market; tablets of these two sizes in our random sample are produced only by Apple. The iPad mini is 7.9 inches; different versions of iPad and the iPad Air are 9.7 inches. The 7.9-inch tablet users serve as the control group, while the 9.7-inch tablet users serve as the treatment group. Table 7 summarizes the comparison results based on propensity score matching. In Panel A, when the outcome variable is the number of hours spent on streaming, we find significant differences between the control and treatment groups. The time spent on streaming on 9.7-inch tablets is 78 to 86 hours less than that on 7.9-inch tablets in a month. In Panel B, when the outcome variable is the amount of data transmitted, we also observe negative differences, but they are no longer statistically significant at the 10% level. The amount of data transmitted on 9.7-inch tablets is 32 to 48 MBs less than that on 7.9-inch tablets. These results confirm that there is a negative relationship between screen size and time spent on tablets.

	Panel A: ***Hour***					**Panel B:** ***MB***				
Matching Method	Treated	Controls	Diff.	Std.Err.	t-stat	Treated	Controls	Diff.	Std.Err.	t-stat
Nearest Neighbor	1,000	624	-121.36	30.59	-3.97	1,000	624	-140.73	19.19	-7.33
Kernel	1,000	973	-124.55	17.96	-6.94	1,000	973	-151.30	14.53	-10.41
Stratification	1,000	973	-121.47	26.04	-4.67	1,000	973	-150.20	17.41	-8.63
Radius (0.1)	1,000	973	-152.69	20.19	-7.56	1,000	973	-175.31	15.89	-11.03

Table 6. Comparison between 4-inch and 3.2-inch Phones.

	Panel A: *Hour*					Panel B: *MB*				
Matching Method	Treated	Controls	Diff.	Std.Err.	t-stat	Treated	Controls	Diff.	Std.Err.	t-stat
Nearest Neighbor	999	904	-78.40	19.18	-4.09	999	904	-31.85	61.16	-0.52
Kernel	999	998	-86.29	11.21	-7.70	999	998	-48.22	58.90	-0.82
Stratification	999	998	-83.60	13.78	-6.07	999	998	-38.18	54.24	-0.70
Radius (0.1)	999	998	-80.86	12.53	-6.45	999	998	-41.40	58.12	-0.71

Table 7. Comparison between 7.9-inch and 9.7-inch Tablets.

5.2 Difference-in-difference

The validity of propensity score matching depends on the assumption that unobserved characteristics would not affect both participation in treatment and the outcome variables. Although we have controlled for many observed individual and service plan characteristics constructed from our rich dataset, we cannot rule out the possibility that other unobserved factors such as income may potentially affect people's choice of screen size and their cellular data usage. To overcome such challenges in cross-sectional analyses, we adopt the difference-in-difference approach to mimic an experimental design in a panel data setting.

We take advantage of the fact that people change devices over time to implement a pre-post test design. We select a random sample of users who have used two different phones to connect to the mobile network over the time period from February to July 2014. To rule out the effect of service plans on data usage, we only consider users whose service plans do not change over the sample period. Users who adopt a phone with the same screen size as before serve as the control group; users who adopt a phone with a different screen size from before serve as the treatment group. Adoption of a phone with a different screen size is regarded as the intervention. We observe each user's cellular data usage over six months, so we can examine the difference between the control and treatment groups before and after the intervention.

	Panel A: $Hour_{it}$				Panel B: MB_{it}			
	(1) Phone <7"	(2) Phone >=3"	(3) Phone <3"	(4) Phone >=3" & <3"	(1) Phone <7"	(2) Phone >=3"	(3) Phone <3"	(4) Phone >=3" & <3"
$Screen_k$	23.51^{***} (5.34)	-3.02 (8.19)	-47.63 (40.35)	49.70^{***} (6.84)	48.72^{*} (26.13)	62.58 (51.86)	10.15 (11.18)	35.23^{***} (7.57)
#User	2,720	2,281	30	409	103	2,281	30	409
Obs	14,305	12,160	118	2,027	290	12,160	118	2,027
Within R^2	0.021	0.018	0.123	0.051	0.023	0.003	0.062	0.023

Note: * p-value<0.1, ** p-value<0.05, *** p-value<0.01; monthly dummies are included in regressions but omitted from the table.

Table 8. Difference-in-Difference Results.

We employ a fixed effects model to conduct the difference-in-difference analysis:

$$DV = Screen_{it} + MonthDummies + f_i + \sigma \tag{3}$$

The dependent variable in Equation (3) can be either $Hour_{it}$ or MB_{it}, where i denotes a user and t denotes a month. The main independent variable is $Screen_{it}$, which is the diagonal screen size of the device owned by user i in month t. Five monthly dummies (out of six months) are included in the model to control for any time effects. Any time-invariant (observed or unobserved) individual characteristics are captured by f_i. Standard errors are clustered by users to account for the residual correlation across different observations related with the same user. Table 8 presents the regression results of fixed effects models on four different sets of observations. Panel A contains the results for regressions in which the dependent variable is $Hour_{it}$, and Panel B contains the results for regressions in which the dependent variable is MB_{it}.

When the regressions are on the full sample in Column (1), the coefficient estimates on $Screen_{it}$ are both positive (23.51 and 48.72) and statistically significant at the 1% and 10% levels, respectively, in Panel A and Panel B. This suggests that a one-inch increase in screen size among phones is associated with an additional 23.51 hours spent on streaming and an additional 48.72 MBs in the amount of data transmitted. However, in Column (2), where only phones with screen sizes 3 inches or larger are considered (i.e., users switch between smartphones), the coefficient estimates on $Screen_{it}$ are no longer statistically significant at the 10% level. In Column (3), when the regressions are on phones with screen sizes below 3 inches only (i.e., users switch between traditional phones), we also do not find a significant relationship between screen size and the number of hours spent on streaming or the amount of data transmitted in MBs. In Column (4) of both Panel A and Panel B, the regressions are on the sample of users who switch between traditional phones and smartphones. The coefficient estimates on $Screen_{it}$ are 49.70 and 35.23, respectively; both are statistically significant at the 1% level. This indicates that a one-inch increase in screen size when switching from a traditional phone to a smartphone is on average associated with an additional 49.70 hours spent on streaming and an additional 35.23MBs in the amount of data transmitted in one month. Therefore, across all phones, there is still a positive relationship between screen size and cellular data usage. Results in Column (4) again imply that the sharp difference in cellular data usage on mainstream smartphones and small-screen phones contributes to the significant results we see in Column (1).

In addition, results in Column (2) for mainstream smartphones are also consistent with the results we obtain using propensity score matching in the previous subsection. Both analyses imply that there is no association between screen size and cellular data usage on mainstream smartphones. In contrast with the results from device-level and individual-level regressions, in which omitted variable bias or selection bias may lead to biased estimation, the propensity score matching and difference-in-difference approaches mitigate such concerns and provide more reliable conclusions.

6 CONCLUSION

To build an in-depth understanding of consumer behavior is essential for increasing the average revenue per user (ARPU) for network operators. In this study, we utilize a terabyte dataset to empirically test the relationship between screen size and cellular data usage for both phones and tablets from different perspectives. Exploratory analyses seem to suggest that there is a positive relationship between screen size and cellular data usage on phones. However, after we adopt different sampling strategies and employ the propensity score matching and difference-in-difference approaches to address potential concerns due to omitted variable bias or selection bias, we find that a bigger screen does not lead to more cellular data usage on mainstream smartphones. Our study demonstrates that big data presents a lot of opportunities for utilizing different samples and methods in order to draw causal inference in an observational study. Although the amount of data analyzed in this study is huge, we unfortunately do not observe users' data usage behavior over Wi-Fi networks. Future research can examine how screen size plays a role in affecting users' Wi-Fi and overall mobile data consumption, respectively. The availability of Wi-Fi networks and the choice between free and paid data could potentially complicate the matter and require different kinds of analyses.

Acknowledgments

This work was partly supported by the National Natural Science Foundation of China (No. 71402007) and the Fundamental Research Funds for the Central Universities (No. 2014RC0601).

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