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Going Mobile: The Effects of Smartphone Usage on Internet Consumption

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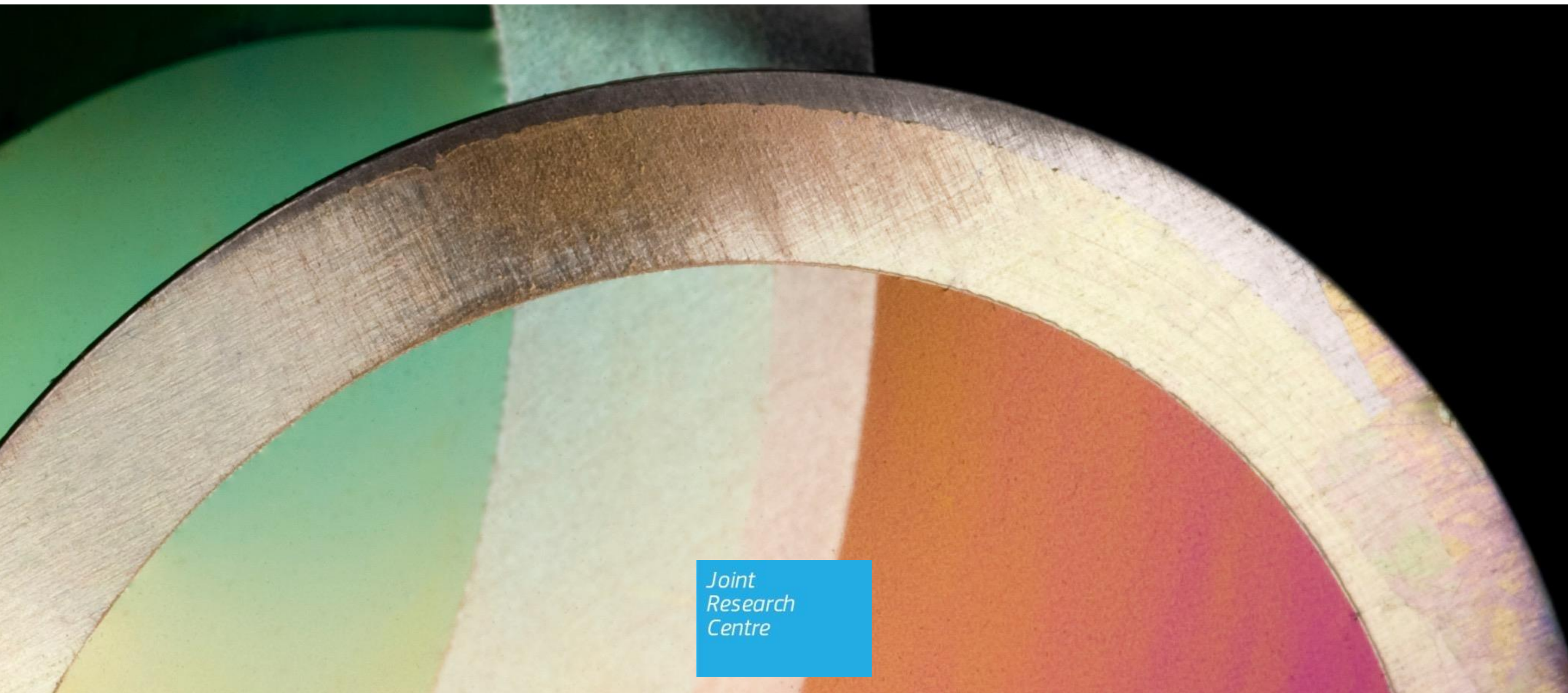

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Abstract

With relatively small screens and limited display, smartphones significantly affect users' online browsing experience relative to fixed devices like the desktop. As consumers increasingly access the Internet through mobile devices, this paper explores the effects of a shift towards smartphone Internet access on the consumption of online content. Using data on the clickstream activity of over 2,900 individuals on both their smartphone and desktop, I estimate the effect of smartphone usage on users' allocation of time across various categories of websites, as well as their diversity and depth of online content consumption. Employing an instrumental variables approach based on updates of the smartphone operating system, the results show an increase in the usage of game and social networking domains at the expense of news and shopping domains - among others - as mobile usage increases relative to desktop. I also find that the diversity of consumption decreases within several categories, whereas consumption depth increases for games and social networking categories and decreases for search and news domains. Results show limited differences across consumer demographics. These results have important implications for website publishers, advertisers, and online competition.

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1 Introduction

Mobile devices - the smartphone in particular - have offered the promise of an almost constant connectivity with the online world. Liberated from the need of a fixed Internet connection, individuals can now search, use, and benefit from online information almost anywhere and at almost any time. Smartphone ownership and Internet usage have been growing importantly in many countries (Pew Research Center, 2016), and mobile devices are increasingly used as an essential means to access the Internet. In the US, the number of Internet users who exclusively employ mobile devices to go online surpassed the number of users who only connect via desktop in March of 2015.[1] In 2016, smartphones were the primary mobile route used to access the web in Germany.[2] Worldwide mobile usage even surpassed desktop usage at the end of 2016.[3]

While smartphones naturally provide access to the same Internet content as fixed devices, some of their characteristics have important implications for the online experience that they offer, potentially affecting individual digital consumption decisions. At least two main characteristics distinguish smartphone and desktop browsing from the perspective of Internet consumption. First, smartphones present much smaller screens than desktops, and their limited display capabilities consequently restrict browsing behavior due to a more costly search and assimilation of information process. Second, because smartphones are mobile by definition, users are more likely to be interrupted when using such devices. Attention on the smartphone is consequently likely to be more fragmented than on the desktop. These characteristics imply higher costs of browsing for information - or search costs - on the smartphone (Hwang et al., 2012; Ghose et al., 2013; Ghose and Park, 2013), and may also have consequences on individual digital consumption decisions.

With these important differences in mind, and as consumers increasingly access the Internet trough their smartphone, this paper explores the effects of a shift towards mobile Internet access on individuals' consumption of online content. The empirical analysis

[1]See `https://www.comscore.com/Insights/Blog/Number-of-Mobile-Only-Internet-Users-Now-Exceeds-Desk` `S`.

[2]According to a study carried out by BurdaForward, 83.5% of smartphone owners polled used their handset every day to access the internet. See `https://www.emarketer.com/Article/Smartphones-Tablets-Drive-Internet-Use-Germany/1013757`.

[3]See `https://techcrunch.com/2016/11/01/mobile-internet-use-passes-desktop-for-the-first-time-stud` and `https://digiday.com/media/mobile-overtaking-desktops-around-world-5-charts/`

relies on a dataset that consists in the full clickstream history of a large set of over 2,900 individuals in Germany between September 2015 and April 2016, a period of high smartphone penetration in the country. For each individual in the data, I observe the time spent on each visited domain through their desktop and their smartphone. For the smartphone, I observe online access made through the browser and through apps. By allowing for a precise measure of the share of Internet content consumed through each device, these very detailed data provide a unique opportunity to explore how various measures of digital consumption are affected by a shift in online access towards the smartphone. In particular, I ask how individuals change the allocation of their total online time across distinct categories of websites as their relative smartphone usage increases. Additionally, I construct measures of users' concentration and depth of digital consumption in order to assess how the diversity and focus of Internet consumption is affected by smartphone usage. These questions relate to similar questions that have been explored in the literature regarding the effects of mobile technologies on consumer behavior (Ghose et al., 2013; Xu et al., 2014, 2016). This paper differs from most of these studies, however, as it does not focus on consumer behavior on a particular platform, but rather explores the effects of the mobile web on overall Internet consumption and behavior.

I employ two empirical approaches to tackle the endogeneity of relative smartphone usage. First, I rely on the panel nature of the data in order to control for (time-invariant) unobserved characteristics across individuals through the inclusion of individual fixed effects. This setting allows to ask how a given individual changes their Internet consumption as their relative smartphone usage changes, controlling for their constant and unobserved characteristics. Second, I employ an instrumental variables approach based on exogenous updates of the smartphone Android operating system (OS). By offering a better smartphone experience overall - and as evidenced further below - newer versions of the OS positively affect the share of total online time spent on the smartphone. At the same time, such OS updates do not directly affect overall Internet content consumption. OS updates therefore provide exogenous variation that allow for the identification of the effect of smartphone usage on overall Internet consumption.

The empirical analysis presents several findings. First, I document significant differences in browsing behavior across the smartphone and the desktop. Browsing concentration

- measured through the Herfindahl-Hirschman Index (HHI) of concentration as well as various concentration-ratio indexes - is much higher on the smartphone than it is on the desktop. Controlling for individual fixed effects and for total browsing time on each device, the browsing HHI is over 570 points higher on the smartphone, corresponding to a 17% difference relative to the desktop. Concentration ratios also present significant differences in concentration. Browsing depth - measured through the share of domain visits that exceed 10 minutes in duration - is much lower on the smartphone. Using a similar specification, results show that the share of long visits on the smartphone are about 10 percentage points lower on the smartphone, corresponding to a 28% difference relative to the desktop. While these results indicate large differences in consumers' browsing activity between the smartphone and the desktop, I also find a significant level of heterogeneity across domain categories. For instance, while concentration is - relative to the desktop - higher on the smartphone within shopping or price comparison domains, the difference is lower for gaming or communication domains. Perhaps unsurprisingly, the latter type of domains are often better suited for the smartphone than the former. Depth of browsing is significantly lower on the smartphone than on the desktop for all domain categories except gaming, where it turns out to be 17 percentage points higher on the smartphone. Second, I find that an increase in the relative share of smartphone usage leads to a reallocation of overall browsing time towards domain types that are arguably better suited for smartphone usage. In particular, I find that the share of online time dedicated to gaming and social networking domains increase with smartphone usage at the expense of news, shopping, and search domains, among others. For instance, a increase in the share of total smartphone usage by 5 percentage points leads to a 1.5 percentage points increase in the share of total online time allocated to gaming domains, and in a 0.8 percentage points decrease in the share of total online time allocated to shopping domains. Third, results show that smartphone usage also has effects on within category concentration and depth of browsing. For instance, browsing concentration and depth both increase within the gaming and social networking categories. Browsing diversity also decreases within the media on-demand category, while browsing depth is unaffected. Browsing depth and diversity both decrease within the news category. Finally, I also explore the heterogeneity of these effects across consumers according to their age and income. While differences are limited, results show that - as their smartphone usage increases - younger individuals increase the depth of their browsing as well as the share of their online time spent on social networking domains to a larger extent compared to older individuals.

The paper proceeds in five sections after the introduction. Section 2 presents a review of the literature regarding the various effects and implications of mobile Internet use. Section 3 presents the data used in the analysis, introduces various measures of Internet browsing behavior, and explores the determinants of smartphone and desktop browsing usage. Section 4 explores differences in browsing behavior across smartphone and desktop, showing how smartphones' characteristics can affect Internet consumption by imposing higher search costs. Section 5 turns to the main question of the paper and to the identification of the causal effect of smartphone usage on Internet consumption in terms of allocation of online time across various domain categories as well as within category concentration and depth of consumption. It also explores the heterogeneity of these effects across various individual groups. Section 6 discusses the implications of the results and concludes.

2 Relationship to Existing Literature

The research question posed in this paper - on the effects of smartphone usage on Internet consumption - relates to several strands of research pursued by information systems, marketing, and economics scholars on the various effects of the mobile web.

2.1 Internet and Search Costs

This paper first relates to the literature on the effects of reduced search costs online, and how they affected prices and product variety, among others. The advent of the Internet allowed an important decrease in the costs of searching for information (Bakos, 1997), which consequently had a negative impact on prices and on price dispersion.[4] A reduction in search costs may also affect product variety through an increase in sales of products that are more difficult to find offline, or products that are not popular enough

[4]See, for instance, Brynjolfsson and Smith (2000); Morton et al. (2001); Brown and Goolsbee (2002); Ellison and Ellison (2009).

to be available in brick-and-mortar stores. In other words, lower search costs can enable sales of products located in the long-tail (Anderson, 2006; Yang, 2013). Brynjolfsson et al. (2003) show that online channels increase the variety of products available, and Brynjolfsson et al. (2011) show that the Internet channel exhibits a significantly less concentrated sales distribution when compared with traditional channels. They conclude that the Internet's long tail is not only due to an increase in product selection but also partly reflect lower search costs online. Kuksov (2004) shows how lower search cost for consumers may also increase product variety if they lead to higher incentives for firms to differentiate their products. In the context of the music industry, Zhang (2016) provides evidence that lower search costs may enable the discovery of lesser-known products.[5] If mobile devices impose - as documented below - higher search costs on their users, one could expect an increase in the usage of smartphones to affect the nature and variety of Internet consumption.

2.2 Search Costs Are Higher on Mobile

Due of the inherent characteristics of mobile devices, there are reasons to believe search costs to be higher for online activities performed through the smartphone compared to the desktop. There are two main characteristics that distinguish smartphone browsing from desktop browsing. First, smartphones present much smaller screens than desktops and laptops. Their limited display capabilities consequently restrict browsing in several ways as users are often required to perform numerous scrolling maneuvers in order to read and retrieve information. Additionally, mobile browsers typically only offer single window browsing, and the screen cannot be split. Mobile users therefore need to provide important cognitive efforts and rely on their short-term memory in order to refer to the information and content from a webpage that they already viewed and that is not visible on the screen (Albers and Kim, 2000; Adipat et al., 2011). Several studies have already documented how smaller screens restrict the visualization of information on mobile devices (Chittaro, 2006) and affect the navigation behavior and perceptions of mobile Internet users (Chae and Kim, 2004) as well as their ability to find specific information (Jones

[5]Despite the important reduction in search costs provided by the Internet, the empirical literature indicates that consumers still face nontrivial search costs in online markets. See, for instance, Brynjolfsson et al. (2010) and Hann and Terwiesch (2003).

et al., 1999; Sweeney and Crestani, 2006). Smaller screens have also been shown to inhibit the effectiveness of the learning experience (Maniar et al., 2008; Kim and Kim, 2012), invoke lower reactivity to the media being consumed (Naylor and Sanchez, 2017), and reduce the effectiveness of mobile advertising (Shankar and Hollinger, 2007; Shankar et al., 2010). Second, because smartphones are mobile by definition, individuals are more likely to be interrupted while using their smartphone than while using their desktop. Attention on the smartphone is consequently likely to be more fragmented than on the desktop. Andrews et al. (2015) find that commuters in crowded subway trains are about twice as likely to respond to a mobile offer by making a purchase vis-à-vis those in noncrowded trains. They explain this result by the fact that crowding may pose physical constraints that make people turn inward and engage in higher mobile immersion. A reduction in external distractions therefore increases engagement on the smartphone.[6] Taken together, this empirical evidence indicates that search costs are larger on the smartphone than on desktop.

2.3 The Effects of the Mobile Web

Most studies analyzing the effects of the mobile web have focused on specific platforms. Ghose et al. (2013) exploit exogenous variation in the ranking mechanism of posts on a microblogging website to identify ranking effects on both desktop and mobile phones. They find that ranking effects are higher on mobile phones, suggesting higher search costs, and that the benefit of browsing for geographically close matches is higher on mobile phones. Using data on e-book transactions, Ghose and Park (2013) study the impact of mobile devices on niche product consumption. They find that smartphone users' product sales are more concentrated than those of PC users, showing that mobile commerce markets follow a Pareto principle rather than a long tail phenomenon in terms of sales diversity. Relying on data from an Internet-based grocery retailer, Wang et al. (2015) analyze changes in customers' spending behavior upon adopting mobile shopping. Their results show that the limited screen size and functionalities of mobile devices lead customers to purchase habitual products - i.e. products that they have purchased before

[6] Related, Ghose et al. (2019) investigate how contextual targeting affects user redemptions of mobile coupons with commuting.

or are already familiar with - and that customers are less likely to purchase items or brands that require research, planning, or consideration. Ghose and Han (2014) find that mobile apps have increased consumer surplus by about $33.6 billion annually in the US. Han et al. (2016) use individual-level mobile app time consumption data to estimate users' baseline app utility, finding that the latter diverges substantially across app categories, and that users' demographic characteristics explain a substantial amount of heterogeneity in baseline utility and satiation.

Several papers have also looked at the effect of specific apps' adoption on subsequent behavior. Xu et al. (2016) evaluate the impact of tablet adoption on e-commerce sales. Relying on data from Alibaba, they find that the introduction of the firm's *iPad* app enhanced the overall growth of its e-commerce market. Their results also demonstrate that the tablet acts as a substitute for the PC while it acts as a complement for the smartphone. Einav et al. (2014) show that the adoption of eBay's mobile shopping application is associated with both an immediate and sustained increase in total platform purchasing. Xu et al. (2014) show that the introduction of the Fox News app lead to a significant increase in demand at the mobile news website. Lee (2016) looks at the effects of smartphone adoption on usage of other digital devices and overall digital consumption. Also related to the present study, Xu et al. (2019) investigate how the quality of local fixed fixed-line and mobile Internet influences the adoption and use of the mobile Internet. Their results show that local fixed-line Internet speed has a negative impact on mobile Internet adoption and use. While there is a large and growing literature analyzing the various effects of the mobile web, research analyzing the effects of smartphone usage on overall Internet consumption is - to my knowledge - non-existent.

Finally, this paper also relates to the literature analyzing the economics of online attention. In particular, the analysis is close to the one of Boik et al. (2016), which assesses how US households changed their desktop time allocation across and within domains over a period of time that saw a large increase in online offerings. Their results show that households changed where they allocated their time, yet did not change how they allocated it, both in terms of concentration and intensity of attention. Their analysis, however, only focuses on difference in online browsing on a fixed device and does not include mobile browsing.

3 Data and Descriptives

3.1 Data

The data used in this paper were collected by the *Gesellschaft für Konsumforschung* (GfK), Germany's largest market research institute.[7] The dataset consists in a panel of individuals aged 14 and older that are followed in Germany during 32 weeks between September 2015 and May 2016. The dataset reports the full clickstream activity of more than 2,900 Android users on both their smartphone and desktop. It also reports demographic information on the users, such as gender, age, household income, education, occupation, and region of residence. Since not all individuals are observed in every week, the final sample used in this paper focuses on individuals that are observed during at least 24 weeks (out of the 32 weeks period observed) on either their desktop and smartphone, resulting in a total of 2,948 individuals.

The question addressed in this paper - how smartphone usage impacts Internet use - requires various measures of browsing behavior, both across devices and overall. For each individual in the sample, the analysis therefore requires the identification and the level of usage of each domain on both the desktop and the smartphone. Note that while a given domain can only be reached through the web browser on the desktop, it can be accessed on the smartphone via the browser or via an app. It is therefore necessary to match each domain with its corresponding app whenever the latter exists. While the app data include a unique identifier for each app (along with the app's name), the data unfortunately do not provide a unique identifier that permits a straightforward matching between apps and domains.[8] I therefore engaged in a manual and tedious matching procedure based on apps' names and on the information retrieved from their identifier.[9] There is a total of 20,402 distinct apps that correspond to the smartphone usage of the 2,948 users included in the final sample. Fortunately, apps' usage is very concentrated, and I therefore focus the matching on the top 2,800 most used apps to find

[7]See `http://www.gfk.com/`.

[8]The data initially come in three sets. The first one corresponds to the clickstream activity of each individual through the desktop. The second and third datasets correspond to the smartphone usage and differentiate between usage made through the smartphone browser and through apps.

[9]The app identifier corresponds to the app's package name.

their corresponding domain, noting that these account for 98% of the overall app usage in the sample. It is important to note that not all apps necessarily have a corresponding domain. Because the goal of this paper is to focus on browsing behavior across devices, smartphone apps are only considered whenever they act as a substitute to visiting the corresponding domain through the browser (e.g. using the *Amazon* app instead of using the browser to visit the *Amazon* mobile website) or when they correspond to an online activity that could have been carried out through the desktop's browser (e.g. an online game that is available as an app but does not necessarily have an established counterpart on a website, or apps that allow setting up various email accounts on the smartphone but do not necessarily have a corresponding domain on the desktop).[10] On the other hand, apps that are used to clean the phone, take photographs, or organize files will not have a corresponding domain that is visited through the browser and are therefore not considered as part of a browsing activity. Such apps are therefore not included in the final sample. Out of the 2,800 apps considered in the matching procedure, 2,050 are matched to a domain or considered part of a browsing activity. Performing the above matching results in a dataset that provides, for each of the 2,948 individual in the sample, the time spent on each visited domain in a given week and through each device. This results in a total of 2,976,755 individual-domain-week-device observations.

3.2 Descriptives

The next subsection presents basic descriptives in terms of the sample composition. I then turn to descriptive statistics regarding online behavior, including the device-specific determinants of total Internet usage as well as additional measure of browsing behavior.

3.2.1 Sample Composition

Basic descriptives regarding the composition of the final sample are presented in Table 1. Fifty percent of the individuals in the sample are women. The distribution of individuals is quite even across income levels, with a larger share of individuals within the 3,000-3,999 euros monthly income bracket. 21% of the sample obtained a university degree and 11%

[10]Game apps are often difficult to match to a particular domain based on the name of the game or app. I therefore match them to the corresponding game developer's domain whenever available.

completed a technical or vocational school. About 48% of the individuals in the sample are aged between 14 and 44 years old, with a quarter of the sample aged between 35 and 44. Individuals aged between 45 and 54 make up for 26% of the sample. In terms of occupation, the majority of the individuals in the sample are employees.

3.2.2 Desktop and Smartphone Usage

Since the data allows for a precise measure of the amount of online time spent on each device, I can calculate the weekly share of Internet usage accounted for by the smartphone for each individual in the sample.[11] Figure 1 presents the weekly median share of smartphone Internet use for all the individuals in the sample. The figure clearly illustrates the important growth in the share of Internet usage accounted for by the smartphone. While the smartphone accounted for about a third of Internet use at the beginning of the sample period, it has been growing steadily during 2016, ultimately reaching levels of close to 50%.

It is perhaps natural to expect differences in smartphone and desktop Internet usage across various demographic groups. Previous literature has already established important differences in desktop usage across income levels, showing how higher income households spend less time on their home device likely due to differences in the opportunity cost of leisure time (Goolsbee and Klenow, 2006; Goldfarb and Prince, 2008; Boik et al., 2016). Likewise one could perhaps expect differences across different age groups. In order to explore differences in the determinants of total online time across the desktop and the smartphone, I regress the total online time spent on each device on a set of demographic characteristics and week fixed effects. Beyond age and income, variables measuring education, occupation, gender, and the region where the individual lives are included. Table 2 presents the result of this exercise, with the second and third columns showing the determinants of browsing time through desktop and smartphone, respectively. The results show striking differences in the determinants of Internet use across devices. Desktop

[11] Throughout the paper, I define smartphone usage as the time spent browsing through the mobile browser and through the matched apps as described in Section 3.1. This measure therefore excludes the smartphone time spent on apps that are not directly related to mobile browsing (e.g. apps that are used to clean the phone, take photographs, or organize files, etc.).

Table 1: Sample Composition.[†]

	No. of individuals	Mean	s.d.
Female	1463	0.50	0.50
Household Net Monthly Income			
Up to 1499	533	0.18	0.38
1500-1999	403	0.14	0.34
2000-2499	484	0.16	0.37
2500-2999	415	0.14	0.35
3000-3999	707	0.24	0.43
4000 and over	406	0.14	0.34
Education Level			
Hauptschule	444	0.15	0.36
Mittlere Reife	1174	0.40	0.49
Abitur	383	0.13	0.34
Technical or vocational school	336	0.11	0.32
University Degree	611	0.21	0.41
Age			
14-24 years	175	0.06	0.24
25-34 years	488	0.17	0.37
35-44 years	737	0.25	0.43
45-54 years	766	0.26	0.44
55-64 years	497	0.17	0.37
65+ years	285	0.10	0.30
Occupation			
Housewife/-man	209	0.07	0.26
Pensioner, unemployed	597	0.20	0.40
Apprentice	50	0.02	0.13
Student	165	0.06	0.23
Employee	1657	0.56	0.50
Magistrate	151	0.05	0.22
Self-employed	119	0.04	0.20
Region			
Baden-Württemberg	282	0.10	0.29
Bayern	433	0.15	0.35
Berlin	149	0.05	0.22
Mid (HE, RP, SL)	444	0.15	0.36
Nordrhein-Westfalen	523	0.18	0.38
North (SH, HH, HB, NS)	461	0.16	0.36
Northeast (MV, BB, SA)	304	0.10	0.30
Southeast (TH, SN)	352	0.12	0.32

[†] The sample contains 2,948 individuals observed on their smartphone and desktop.

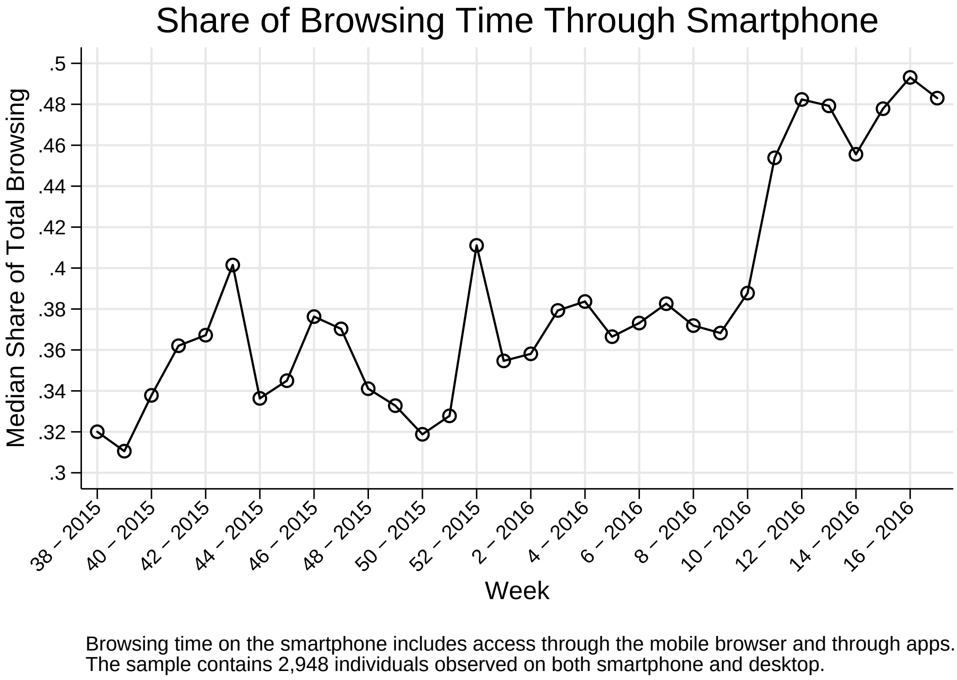

Figure 1: Share of Browsing Through Smartphone.

browsing is negatively related to levels of income. Individuals making between 1,500 and 2,000 euros per month spend 336 more minutes per week (about 48 minutes per day) on their desktop than individuals earning more than 4,000 euros per month (p-value=0.000). Individuals who earn between 2,000 and 2,500 euros a month spend 228 more minutes per week browsing on their desktop than individuals who earn more than 4,000 euros per month (p-value=0.0016). Smartphone Internet use, however, presents no significant differences across the various income groups. On the other hand, smartphone Internet usage is negatively and significantly related to age. Individuals aged between 45 and 54 spend 237 minutes less per week (about 34 minutes per day) browsing on their smartphone compared to individuals aged between 25 and 34 (p-value=0.000). They spend 129 minutes less per week using the Internet through their smartphone relative to individuals aged between 35 and 44 (p-value=0.000). There is also some evidence of a positive correlation between desktop usage and age, although less striking than for smartphone usage. Because smartphones can be used at almost any location and point in time regardless of income levels, one explanation for these differences is that the opportunity cost of leisure time does not affect smartphone usage as much as it does desktop. Individuals aged between 45 and 54 in particular spend more time accessing the Internet through their fixed device relative to younger individuals.

The results presented above indicate that while income is the most important determinant of desktop usage, age is a much more relevant determinant of smartphone Internet usage. I now turn to additional measures of browsing behavior which will allow for a more detailed comparison of smartphone and desktop Internet behavior.

3.2.3 Browsing Behavior

In order to compare desktop and smartphone Internet use, one naturally needs to define clear measures of browsing behavior. I will mainly focus on two broadly defined measures. The first one relates to the concentration of consumption and asks how individuals allocate their Internet time across different domains through each device. The second measure relates to the depth of Internet usage and asks how individuals focus their attention within each domain through each device.[12] These variables are now defined and presented in detail.

Browsing Concentration

The first measure of browsing behavior relates to the concentration of consumption across domains. For each individual i in week t, define T^d_{ijt} as the time spent on domain j through device d, with $d \in \{Desktop, Smartphone\}$. The weekly time share allocated to each domain j by individual i through device d is therefore given by

$$TS^d_{ijt} = \frac{T^d_{ijt}}{\sum_{j=1}^{J^d_{it}} T^d_{ijt}},$$

where J^d_{it} is the number of distinct domains visited by individual i in week t through device d. It follows that the Herfindahl-Hirschman Index (HHI) of concentration for

[12] I focus on similar measures as the ones employed by Boik et al. (2016), which relies on US clickstream data to compare the breadth and depth of desktop browsing in 2008 and 2013. Huang et al. (2009) also looks at similar measures to study differences in the browsing and purchasing behavior of consumers for search and experience goods.

Table 2: Total Browsing Online - Desktop vs Smartphone.†

	(Desktop) Coef./s.e.	(Smartphone) Coef./s.e.
Age (ref. cat: 14-24 years)		
25-34 years	86.578	-61.855
	(118.42)	(60.10)
35-44 years	202.934*	-169.929***
	(123.25)	(60.81)
45-54 years	320.276***	-299.007***
	(123.76)	(61.46)
55-64 years	256.374**	-349.646***
	(129.28)	(62.27)
65+ years	136.465	-408.889***
	(153.29)	(68.67)
Income (ref. cat: up to 1499 euros)		
1500-1999 euros	-177.042**	27.438
	(74.25)	(31.02)
2000-2499 euros	-285.125***	21.809
	(70.64)	(27.86)
2500-2999 euros	-319.322***	-5.215
	(75.88)	(29.15)
3000-3999 euros	-397.261***	-1.245
	(64.98)	(25.23)
4000 euros and up	-513.371***	-35.407
	(73.77)	(28.64)
Education (ref. cat: Hauptschule)		
Mittlere Reife	101.417	23.646
	(64.25)	(24.35)
Abitur	95.221	-31.208
	(79.56)	(31.81)
Technical or vocational school	-34.737	11.074
	(77.19)	(32.65)
University Degree	127.780*	-19.716
	(74.66)	(27.61)
Occupation (ref. cat: Housewife/-man)		
Pensioner, unemployed	97.946	-4.861
	(108.13)	(40.27)
Apprentice	-125.066	-44.106
	(179.62)	(92.82)
Student	90.217	-16.807
	(136.47)	(62.88)
Employee	-203.096**	1.656
	(86.70)	(33.88)
Magistrate	-169.548	-16.869
	(120.63)	(48.71)
Self-employed	359.458**	78.120
	(146.75)	(55.88)
Female	-237.701***	7.849
	(40.06)	(17.04)
Constant	1233.076***	587.336***
	(170.91)	(74.93)
R^2	0.070	0.068
No. of Obs.	60968	69195

† The dependent variable is the total browsing time (in minutes) spent on a given device per week. Browsing time on the smartphone includes access through the mobile browser and through apps. All specifications include region and week fixed effects. Standard errors are clustered on the individual level and are in parenthesis.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

individual i on device d and week t is given by

$$HHI_{idt} = \sum_{j=1}^{J_{it}^{d}} \left(TS_{ijt}^{d}\right)^{2}. \tag{1}$$

For each individual in the sample, the variable HHI_{idt} therefore provides a measure of how concentrated their browsing activity is (across domains) in a given week and on a particular device. The HHI takes a value between 0 and 10,000, with larger values indicating higher concentration of total browsing time on a smaller set of domains.

An alternative measure of concentration is given by the share of total usage accounted for by the X most used domains. For individual i in week t, the concentration ratio for the X most used domains (CR-X) on device d is therefore defined as follows:

$$CR\text{-}X_{idt} = \frac{\sum_{j \in \text{Top}X} T_{ijt}^{d}}{\sum_{j=1}^{J_{it}^{d}} T_{ijt}^{d}} = \sum_{j \in \text{Top}X} TS_{ijt}^{d}, \tag{2}$$

where Top X is defined as the set of X most used domains by individual i in week t and through device d. Below I will focus on the Top 1, 3, 5, and 8 most used domains.

Browsing Depth

The second measure of browsing behavior relates to the depth of browsing. That is, it asks how much a given individual "dives" into a given domain. A natural measure would be to simply look at the total weekly time spent on each domain. I measure the depth of Internet usage by the share of domain visits that exceed a given amount of time.[13] For instance, what fraction of the total weekly domain visits made by individual i on device d exceeds 10 minutes? To construct this measure, one needs to account for the fact that *weekly* domain visits may mask important differences in *daily* domain visits. Consider, for instance, an individual who spent 20 minutes on a given domain in week t. While these 20 minutes may have been spent on a single 20-minutes visit in a given day of the week, they may also be the result of 4 distinct daily visits (within week t) lasting each

[13]This is the definition employed by Boik et al. (2016).

5 minutes. To account for these differences, I focus on the distinct *daily* domain visits within a given week to construct a measure of the share of domain visits that exceed 10 minutes within a week. For a given individual i using device d in week t, the share of domain visits that last more than 10 minutes (i.e. the share of long visits; SLV) is therefore given by:

$$SLV_{idt} = \frac{\sum_{k \in t} \mathbb{1}\left(T^d_{ijk} > 10\right)}{\sum_{k \in t} J^d_{ik}}, \tag{3}$$

where, for individual i, T^d_{ijk} is the time spent on domain j during day k of week t through device d, and J^d_{ik} is the number of distinct domains visited by individual i in day k through device d.[14]

Table 3 presents descriptive statistics for the variables reflecting browsing behavior, distinguishing between desktop and smartphone. The table presents important differences across devices for all the variables considered. The (unconditional) average weekly number of distinct domains visited is over 60% higher on the desktop than on the smartphone. Of course, this may naturally be driven by the fact that the browsing time on the desktop is also much larger than on the smartphone, as indicated in the second row of the table. Individuals spend an average of 16.7 hours browsing on their desktop, while their weekly smartphone Internet use is of 7 hours.[15] Controlling for total browsing time within a regression of the number of distinct domains on an indicator variable for smartphone usage indicates that the difference in the number of distinct domains visited between desktop and smartphone reduces to around 0.57 domains (p-value=0.000).

Regarding browsing concentration, the table presents important differences across desktop and smartphone. For all the concentration measures considered, browsing concentration is higher on the smartphone than on the desktop, and these differences are all statistically

[14]As a robustness check the estimations presented below were also performed using alternative cutoffs. In particular, I consider visits longer than 15, 30, and 45 minutes. The results are robust to these distinct cutoff values.

[15]Recall that this figure only accounts for the time spent browsing on the smartphone, defined as the time spent browsing through the mobile browser and through the matched apps as described in Section 3.1. It therefore excludes time spent on apps that are not directly related to mobile browsing (e.g. apps that are used to clean the phone, take photographs, or organize files, etc.) and gives, by definition, a lower measure than the *total* smartphone usage.

and economically significant. In terms of HHI, the concentration index equals 3,287 on the desktop and reaches 4,400 on the smartphone.[16] Alternative measures of concentration show similar differences across devices. While the weekly most visited domain accounts for 45% of the total weekly browsing on the desktop on average, the corresponding figure is of 57% on the smartphone. Similarly, the weekly top 3 domains account for 72% of weekly browsing on the desktop on average, while the corresponding figure is of 84% on the smartphone. Finally, the share of visits lasting more than 10 minutes is 13 percentage points lower on the smartphone than it is on the desktop. This indicates that individuals dive much less into a given domain when accessing the Internet trough their smartphone.

Table 3: Descriptive Statistics - Browsing Behavior.†

	Desktop $N = 61,230$		Smartphone $N = 69,360$		
	mean	s.d.	mean	s.d.	Difference
# of Distinct Domains Visited	28.69	30.37	17.60	17.82	-11.09***
Time Spent Browsing (hours)	16.69	18.36	6.97	8.17	-9.73***
Daily Time Spent per Domain (minutes)	22.06	18.37	11.33	14.82	-10.73***
Concentration - HHI	3286.51	2475.63	4400.43	2565.82	1113.92***
Concentration Ratio Top 1 (CR-1)	0.45	0.24	0.57	0.24	0.11***
Concentration Ratio Top 3 (CR-3)	0.72	0.21	0.84	0.16	0.11***
Concentration Ratio Top 5 (CR-5)	0.83	0.16	0.91	0.11	0.09***
Concentration Ratio Top 8 (CR-8)	0.90	0.12	0.96	0.07	0.05***
Share of Visits Lasting > 10 mins	0.33	0.18	0.21	0.18	-0.13***

† The table presents individual weekly averages. The sample contains 2,948 individuals observed on their smartphone and desktop.
*** Significant at the 1% level.

3.2.4 Domain Categories

Domains and apps that were visited by any of the individuals appearing in our sample can be classified into distinct categories. The original GfK data, together with additional

[16] While there are no clear guidelines on how to interpret HHI values in the context of individual browsing, one can alternatively rely on the Horizontal Merger Guidelines provided by the U.S. Department of Justice. According to the latter, the Department of Justice and the Federal Trade Commission generally classify markets into three types: Unconcentrated Markets (HHI below 1,500), Moderately Concentrated Markets (HHI between 1,500 and 2,500), and Highly Concentrated Markets (HHI above 2,500). See https://www.justice.gov/atr/horizontal-merger-guidelines-08192010.

app category information obtained from the Google Play Store, allows to classify the domains visited into 13 distinct categories: Communication, Gambling, Gaming, Media On-demand, Media broadcasting, News/Information, On-Site Search, Money Management, Shopping/Auctions/Rent, Price/Product Comparison, Social Networking, Web Search, and X-Rated/Adult.[17]

Table 4 presents the top 25 domains visited on each device by the individuals in the sample, along with their corresponding category. For the smartphone, the domains visit are split between visits made through the mobile browser and through apps. Facebook is the most visited domain on both the desktop and the smartphone, and there is quite some overlap between the most visited domains on both devices. A significant share of the top visited domains on the smartphone come from the gaming category. Table 5 similarly presents the top 10 domains visited on each device, within each of the 13 categories. The smartphone ranking now includes visits done through either the browser or the corresponding app. Except for the gaming category, there is a substantial overlap in the most visited domains across devices.

[17] All domains that were not classified into one of the above categories are included in an additional "other domains" category.

Table 4: Top 25 Domains Visited, By Device.[†]

	Desktop		**Smartphone (Browser)**		**Smartphone (Apps)**	
Rank	Domain	Category	Domain	Category	App	Category
1	facebook	social networking	google	web search	facebook	social networking
2	google	web search	facebook	social networking	candy crush soda	gaming
3	ebay	shopping	bild.de	news/info	youtube	media on-demand
4	youtube	media on-demand	amazon	shopping	candy crush saga	gaming
5	web.de	web search	ebay	shopping	farm heroes saga	gaming
6	amazon	shopping	wikipedia	on-site search	android email	communication
7	t-online	news/info	youtube	media on-demand	hay day	gaming
8	gmx	communication	web.de	web search	google app	web search
9	ebay-kleinanzeigen	shopping	t-online	news/info	quizduell premium	gaming
10	msn	news/info	gmx	communication	tvsmiles	other activity
11	bild.de	news/info	xhamster	adult	ebay	shopping
12	yahoo	web search	ebay-kleinanzeigen	shopping	clash of clans	gaming
13	planetromeo	social networking	chefkoch	other activity	maps	other activity
14	royalgames	gaming	spiegel	news/info	web.de mail	communication
15	wikipedia	on-site search	otto	shopping	gummy drop!	gaming
16	gameduell	gaming	yahoo	web search	quizduell	gaming
17	playchess	gaming	jappy	social networking	springfield	gaming
18	live	communication	samsung	other activity	familyfarm	gaming
19	bigpoint	gaming	upjers	gaming	ebay kleinanzeigen	shopping
20	jappy	social networking	chatiw	communication	pet rescue saga	gaming
21	spiegel	news/info	vodafone	other activity	gmx	communication
22	aol	news/info	focus	news/info	candy crush jelly	gaming
23	myfreefarm	gaming	live	communication	gmail	communication
24	streamcloud	media on-demand	accuweather	news/info	messenger	social networking
25	payback.de	price comparison	bahn	other activity	focus online	news/info

[†] For domains visited through the smartphone, the table differentiates between visits through the browser and through apps.

Table 5: Top 10 Domains Visited, By Device and Category.†

Rank	Desktop	Smartphone	Desktop	Smartphone
	Communication		**Gaming**	
1	gmx	android email	royalgames	candy crush soda
2	live	web.de mail	gameduell	candy crush saga
3	1und1	gmx	playchess	farm heroes saga
4	whatsapp	gmail	bigpoint	hay day
5	studivz	line	myfreefarm	quizduell premium
6	mail.ru	t-online mail	forgeofempires	clash of clans
7	ecards4u	yahoo mail	diesiedleronline	gummy drop!
8	knuddels	knuddels	die-staemme	quizduell
9	livinghandy	1und1 mail	spielesite	solitaire
10	ojooo	outlook	upjers	springfield
	Media On-Demand		**Media Broadcasting**	
1	youtube	youtube	sky.de	twitch
2	streamcloud	spotify	zdf	zdf
3	maxdome	9gag	twitch	tunein
4	nowtv	audible	ndr	sky.de
5	netflix	deezer	ardmediathek	radio
6	pr0gramm	google music	tvspielfilm	tvspielfilm
7	kinox	netflix	rtl.de	zattoo
8	fernsehserien	maxdome	myvideo	parom
9	movie-blog	napster	tvnow	heute.de
10	onlinetvrecorder	swagbuckstvmobile	reallifecam	younow
	On-Site Search		**Money Management**	
1	wikipedia	wikipedia	postbank	paypal
2	immobilienscout24	mobile.de	fiducia	postbank
3	mobile.de	immobilienscout24	paypal	commerzbank
4	arbeitsagentur	here	deutsche-bank	etoro
5	geocaching	wattpad	ing-diba	ing-diba
6	gutefrage	autoscout24	commerzbank	vr-bank
7	autoscout24	gutefrage	sparda	comdirect
8	flightradar24	fanfiktion	dkb	dkb
9	dasoertliche	imdb	comdirect	sparda
10	bs	arbeitsagentur	targobank	deutsche-bank
	Price/Product Comparison		**Social Networking**	
1	payback.de	payback.de	facebook	facebook
2	check24	clever-tanken	planetromeo	planetromeo
3	booking	booking	jappy	instagram
4	holidaycheck	mein-deal	meinvz	lovoo
5	cashbackdeals	idealo	ok	twitter
6	idealo	holidaycheck	twitter	snapchat
7	quoka	check24	stayfriends	google+
8	dealdoktor	dealbunny	finya	pinterest
9	verivox	tripadvisor	qtalk	grindr
10	ab-in-den-urlaub	mytopdeals	lablue	badoo

Continued on next page

Table 5: Top 10 Domains Visited, By Device and Category.†

Rank	Desktop	Smartphone	Desktop	Smartphone
	News/Information		**Gambling**	
1	t-online	bild.de	tipp24	tipp24
2	msn	focus	winner	winner
3	bild.de	kicker	bet-at-home	tipico
4	spiegel	t-online	stargames	lottoland
5	aol	spiegel	tipico	bwin
6	freenet.de	n-tv.de	lottoland	lotto-bayern
7	chip.de	telegram.org	bet365	lotto24
8	kicker	wetter	westlotto	bet365
9	arcor	accuweather	lotto-hessen	bet-at-home
10	focus	flipboard	lotto-bayern	stargames
	Shopping		**Web Search**	
1	ebay	amazon	google	google
2	amazon	ebay	web.de	web.de
3	ebay-kleinanzeigen	ebay-kleinanzeigen	yahoo	yahoo
4	otto	wish	bing	bing
5	tchibo	shpock	ask	ecosia
6	egun	otto	ebesucher	ask
7	bonprix	kleiderkreisel	ixquick	ixquick
8	mamikreisel	mamikreisel	ecosia	fireball
9	groupon	groupon	startpage	trovit
10	aldi-sued	deutschlandcard	tixuma	yandex
	Adult			
1	xhamster	xhamster		
2	poppen	youporn		
3	xdates18	poppen		
4	joyclub	storiesonline		
5	youporn	einfachporno		
6	eroprofile	pornhub		
7	chaturbate	joyclub		
8	cam4	kaufmich		
9	pornhub	eroprofile		
10	xvideos	xvideos		

† For domains visited through the smartphone, the table combines visits through the browser and through apps.

As discussed above, the smaller screen inherent to the smartphone and its limited display tend to restrict browsing and Internet usage relative to devices offering larger screens, such as the desktop. There is, however, a large amount of heterogeneity in the types of activities that the smartphone offers, and certain types of domains could be better suited for certain devices. It is indeed likely that some categories of domains are well suited for the smartphone. Domains that require the processing of large amounts of information and consequently require a broader display - like price/product comparison, shopping, or money management websites for example - are likely to be better suited for the desktop than the mobile phone, even if apps have been made available to ease their use. On the other hand, other types of domain categories - like gaming, social networking, or communication - are likely to be relatively well suited for the smartphone. To get a better idea about this, Figure 2 presents the share of each domain category consumption that is accounted for by each device. On average, over 75% of the time dedicated to the gaming category is accounted for by smartphone usage, while a quarter comes from the desktop. Unsurprisingly, the smartphone is also the main channel used to access domains included in the communication category. A similar pattern is observed for social networking domains, perhaps because the latter are often well designed and adapted for the smartphone. Media on-demand domains are equally accessed through the smartphone and the desktop. Domains that are a priori better suited for the desktop - shopping, price/product comparison, money management, search - indeed show that they are mostly accessed through the desktop.

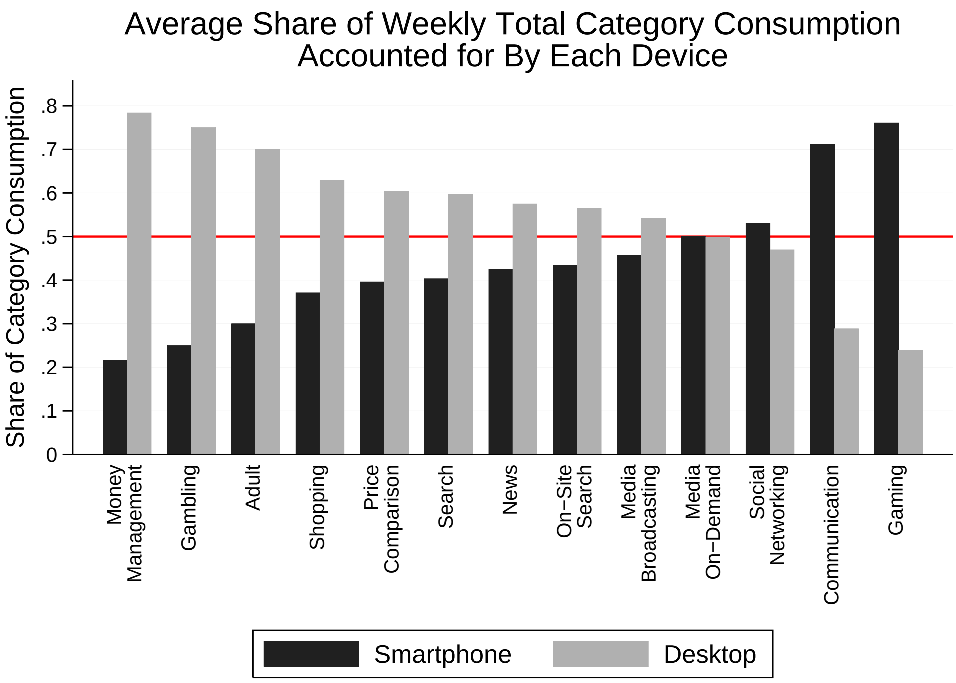

Figure 2: Share of Device Usage, by Domain Category.

4 How does Browsing Differ Across Devices?

As a first step towards exploring the effects of the mobile web on overall Internet usage, this section turns to a detailed analysis of differences in browsing behavior across the desktop and the smartphone. In particular, I present evidence of important differences in both the variety and depth of Internet usage across devices, most likely driven by smartphones' characteristics.

Since the data allow to observe each individual in the sample on both their desktop and smartphone, one can directly compare their Internet use on each device. More specifically, I run the following regression to identify differences between mobile and desktop browsing behavior:

$$y_{idt} = \alpha + \beta X_{idt} + \delta Smartphone_{it} + \eta_i + \nu_t + \varepsilon_{idt}, \tag{4}$$

where y_{idt} is a measure of browsing behavior by individual i at time t and on device d, with $d \in \{Desktop, Smartphone\}$. In the estimations below, y_{idt} will consist of the various measures presented in Section 3.2.3. The vector X_{idt} includes a measure of individual- and device-specific behavior, weekly total browsing time. The variable $Smartphone_{it}$ is an indicator equal to 1 for Internet usage made through the Smartphone by individual i. I include a vector of individual fixed effects η_i to control for variation in Internet usage across individuals that is constant over time. The set of week fixed effects ν_t controls for variation in Internet usage that is common to all individuals and devices, and ε_{idt} is an individual, device, and time specific error term. The main coefficient of interest is given by δ, as it corresponds to the difference in browsing behavior on the smartphone relative to the desktop. The empirical approach therefore relies on the within-individual variation to ask whether an individual's browsing behavior in a given week differs on the smartphone relative to the desktop. Equation (4) is estimated using OLS and standard errors are clustered at the individual level since the error term ε_{idt} is likely to be correlated over time within individuals.

The results of estimating equation (4) using the various measures of browsing behavior from Section 3.2.3 are presented in Table 6. Columns (1) to (3) use the HHI as a dependent variable. The next four columns use the concentration ratios ($CR-1$, $CR-3$, $CR-5$, $CR-8$), and the last column uses the share of visits lasting more than 10 minutes (SLV) as the dependent variable. All specifications in the table control for week fixed effects. Comparing HHI levels across desktop and smartphone, column (1) excludes any additional control variables. It shows how the HHI on the smartphone is about 1,114 points higher than on desktop. Because individuals spend more time browsing on their desktop than their smartphone (as indicated in Table 3), and if more browsing leads to less concentration, then failing to control for total browsing time when comparing HHI across devices may lead to an overestimate of the difference in concentration. Specification (2) adds the weekly total browsing time on each device as a control variable. The coefficient on the Smartphone variable decreases by over 400 points, indicating a 689 HHI points difference between the smartphone and the desktop. Specification (3) additionally controls for individual fixed effects. The coefficient of interest again drops compared to specifications (1) and (2), showing a 570 HHI points difference between the smartphone and the desktop. This last specification therefore indicates that the browsing concentration is 17.3% higher on the smartphone than it is on the desktop.

Columns (CR-1) to (CR-8) use the various measures of the concentration ratios as dependent variables. Each of the four specifications includes week fixed effects, individual fixed effects, and controls for weekly total browsing time. The first specification considers the CR-1 as a dependent variable, i.e. the weekly share of total usage accounted for by the most visited domain on each device. Results show that this share is over 6.7 percentage points higher on the smartphone than it is on the desktop, indicating that browsing concentration - as measured by the CR-1 - is 14.7% higher on the smartphone. The following three specifications of the table consider the CR-3, CR-5, and CR-8 as dependent variables, respectively. In each case, the results show a positive and statistically significant difference in concentration on the smartphone relative to the desktop. The weekly share of total usage accounted for by the top 3 domains on each device is 6 percentage points higher on the smartphone, which corresponds to a concentration level that is 8% higher relative to desktop. The corresponding shares for the weekly top 5 and top 8 domains are 4 and 2 percentage points higher on smartphone.

The last column of Table 6 focuses on differences in browsing depth across devices and presents the results of estimating (4) using the share of long visits (i.e. the share of visits longer than 10 minutes) as a dependent variable. Controlling for week fixed effects, individual fixed effects, and for weekly total browsing time, results indicate a difference of about 10 percentage points. This last specification therefore indicates that the share of long visits is about 29% higher on the smartphone than it is on the desktop.

4.1 Analysis by Domain Category

While the costs of searching and processing information are higher on the smartphone, it is likely - as explained above - for certain types of domains to be better suited for the smartphone relative to others. Domains that offer a relatively better experience on mobile devices would likely impose lower search and processing costs to users - relative to domains that are ill-suited for the smartphone. To test for these potential differences, I estimate equation (4) separately for each of the 13 domain categories in the sample. For each of them, I construct similar measures of concentration and depth of browsing at the category level. For instance, I define the variable HHI^c_{idt} as the concentration of browsing of individual i within category c on week t and device d.[18] The coefficient of interest δ on the $Smartphone_{it}$ variable therefore indicates the difference in concentration between the smartphone and the desktop within category c.

Figure 3 presents the 13 coefficients resulting from the estimations performed at the category level using the HHI as the dependent variable, along with their respective 95% confidence intervals. Results show significant heterogeneity in the within category HHI differences between smartphone and desktop. Perhaps unsurprisingly, categories for which search costs are expected to be relatively higher show larger differences in concentration. For instance, concentration levels are about 530 HHI points higher on the smartphone for money management domains. For shopping and price/product comparison domains, these differences amount to 479 and 385 HHI points differences, respectively. Gaming and communication domains, on the other hand, present concentration levels that are 976

[18] More specifically, $HHI^c_{idt} = \sum_{j=1}^{J^{dc}_{it}} (TS^{dc}_{ijt})^2$, where $TS^{dc}_{ijt} = T^{dc}_{ijt} / \left(\sum_{j=1}^{J^{dc}_{it}} T^{dc}_{ijt} \right)$ is the weekly time share allocated to each domain j by individual i within category c through device d and where J^{dc}_{it} is the number of distinct domains visited by individual i on category c and in week t through device d.

Table 6: Concentration of Usage - Desktop vs Smartphone.[†]

	HHI			Concentration Ratios				Share of Visits > 10 mins
	(1) Coef./s.e.	(2) Coef./s.e.	(3) Coef./s.e.	(CR-1) Coef./s.e.	(CR-3) Coef./s.e.	(CR-5) Coef./s.e.	(CR-8) Coef./s.e.	(8) Coef./s.e.
Smartphone	1113.640***	688.851***	569.824***	0.067***	0.062***	0.041***	0.021***	-0.096***
	(48.49)	(48.62)	(49.71)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Time Spent Browsing (in hours)		-43.630***	-52.408***	-0.004***	-0.005***	-0.004***	-0.003***	0.003***
		(2.44)	(2.55)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Week Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Individual Fixed Effects	✗	✗	✓	✓	✓	✓	✓	✓
% Difference Relative to Desktop	33.89	20.96	17.34	14.69	8.63	4.99	2.31	-28.90
R^2	0.047	0.102	0.394	0.381	0.495	0.531	0.547	0.391
No. of Obs.	130590	130590	130590	130590	130590	130590	130590	130590

[†] In columns (1) to (3), the dependent variable is the HHI for the duration spent at domains visited. In columns (CR-1), (CR-3), (CR-5), and (CR-8), the dependent variable is the share of usage accounted for by the top $X \in \{1, 3, 5, 8\}$ domains in terms of duration, respectively. The dependent variable in column (8) measures the average weekly time spent per domain, in minutes. Standard errors are clustered on the individual level and are in parenthesis.

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

and 632 HHI points lower on the smartphone, respectively. This is perhaps not surprising given that these domains tend to be well suited for the smartphone, sometimes more so than the desktop.

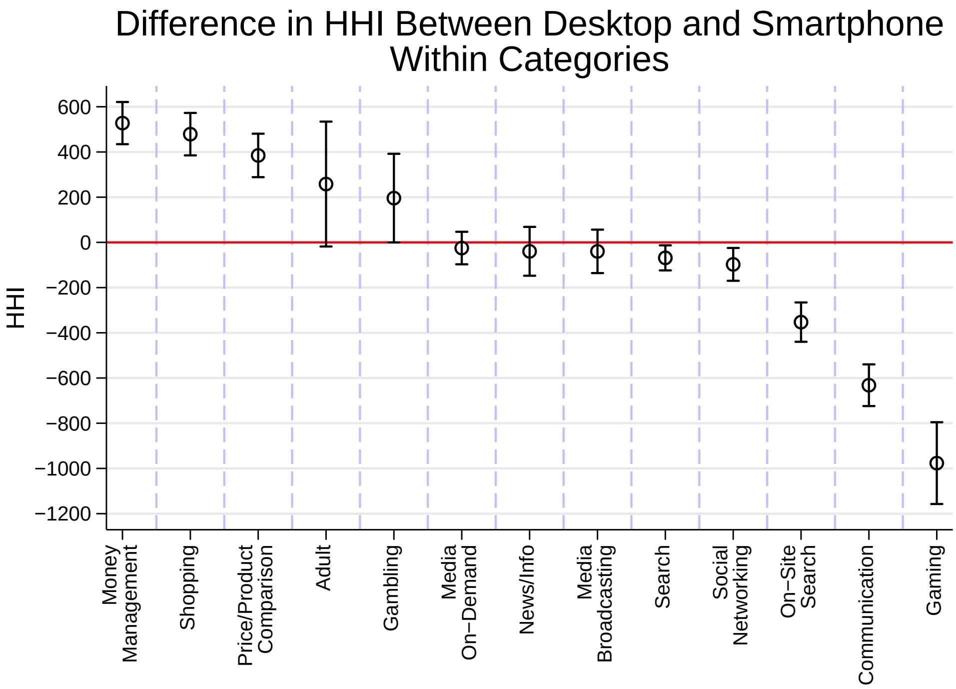

Figure 3: Difference in HHI Across Devices, by Category.

Figure 4 presents within category differences in the share of long visits between the smartphone and he desktop, along with their corresponding 95% confidence intervals. This difference remains significantly negative for all categories except for games. For the latter, the share of visits lasting more than 10 minutes is 17 percentage points higher on the smartphone than on the desktop. For news domains, this share is about 20 percentage points lower on the smartphone relative to the desktop.

Overall, the results presented above show significant differences in browsing behavior across desktop and smartphone. In particular, smartphone browsing displays higher concentration levels - meaning that the variety of Internet use is reduced on the smartphone as individuals focus their attention on a more limited set of domains - and much lower depth of attention - meaning that individuals dive much less into domains when they access the Internet through their smartphone. These results are consistent with smart-

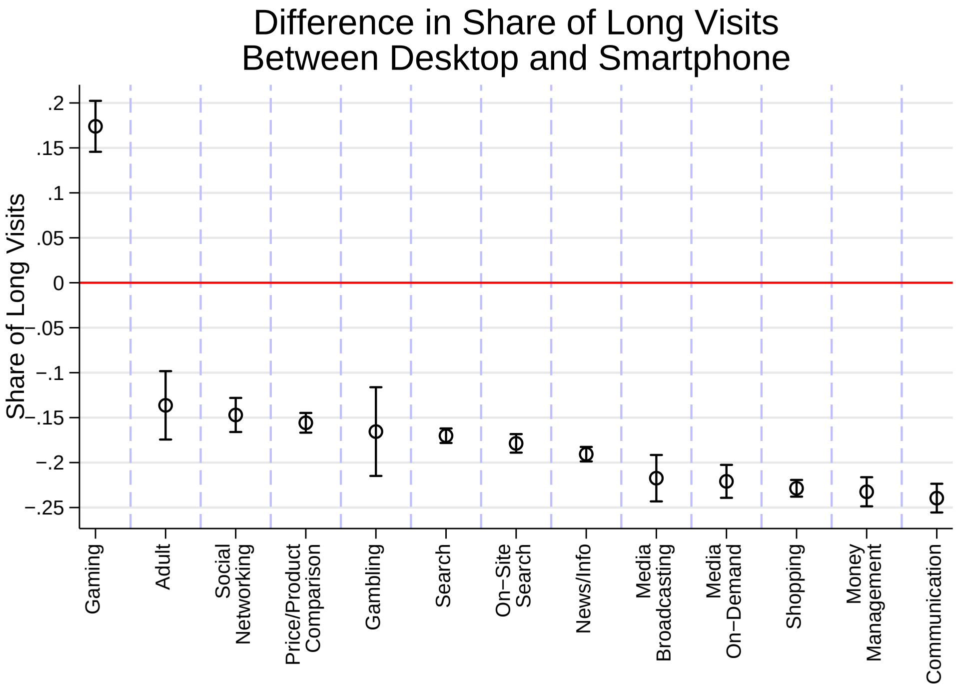

Figure 4: Difference in Share of Long Visits Across Devices, by Category.

phones imposing higher search costs on Internet use, as documented in the literature.

5 The Effect of Smartphone Usage on Internet Consumption

Differences in browsing experience induced by device-specific characteristics - e.g. smaller screen size and limited display of the smartphone's screen relative to desktop - naturally have important implications as consumers increasingly access the Internet through the smartphone (see Figure 1). I now turn to the main question of this paper and ask how individuals change the nature of their Internet consumption as their online connectivity increasingly moves towards the smartphone. In order to assess the effects of an increase in the relative usage of the smartphone on Internet consumption, I can rely on the following specification:

$$y_{it}^{c} = \alpha + \beta X_{it} + \delta^{c} ShareSmartphone_{it} + \eta_i + \nu_t + \varepsilon_{it}, \tag{5}$$

where $ShareSmartphone_{it}$ is the share of total browsing time spent on the smartphone by individual i in week t, and the rest of the independent variables are as presented in (4). I will focus on several outcome measure to assess the effect of an increase in mobile Internet use. First, I explore the effect of moving to the mobile Internet on the nature of Internet consumption, asking how individuals reallocate their time across various categories of websites as their Internet access turns mobile. For that purpose, I use the share of total online time spent (smartphone and desktop combined) on a given domain category c as the dependent variable and estimate (5) separately for each of the 13 distinct domain categories. I then turn to the question of how the within domain category concentration and depth of Internet consumption are affected by an increase in smartphone usage.

5.1 Identification

Identifying δ^c from equation (5) requires controlling for potential confounding factors that may affect both the share of of total online time spent on a given domain category as well as the share of online time spent through the smartphone. The panel nature of the data enables me to include individual fixed effects η_i, which allow to control for time-invariant and unobserved individual characteristics that may otherwise challenge the identification of a causal effect. Assuming that the growth in relative smartphone usage depicted in Figure 1 is driven by technological change that allow for a better Internet access through mobile devices and not by the relative appeal of the content offered on the smartphone, one can estimate δ^c from equation (5) using OLS. There is, however, still a concern that the variable $ShareSmartphone_{it}$ remains endogenous, even after controlling for individual fixed effects. Suppose that, for whatever reason, a certain (category of) domain increases in popularity. As a result, the share of total online time spent on that particular domain category will increase. At the same time, this increase in popularity may also affect the share of time spent on the smartphone relative to the desktop depending on the suitability of the particular domain for the smartphone. If the domain in question is better (worse) suited for the smartphone relative to the desktop, we could expect a positive (negative) bias in the estimate of δ. Identifying the causal effect of smartphone usage on the share of total online time spent on a specific domain category is therefore challenging. In particular, it requires a source of exogenous variation in the share of relative smartphone usage. Fortunately, one such source of variation can be found in the version updates of the smartphones' Android operating system (OS). Users' experience on their Android smartphone naturally depends on the OS version that they have available, and a more recent OS version should - everything else constant - increase an individual's smartphone experience and consequently positively affect their smartphone usage time relative to desktop. At the same time, these OS updates should not directly affect the share of total online time spent on specific domain categories after controlling for individual and time fixed effects. Because Google determines the timing of releases of its Android OS versions, the appearance of a new OS version can be considered exogenous from the perspective of the final user. I observe nine distinct Android OS versions in the sample. These are, in chronological order of release: Android 2.3, Android 4.0, Android 4.1, Android 4.2, Android 4.3, Android 4.4, Android 5.0, Android 5.1, and Android 6.0. I group them into broader categories according to their corresponding Android code names, resulting in six distinct versions: Android 2.3 (Gingerbread), Android 4.0 (Ice Cream Sandwich), Android 4.1-4.3 (Jelly Bean), Android 4.4 (KitKat), Android 5.0-5.1 (Lollipop), and Android 6.0 (Marshmallow).[19]

The left panel of Figure 5 shows the average weekly time spent browsing per device (in hours) according to the smartphones' Android OS version used. The figure clearly shows how users increase their time spent on the smartphone with more recent OS versions as the latter provides them with a better overall smartphone experience. Users whose smartphone operates under version 6.0 of Android spend about twice as much time on their mobile device as do individuals whose smartphone operates under version 4.4. Desktop also shows an overall negative relationship with smartphone OS version (suggesting a negative relationship between smartphone and desktop usage), although the pattern is less strong. The right panel of Figure 5 presents the relationship between the smartphone Android OS version and the smoothed share of smartphone usage (solid line). It clearly shows that as the OS version improves, users indeed tend to spend a larger share of their total online time on their smartphones. In what follows I exploit the variation presented in Figure 5 both across and within individuals to identify the causal effect of an increase in the share of smartphone usage on overall Internet consumption. In particular, I estimate equation (5) using a two-stage fixed-effects approach, where the first stage

[19]See https://en.wikipedia.org/wiki/Android_version_history#Code_names.

consists in a regression of the endogenous variable of interest ($ShareSmartphone_{it}$) on the exogenous instrument (OS version) as well as all control variables. The second stage involves regressing the outcome variable y^c_{it} on the predicted values of the endogenous variable (from the first stage) as well as all the remaining control variables. This will be estimated in a single step, clustering the standard errors at the individual level since the error term ε_{it} is likely to be correlated over time within individuals. In the first stage regression, the coefficient on the OS version variable show that more recent versions of the OS are indeed accociated with a higher share of smartphone usage relative to the desktop (see column (1) of Table 7). The F-stat of excluded instruments shows a value of 43.48, well above the recommended critical value of 10 (Angrist and Pischke, 2008). I then turn to instrumenting $ShareSmartphone_{it}$ with the the smartphone OS version variable in equation (5) for each of the 13 distinct domain categories separately. The results are discussed below.

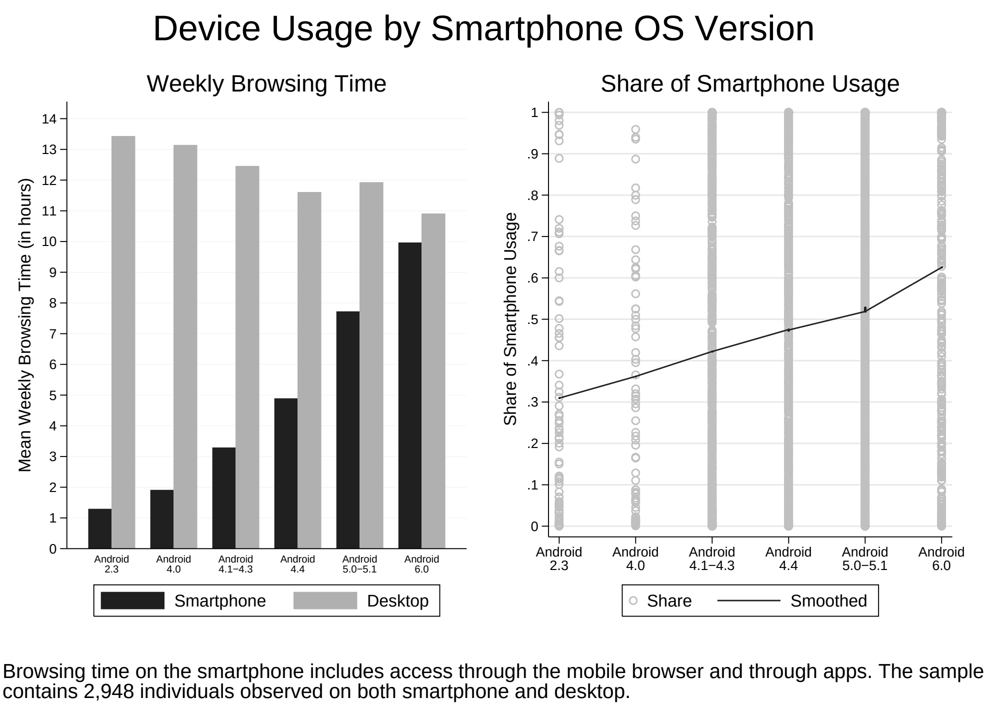

Figure 5: Browsing Usage by Device and Smartphone OS Version

Table 7: First Stage Results.[†]

	Overall	By Income Group			By Age Group		
	(1)	$(< 2,500)$	$(2,500 - 2,999)$	$(> 3,001)$	$(14 - 34)$	$(35 - 44)$	$(45+)$
	Coef./s.e.	Coef./s.e.	Coef./s.e.	Coef./s.e.	Coef./s.e.	Coef./s.e.	Coef./s.e.
Smartphone OS Version	5.156***	4.403***	8.682***	4.709***	5.534***	5.181***	4.995***
	(0.78)	(1.19)	(2.00)	(1.17)	(1.66)	(1.68)	(1.03)
Time Spent browsing (in hours)	-0.695***	-0.685***	-0.634***	-0.743***	-0.410***	-0.600***	-0.850***
	(0.03)	(0.03)	(0.08)	(0.05)	(0.06)	(0.06)	(0.04)
Individual Fixed Effects	✓	✓	✓	✓	✓	✓	✓
Week Fixed Effects	✓	✓	✓	✓	✓	✓	✓
F-Stat excluded instruments	43.480	13.730	18.869	16.226	11.176	9.508	23.734
P-value	0.000	0.000	0.000	0.000	0.001	0.002	0.000
No. of Obs.	81508	38991	11400	31117	17144	20175	44189

† The dependent variable is the share of the total browsing time accounted by the smartphone. Robust standard errors are in parenthesis.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

5.2 Allocation of Time Across Domain Categories

Figure 6 presents the estimates of δ^c for each of the 13 distinct categories using the IV approach presented above, along with their respective 95% confidence intervals. It also presents the corresponding estimated coefficients when (5) is estimated without instrumenting $ShareSmartphone_{it}$. Results show that the share of total online time spent on gaming and social networking domains increases as the share of online access made through the smartphone increases. In particular, a 1 percentage point increase in the share of relative smartphone usage leads to an increase in the shares of total time spent on gaming and social networking domains of 0.37 and 0.25 percentage points, respectively. To put these figures into perspective, an increase in the share of smartphone usage by 5 percentage points leads to a 10.8% and 8.3% increase in the share of time spent on gaming and social networking domains, respectively. On the other hand, an increase of 1 percentage point (p.p.) in the share of relative smartphone usage leads to a decrease in time spent on shopping (0.23 p.p.), news (0.13 p.p.), search (0.1 p.p.), money management (0.06 p.p.), and price/product comparison (0.03 p.p.) domains. An increase in the share of smartphone usage by 5 percentage points leads to a decrease in the share of time spent on shopping, money management, and price/product comparison domains of about 10%. For search and news domains, the corresponding decrease is of 5.6 and 3.7 percent, respectively. Perhaps not surprisingly, these are the domains for which smartphone usage is likely to be ill-suited, as discussed in Section 4.

5.3 Within Categories Concentration and Depth

Another question of interest is whether an increase in smartphone usage affects the concentration and depth of consumption *within* domain categories. This naturally has important implications for online competition within domain categories as individuals increasingly move towards mobile online consumption. To explore this question, I again estimate equation (5) following the IV approach presented above, using the within category HHI as well as the within category share of visits that last more than 10 minutes as

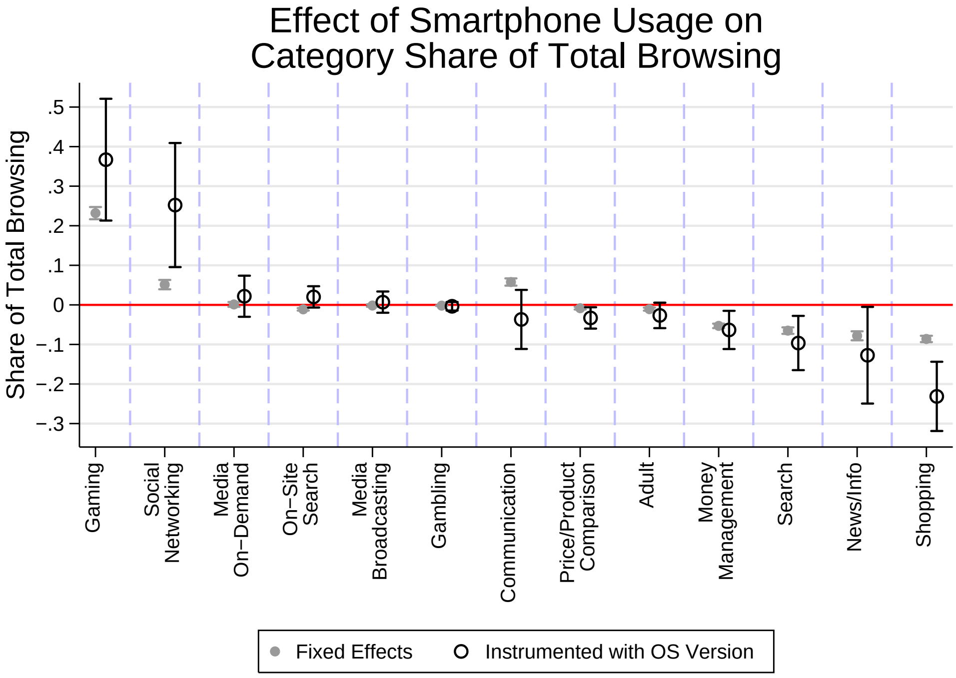

Figure 6: Changes in Category Share of Total Browsing.

dependent variables.[20]

Figure 7 presents the coefficients resulting from estimating equation (5) using the within category HHI as a dependent variable, together with their respective 95% confidence intervals. The results show how a relative increase in smartphone usage increase the concentration of consumption within certain categories of domains. Relying on the IV estimates, a 1 percentage point increase in the share of smartphone usage leads to an increase of 52 HHI points within the gaming category. Given that the average HHI in this category is of 4,519 points, this corresponds to a 1.15% increase. Social networking, communication, and news domains present positive but lower increases in concentration - of 47, 33, and 25 HHI points, respectively.

[20]Following the HHI variable defined under (1), I construct a measure of the concentration of consumption of individual i within category c in week t as $HHI_{ict} = \sum_{j=1}^{J_{it}^c}(TS_{ijt}^c)^2$, where $TS_{ijt}^c = T_{ijt}^c / \left(\sum_{j=1}^{J_{it}^c} T_{ijt}^c\right)$ is the weekly time share allocated to each domain j by individual i within category c and where J_{it}^c is the number of distinct domains visited by individual i on category c and in week t. I similarly follow (3) and construct the within category share of visits that last more than 10 minutes as $SLV_{idt} = \left[\sum_{k\in t} \mathbb{1}\left(T_{ijk}^d > 10\right)\right] / \left[\sum_{k\in t} J_{ik}^d\right]$, where T_{ijk}^c is the time spent on domain j within category c during day k of week t, and J_{ik}^c is the number of distinct domains visited by individual i in day k within category c.

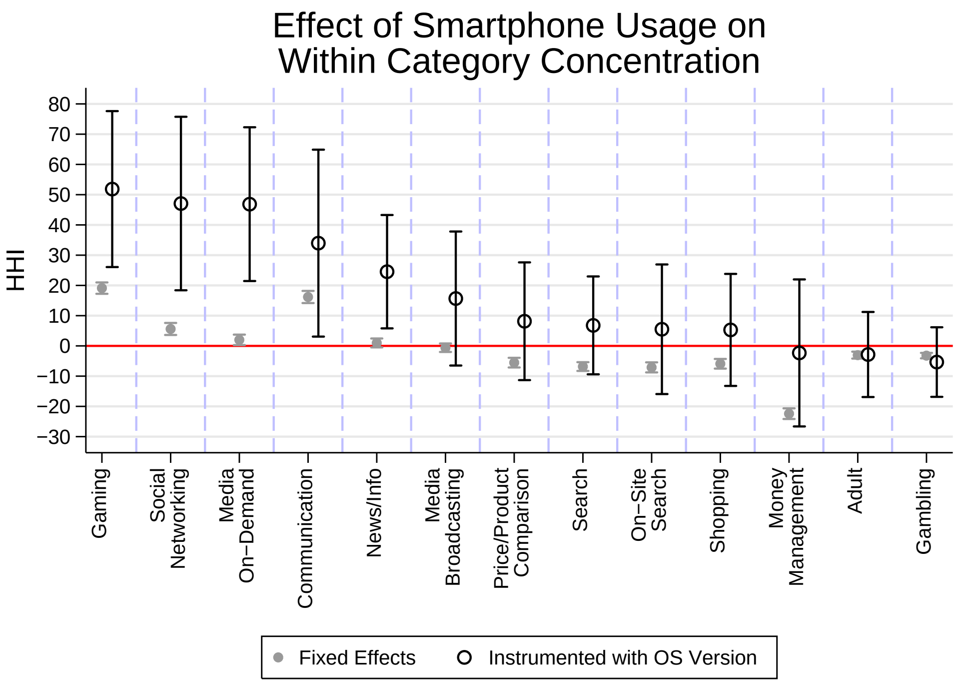

Figure 7: Effect of Smartphone Usage on Within Category HHI.

Figure 8 shows the coefficients resulting from estimating equation (5) using the within category share of visits lasting more than 10 minutes as a dependent variable, along with their respective 95% confidence intervals. Results show how an increase in relative smartphone usage leads to a higher depth of Internet consumption for social networking and gaming domains. The estimates indicate that a one percentage point increase in the share of relative smartphone usage leads to an increases in 0.56 and 0.52 percentage points in the share of long visits, respectively, corresponding to increases of 1.9 and 1.7 percent in these categories' depth of consumption, respectively. On the other hand, higher relative smartphone usage has negative effects on the depth of consumption for search, shopping, news, and price/product comparison categories of domains. The effects are not statistically significant for the remaining categories.

5.4 Heterogeneity

As shown in Section 3, patterns of Internet consumption and device usage vary across consumer groups, in particular with respect to income and age (see Table 2). I now explore

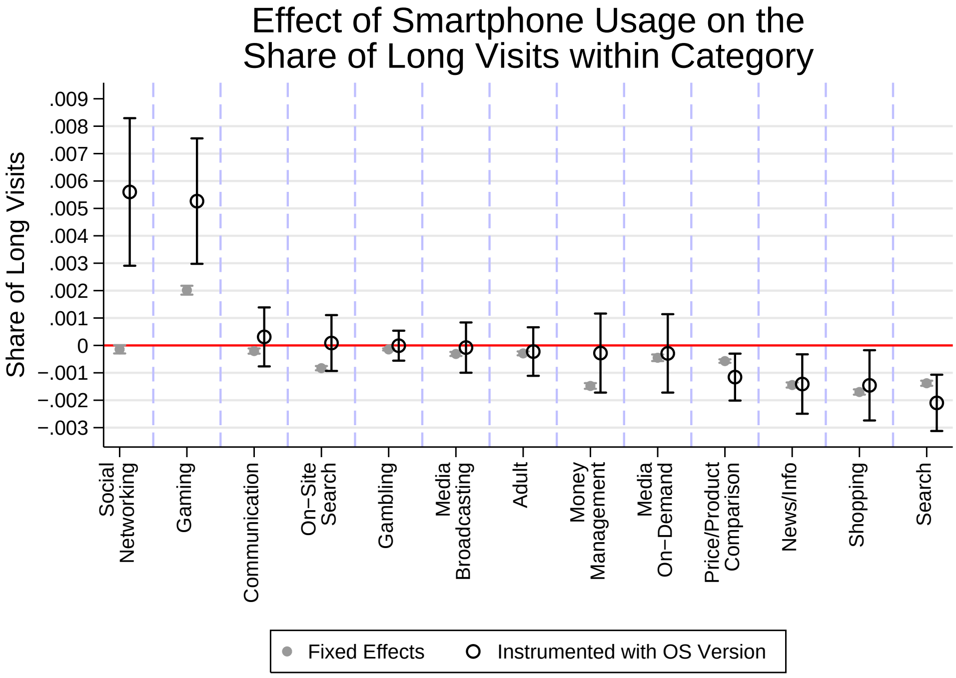

Figure 8: Effect of Smartphone Usage on Share of Long Visits.

the heterogeneity of the effect of an increase in relative smartphone usage on Internet consumption across various groups of consumers. To do so, I repeat the estimations performed above by splitting the sample into distinct groups of individuals, according to their income levels and to their age. I rely on a similar IV strategy, instrumenting the share of relative smartphone usage with the smartphone OS version updates. Table 7 presents the first stage results of regressing the share of smartphone usage on the OS version - together with the remaining control variables - for each of the different groups of individuals. I create three distinct income level groups (less than 2,500 euros per month, 2,500-3,000 euros per month, and over 3,000 euros per month) as well as three distinct age groups (14-34 years old, 35-44 years old, over 45 years old). As expected, the first stage results show a positive and significant effect of the OS version on the share of smartphone usage for each of these groups. Except for the group of individuals aged 35-44, which shows an F-stat slightly below 10, all other groups presents statistics on the excluded instrument that are above that critical value.

Figure 9 shows the results of estimating equation (5) for the three distinct income groups using the share of total online spent on each domain category as the dependent variable and using the IV approach presented above. Coefficients' 95% confidence intervals are reported. The results present no statistically significant differences across income groups regarding the effects of an increase in relative smartphone usage on the allocation of online time. Figure 10 presents the results of estimating the same set of regressions, splitting the sample into three age groups instead of income. Again, the results are not statistically distinguishable across age groups for most domain categories. Individuals aged 14-34 nevertheless tend to increase the share of their online time spent on social networking domains to a larger extent than individuals aged 45 and above (by 0.12 percentage point for each percentage point increase in the share of relative smartphone usage), although this difference is only significant at the 90% level of confidence.

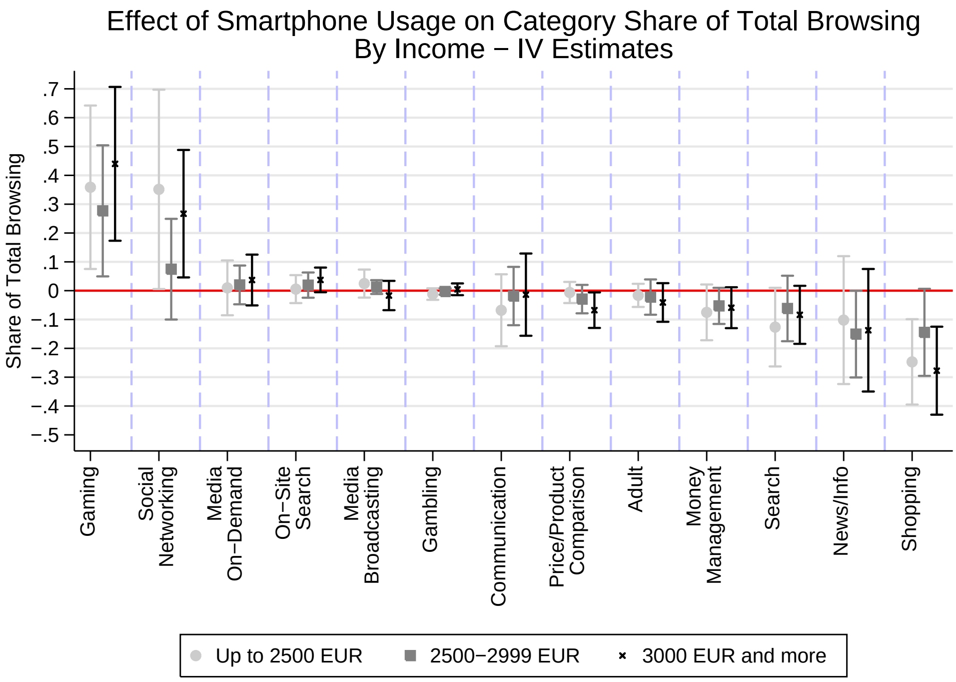

Figure 9: Changes in Category Share of Total Browsing, by Income.

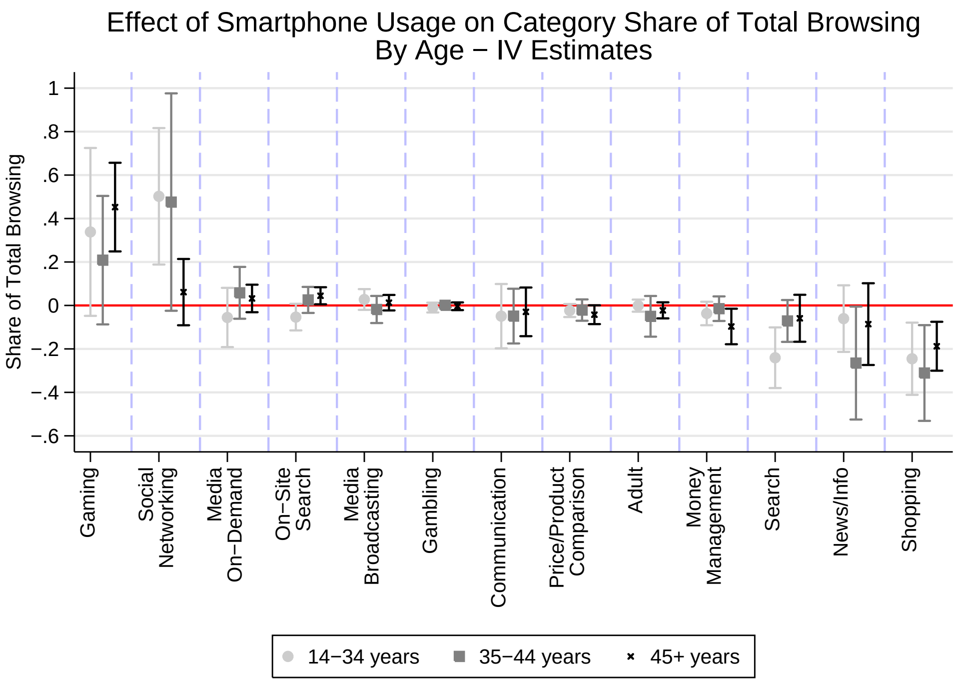

Figure 10: Changes in Category Share of Total Browsing, by Age.

Focusing on within category concentration, Figures 11 and 12 look at the effects of smartphone usage for the various income and age groups, respectively. Again, the figures show that the results are typically not statistically significant across the different income or age groups. Finally, Figures 13 and 14 focus on the within category depth of consumption. These again show results that are rather similar across demographic groups. The most relevant difference appears within the social networking category of domains, where the share of visits longer than 10 minutes made by individuals aged 14 to 34 years old is four times as large as their counterpart for individuals aged 45 and above.[21]

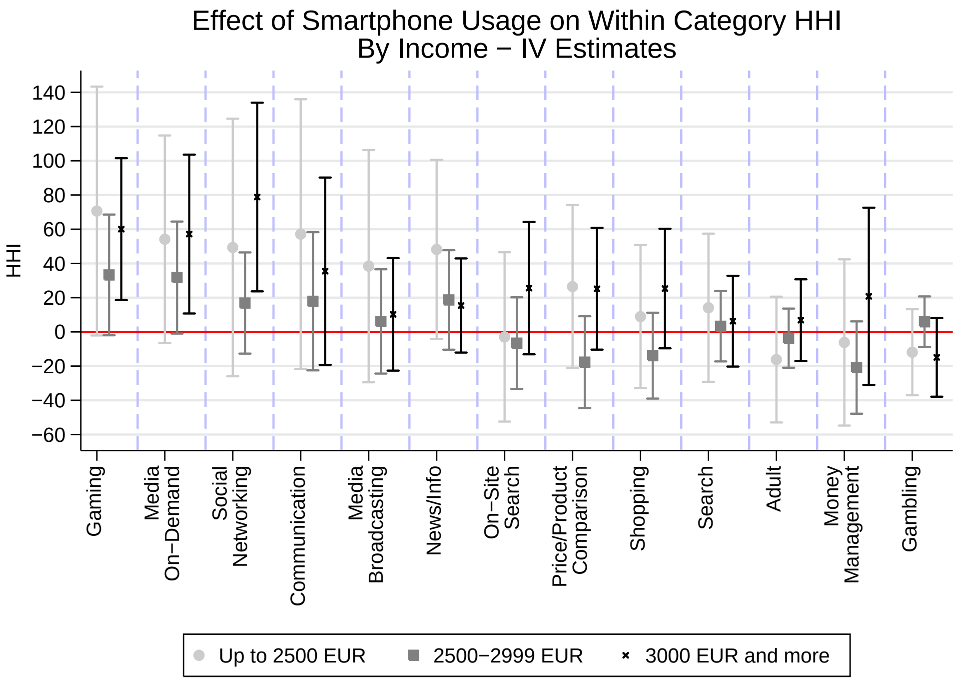

Figure 11: Effect of Smartphone on Within Category Concentration, by Income.

[21]This difference is again only significant at the 90% level of confidence.

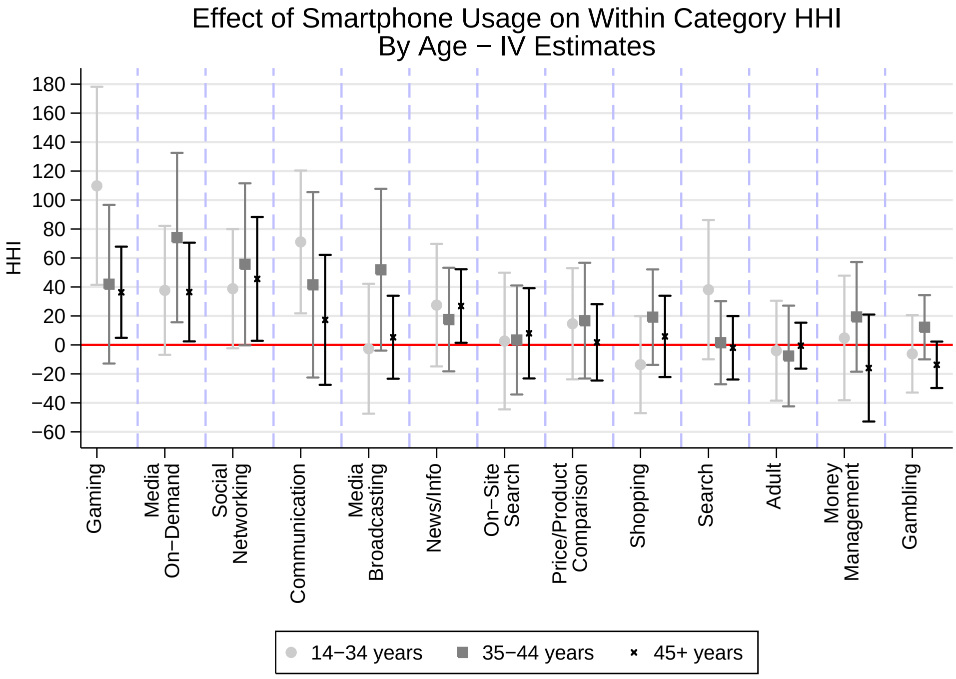

Figure 12: Effect of Smartphone on Within Category Concentration, by Age.

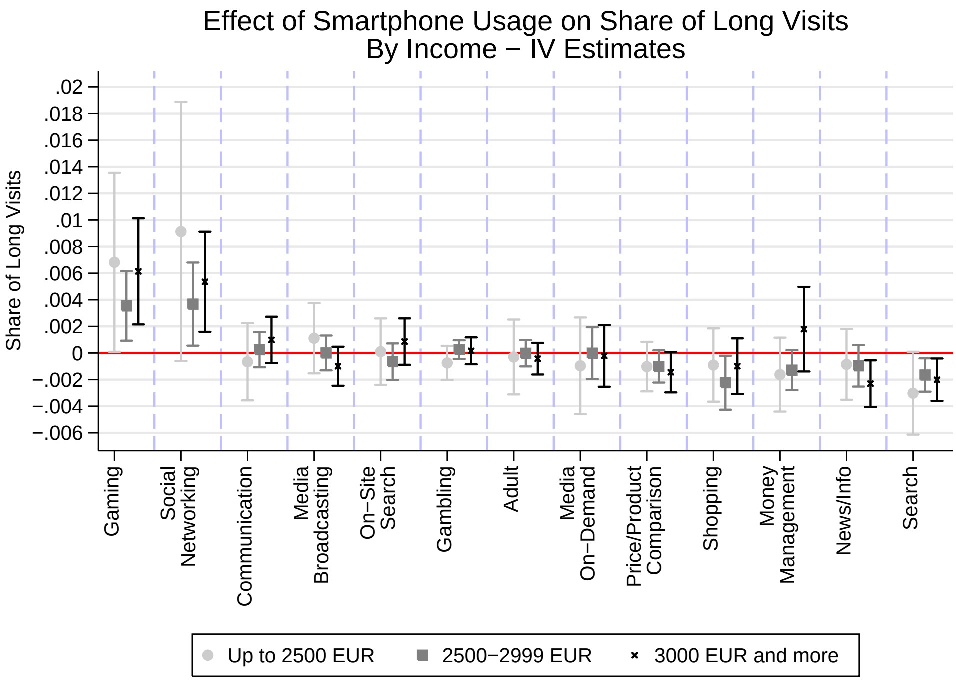

Figure 13: Effect of Smartphone Usage on Weekly Time Spent per Domain, by Income.

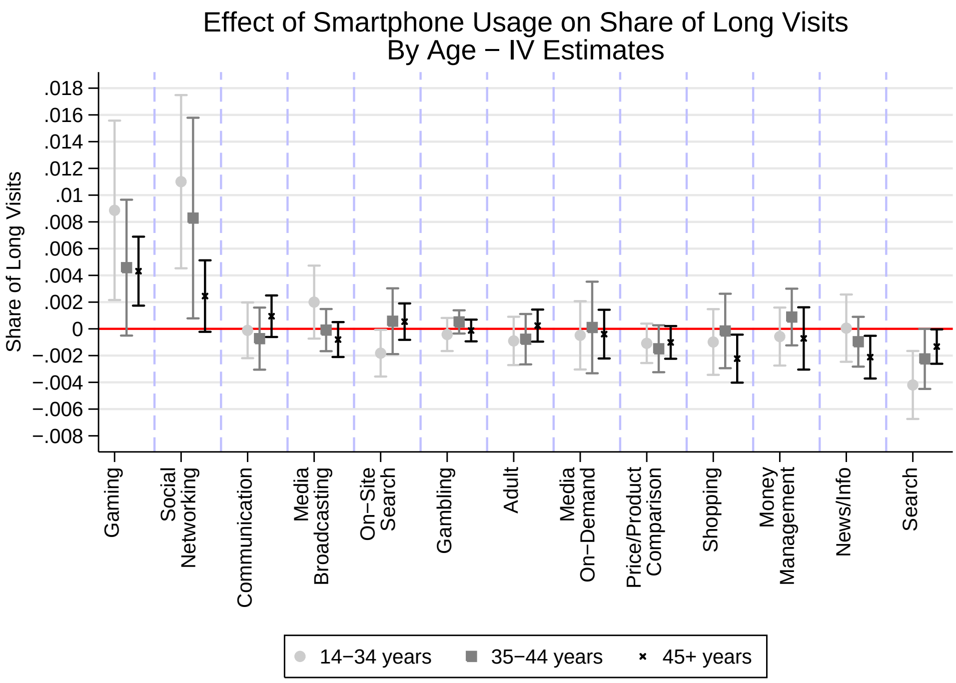

Figure 14: Effect of Smartphone Usage on Weekly Time Spent per Domain, by Age.

6 Conclusion

Over the past years, the advent of the smartphone has offered the promise of an almost constant connectivity with the online world, liberating consumers from the need of a fixed Internet connection. The immediate Internet access provided by smartphones naturally allows for an important increase in the amount of time and attention that consumers can spend online, allowing marketers to have a more direct and precise access to consumers by both time and location, and offering website publishers more opportunities to reach a given set of consumers (Luo et al., 2013; Andrews et al., 2015; Fang et al., 2015). On the other hand smartphones' smaller screen size and limited display impose new restrictions on users' capacity to search and retrieve information provided by the Internet (Adipat et al., 2011; Ghose et al., 2013). Against this backdrop, and as consumers increasingly access the Internet through their smartphone, understanding how such changes in connectivity patterns affects overall Internet consumption and behavior becomes crucial.

This paper relies on the clickstream data of over 2,900 individuals to explore how individuals change the allocation of their total online time across distinct categories of websites as well as their variety and depth of Internet consumption as their relative smartphone usage increases. I employ an instrumental variables approach based on exogenous updates of the smartphone Android operating system to tackle the endogeneity of smartphone usage. The empirical analysis shows an increase in the usage of social networking and gaming domains as smartphone usage increases relative to desktop. On the other hand, time spent on other domains categories such as shopping, news, search, money management, and price/product comparison decrease with an increase in smartphone usage. Perhaps not surprisingly, and unlike social networking and gaming domains, these are the domain categories for which smartphone usage is likely to be ill-suited. Results also show that concentration and depth both increase within the social networking and gaming domain categories. Browsing diversity decreases within the news and media on-demand categories. Browsing depth increase in the news, shopping, and search domain categories.

These results show how the growth in smartphone-based digital consumption has important implications for website publishers, advertisers, and for online competition. In particular, they imply that consumers' attention will be harder to grab in certain categories as their digital consumption goes mobile. For instance, the depicted increase in concentration within the gaming category implies that consumers could be less likely to discover games located in the tail of the distribution. The latter will consequently find it more difficult to grab consumers' attention in a mobile-oriented digital world, which could also have important dynamic implications as incentives to enter these markets could decrease. In the context of electronic commerce for instance, websites compete for individuals' attention in order to convert it into direct products' sales. As shown above, consumers decrease their share of online time spent on shopping domains as they increase their relative smartphone usage. Likewise, their depth of usage of shopping domains also decreases with a shift towards mobile online access. In that case, competition for consumers' attention would increase on these particular types of domains as well. In other categories of websites – social networking websites, for instance - consumers' attention is typically monetized through sales of advertisement. In that context, the results also have important implications for websites publishers and advertisers. The results above show how concentration increase within the social networking domain category, among others. Again, this increase in competition for consumers' attention implies higher barriers to entry and more difficulties for lesser-known websites in generating revenue from advertisement. This increase in concentration is also likely to affect advertisers' decisions on how to allocate their ads across domains. As browsing concentration increases on a more limited set of domains, the competition for ad space is likely to increase among advertisers. Additionally, advertisers need to decide whether their campaign should emphasize "reach" (the number of distinct users who see the campaign) or "frequency" (the number of times that each consumer sees the campaign). All other things equal, a lower level of concentration - due to users being able to easily switch from one website to the other - will lead advertisers to duplicate their expenses in order to reach consumers. From an advertiser's perspective, a higher concentration of browsing could therefore lead to less waste in terms of reaching the same consumer multiple times (Athey et al., 2016) and may consequently help advertisers looking for higher frequency of ad exposure.

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