Smartphone Impacts on Online Content Consumption Patterns

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Abstract

Smartphones have become the leading medium for online content consumption globally. Despite this major change in how content is consumed, little is known about whether and how the switch from home computers to mobile devices has impacted the way content is consumed. In this paper, we build a simple theory model that captures heterogeneity in opportunity costs across individuals and search costs across mediums. The model generates predictions concerning the differences across mobile devices and home computers in the variety of online consumption and the distribution of session lengths across devices. We test these predictions using data on home computer consumption in 2008 and 2019, along with data on mobile consumption from 2019. Our empirical analysis shows that mobile platforms are associated with shorter, more frequent sessions and more concentrated consumption patterns compared to home devices. As users spend more time online via mobile, they tend to focus on a limited set of high-utility apps or websites, leading to reduced variety compared to desktop and laptops. The reduced variety in mobile consumption suggests a shift toward a more concentrated set of online content suppliers, leading to reduced content diversity.

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1. Introduction

Over the past quarter century, online engagement has gone from comprising just a small sliver of time use and economic activity in the U.S. to being a major component of both. E-commerce is now more than 15% of overall sales (St. Louis Fed, 2023), and the average American now spends nearly seven hours online per day (Supan, 2023). Nested within this broad trend toward online activity is a shift in the method of access. Since the widespread popularization of smartphones in the late 2000's, US internet users have moved their online activity from desktops and laptops to smartphones, with recent studies indicating four and a half hours of daily nonvoice smartphone use as of 2022. Major changes in time spent online and mode of access likely have ramifications for economic outcomes of interest. An ongoing concern is whether digital markets (largely dependent on online consumption) are trending toward higher concentration. One way to assess such a concern is by tracking the variety of online consumption. Hence, we ask how the variety of online consumption relates to time spent online and whether this relationship, and the distribution of session lengths, changed with the massive shift to the smartphone as the means of online access.

While microeconomic intuition suggests behavior should change as users switch between devices, the direction of change is not obvious. The access mode comes with different price structures, and those shape behavior. While most data contracts for wireless devices employ usage pricing (Prince & Greenstein, 2021), household broadband access is priced monthly and is sometimes tied to usage (Nevo et al., 2016). User behavior could change due to significant differences in the design of the devices, such as screen size, navigation setup, and native app play, which could change search costs (Ghose et al., 2013). What will be the consequences of these differences in terms of how online content is consumed? A general forecast is challenging.

The variety of content users consume is a bellwether about the nature of online content competition. If new access methods and more online time appear to lead to, or at least predict, more concentrated consumption – i.e., less consumed variety, such a phenomenon would suggest a significant undercurrent toward a more concentrated set of online content suppliers, and vice versa. The extent that any relationship holds broadly also depends on how individual behavior manifests in the aggregate. For example, it could be that individuals exhibit highly concentrated online consumption; still, due to a high level of cross-sectional heterogeneity in preferences, this may not translate into highly concentrated consumption in the aggregate (due to, e.g., lots of loyal, niche consumption).

Our study stresses that the total time spent on a device plays a crucial role in determining the amount of variety consumed. The analysis introduces the variety-time relationship (highlighting similarities to the variety-income relationship in other applications) and uses it to measure how users react to different devices. We expect users with more time online to consume more variety on both an extensive and intensive margin. However, those facing higher search costs will consume less variety. The analysis begins with a simple model of content consumption, where we analyze the relationship between measures of content consumption and fundamental parameters, namely opportunity costs and transaction costs (which include search costs). Our analysis explicitly incorporates technological differences between laptops/desktops and smartphones by incorporating (greater) heterogeneity in transaction costs for smartphones, motivated by the combined icon-based/touch-screen mobile interface, which leads to very low transaction costs when switching across pre-selected, "iconed" sites but notably higher transaction costs when switching away from this group. This type of heterogeneity in transaction costs is less likely to operate on laptops/desktops. Our model produces predictions about the distribution of session lengths, and the relationship between time spent online and variety, across devices. In particular, our model predicts that there will be a higher proportion of short sessions on mobile and that variety will increase less (or even decrease) with time on mobile vs. laptops/desktops. We test these predictions with our data.

The data comes from ComScore's panel of browser and app usage. The first sample comes from over thirty thousand households consuming online material on desktops and laptops in 2008. We use that as a benchmark for examining the second sample of over thirty thousand households from 2019. It, too, tracks desktop and laptop consumption of online material. The third sample contains smartphone usage for over twelve thousand devices in 2019, specifically user apps and web consumption. We have similar, though not identical, demographic information about the household or user in all three samples. That facilitates two comparisons. The first is between two periods, 2008 to 2019, of online desktops and laptops. The second comparison is between desktops/laptops and smartphones in 2019. Our empirical analysis validates both of our main predictions. By plotting the distribution of session lengths for mobile and laptops/desktops, we see that there is a significantly higher proportion of short sessions on mobile. Using fixed effects regressions, we then show that variety does increase less with time on mobile vs. laptops/desktops, even turning negative for one of our primary variety metrics.

Our study reveals important distinctions in online consumption patterns across mobile and home devices. We find that mobile platforms, despite their frequent use, are associated with more concentrated and repetitive online behavior. This result can be interpreted as a consequence of how users derive value from interactions on these platforms. The characteristics of mobile devices, including smaller screens, app-centric engagement, and touch-screen interfaces encourage users to spend time on a limited set of websites or apps. An apparent consequence is that, as the total time spent on mobile increases, users consolidate their time on a smaller group of familiar, high-utility sites, rather than exploring new content.

In contrast, the larger screen sizes and more flexible interfaces of laptops and desktops facilitate visits to a broader range of websites, supporting more expansive exploration with increased time on the device. These results suggest that the key difference between mobile and home platforms is rooted in how transaction costs shape online consumption. The relatively lower transaction costs associated with a subset of content on mobile devices, such as ease of access to apps with a single tap, combined with relatively higher transaction costs when moving outside this set, reduce the incentive to explore new websites beyond the low-cost set. Users focus on familiar apps or high-frequency websites that provide reliable value in shorter bursts, reinforcing patterns of concentrated consumption. The findings from our robustness tests confirm this finding. When we exclude major content categories like video, social media, and music, the relationship between total time and variety remains largely unchanged.

Understanding the direction and determinants of the variety of online content consumption can be valuable for policymakers and practitioners. For policymakers, it can provide a helpful context for enforcement decisions and analysis; for practitioners, it can aid in identifying opportunities and optimal strategies for entering and/or competing in online content markets. Our findings contribute to a stream of literature analyzing determinants of consumption variety in different contexts, initially with a focus on commodities and food.

Early work on consumption variety studied how the monetary budget affects the number of items in the purchased set. Jackson (1984) showed the variety of commodities purchased increases with expenditure by the hierarchical ranking of commodities. Behrman and Deolalikar (1989) compared food consumption between developing and developed countries. They found that the income elasticity of food consumption was substantially higher than that of calorie intake, which implies a preference for seeking food variety as income increases but inertia in pursuing nourishment variety.

The second stream of literature to which we contribute is research analyzing how recent technological change alters online consumption. One of the earliest investigations into how consumption variety responded to changes in access mode was by Hitt and Tambe (2007). They examined a set of households before and after upgrading from narrow to broadband access, finding a significant increase in time online, particularly for those among the lowest users under narrowband. The variety of websites consumed grew, but not the type of content consumed, which led them to conclude that most consumption was not of new topics but of new suppliers of topics that already interest the user.

Few papers have directly compared the online behavior of desktop and smartphone users. Ghose et al. (2013) are valuable exceptions. They explore a sample of microblogging users in 2009 who employ desktops and smartphones and use exogenous variation in ranking to understand how users react. They infer that the smaller screen on smartphones increases search costs. They also conclude that users are much more likely to use the mobile features of smartphones to search for geographically local topics. We differ in the datasets and the set of time.

A critical difference between Hitt and Tambe and Ghose et al. (2013) is the comparison of devices, laptops, and smartphones over an extended period. We also see behavior many more years after smartphones had deployed, so we see a more comprehensive set of demographics. Though we lack a direct comparison of the same households, we can compare households with similar characteristics.

2. Theory

To establish a foundation for our analysis, we develop a theoretical model that captures differences in content consumption across laptops/desktops (L) and mobile devices (M), while accounting for opportunity costs and transaction costs. The data, described in Section 3, track user activity in 2008 and 2019. By 2008, commercial web browsers had been in use for over a decade, and by 2019, a dozen years had passed since the introduction of the iPhone. This context makes it plausible to assume users have full information about their choices.

Our benchmark model focuses on laptops and desktops, where marginal costs for data usage and time are effectively zero due to flat-rate broadband pricing. As a result, the primary constraint on consumption is the user's total available time. In this model, households allocate their time across three categories of consumption: laptop/desktop (L), mobile (M), and outside goods (O). Each category offers a large number of options, indexed as $L_1, L_2, \ldots L_n, M_1, M_2, \ldots. M_n$, and $O_1, O_2, \ldots.O_n$, where n represents the number of options within each set. For simplicity, we assume n is the same across categories. Suppliers provide these options, and users allocate their time based on the utility derived from consuming each option.

Consumption in our model is continuous in time, with users gaining weakly positive utility from the first second of consumption and experiencing diminishing marginal returns thereafter. The opportunity cost of spending one minute on online consumption is represented by f, reflecting the forgone value of spending that minute on outside goods. In this framework, the allocation of time across options and devices is influenced by transaction costs and opportunity costs.

Transaction Costs and Device-Specific Differences

Transaction costs play a central role in shaping online consumption patterns. On laptops/desktops (L), users face a uniform transaction cost, *c*, when visiting a new site. On mobile devices (M), users encounter a distinct structure of transaction costs due to the app-centric design and touch-based interfaces. Specifically, users can preselect a subset of frequently accessed sites or apps, for which the transaction cost is zero. For all other sites outside this subset, the transaction cost increases to $k > c$. This reflects the convenience of single-tap navigation on mobile devices for pre-selected apps and the higher effort required to navigate to less familiar or non-favored content. In contrast, laptops and desktops lack this extreme disparity in transaction costs across sites, resulting in a more uniform experience when switching between options. We integrate this structure into our theoretical framework and derive three key predictions, linking the parameters *f*, *c*, and *k* to observable patterns in consumption.

Prediction 1: Given a household's total number of sessions, the average session length—and consequently the total time spent online—declines as the opportunity cost of time (f) increases.

Opportunity costs (*f*) represent the value of foregone alternatives when time is allocated to online activities. As *f* increases, users are expected to allocate less time online overall, resulting in shorter session lengths and reduced total time. This relationship arises because users with higher opportunity costs prioritize activities that provide the greatest utility relative to the time spent. Regardless of the device used, higher *f* constrains time allocation, leading to shorter sessions and less overall engagement.

This prediction suggests that individuals with high opportunity costs will not only reduce their session lengths but may also exhibit a steeper decline in total time spent online, as their marginal utility from online engagement diminishes more rapidly. In scenarios where opportunity costs are low (e.g., for individuals with fewer competing time demands), session lengths and total time are expected to be longer, reflecting a higher willingness to engage with content over extended periods. An opposite scenario could arise if individuals with high opportunity costs use online platforms more intensively to achieve specific objectives (e.g., professional or transactional tasks). In such cases, session lengths might remain relatively stable or even increase for certain user groups, as the utility derived from each session compensates for the higher opportunity costs. The device type could moderate these effects; for example, mobile devices may facilitate short bursts of high-utility engagement, while desktops/laptops might support more sustained periods of use.

Prediction 2: The transaction cost structure on mobile devices predicts a higher proportion of short sessions compared to laptops/desktops.

Transaction costs play a crucial role in shaping how users interact with online content. Mobile devices are characterized by a distinctive transaction cost structure. For a subset of frequently used apps or sites (e.g., those accessible via icons), transaction costs are effectively zero. For other content outside this subset, transaction costs increase to $k > c$, where c represents the relatively uniform transaction costs faced on laptops/desktops. This dichotomy makes mobile devices well-suited for brief, targeted interactions with preselected content.

We predict that the proportion of short sessions will be higher on mobile devices than on laptops/desktops. Users on mobile devices are more likely to engage in quick, goal-oriented interactions, driven by the low transaction costs associated with frequently accessed apps. In contrast, laptops/desktops, which lack this sharp disparity in transaction costs, facilitate longer, less frequent sessions that allow for broader engagement with online content. This prediction implies that mobile users optimize their engagement by focusing on a narrow subset of content that can be consumed quickly. However, there may be cases where the transactional design of mobile platforms encourages longer sessions for certain content types, such as video streaming or gaming apps. Conversely, on laptops/desktops, the absence of zero-cost shortcuts may limit the frequency of short sessions, as users spend more time navigating to content or engaging in tasks that require sustained attention.

A potential countervailing scenario could occur if mobile devices evolve to reduce transaction costs for broader exploration, such as through advanced voice-based navigation or improved interface designs. In such cases, the proportion of short sessions on mobile might decrease, narrowing the gap between the two device types.

Prediction 3: As households spend more time online, the variety of content consumed grows more slowly for mobile devices compared to laptops/desktops.

Variety in online consumption refers to the breadth of content consumed, measured by the number of unique sites or apps visited. As total time spent online increases, we predict that the growth in variety will be slower for mobile devices compared to laptops/desktops. On mobile platforms, additional time is disproportionately allocated to a subset of zero-transaction-cost apps or sites, which constrains the exploration of new content. This behavior contrasts with laptops/desktops, where more uniform transaction costs enable users to distribute additional time across a wider range of content.

This prediction suggests that mobile users, when faced with longer online periods, will focus their time on familiar, high-utility apps or sites, reinforcing concentrated consumption patterns. As a result, even substantial increases in total time may yield minimal expansion in variety. On the other hand, laptops/desktops encourage users to allocate additional time to new or infrequently visited sites, resulting in a more pronounced increase in variety with greater total time. Alternative scenario could be that mobile users actively seek diversity within their zero-cost subset, such as rotating among several frequently used apps or exploring new options promoted within the app ecosystem. Alternatively, specific user groups, such as those with high curiosity or niche interests, might defy the general trend and exhibit higher variety growth on mobile platforms. Similarly, laptops/desktops might see slower variety growth if users concentrate on fewer, more time-intensive tasks, such as research or streaming.

3. Data

The data we utilize for this study come from three separate datasets, all from ComScore. Each dataset contains information on highly granular online activity by users at the device level; two contain information for the home computer, and the other contains information for a mobile device. The home computer data come from 2008 and 2019, and the mobile device data come from 2019 only. We begin by describing the home personal computer data. For those data, we observe one machine for each household for the entire year, either 2008 or 2019. The machine should be interpreted as the household's primary home computer, either desktop or laptop. To align these data with our mobile data (described below), we only analyze the three-month period of March, April, and May, since these are the only months we have for mobile.[1]

The information collected for our home PC data includes the name of the sites (which includes apps/sites for mobile) visited on the machine, and how much time was spent at each site in minutes. We consider only the first four weeks of a month, as the usage during the fifth week

[1] In just three months of data, we have over 85 million observations in total, providing a comprehensive dataset for analysis.

varies significantly based on the number of days available, so excluding it provides more consistent data across weeks. Therefore, the maximum number of weeks for a household cannot exceed twelve. We have excluded a small number of households with online usage exceeding 10,080 minutes per week, which was the maximum amount of time allowed and thus the data from these households are presumably the results of a defective tracking device. Our sample is further refined to include households that consistently engage online for a minimum of 60 minutes per week, for a duration spanning at least two-thirds of the entire observational period. For 2008, we are left with 32,459 out of 52,234 households, and for 2019 we are left with 34,303 out of 88,139 households. In both years, this amounts to over 370,000 machine-week observations. We observe an average of 11.59 and 11.50 (medians 12 and 12) machine-weeks per household (s.d. = 0.83 and 0.88) for 2008 and 2019.

ComScore attempts to obtain a balanced sample of households across years. The demographics we observe include (1) household income categories, (2) educational attainment of the head of the household, (3) household size, (4) age of the head of the household, and (5) an indicator for the presence of children. For income, ComScore's sampling of households is known to target higher-income households, and we observe that those income levels are comparable across the 2008 and 2019 data. Unfortunately for education attainment, the education identifiers were mainly missing in 2008 and only available for roughly half of all households in 2019. Meanwhile, for age, there do not appear to be any significant differences in the sample composition across years (the 2019 heads of households are mildly younger). In addition, ComScore provides no information on the speed of the broadband connection except to indicate that virtually no one connects through dial-up.

For our mobile data, we obtained data on the online activity of individual smartphones, where 67% of the devices operate on iOS and the remaining 34% on Android, sourced from ComScore for the three months of March, April, and May in 2019. An observation is a session consisting of a continuous visit to a website (via an app or browser) on a smartphone. The information collected includes the name of the sites visited on the device, how much time was spent at each site, and the number of pages visited within the site. We also observe several corresponding demographic measures for the device user: income, sex, ethnicity, age, whether the user has children, and household size.

Moving now to the collection of all three datasets, we first define a unique session by *device id*×*log-in time*×*duration*×*website id*. In the raw data, there are 34,550,151 sessions for the 2008 Home dataset, 33,895,734 sessions for 2019 Home dataset, and 17,511,990 sessions for the 2019 Mobile dataset. We proceed by excluding outlier sessions. Specifically, we drop any session by users who are over 100-years old or live in an unknown region, and any session with duration of over 6 consecutive hours. This leaves us with 28,748,450 sessions for the 2008 Home dataset, 24,030,458 sessions for the 2019 Home dataset, and 13,756,481 sessions in the 2019 Mobile dataset. Next, we collapse our data into a panel such that a unit of observation is at the week-device level.

Table 1 displays a summary of session-level counts by week of the month across Home 2008, Home 2019, and Mobile 2019 datasets. The distribution of total sessions is almost evenly spread across weeks for all datasets, indicating consistent usage patterns over time. In 2008, home computers were likely the primary means of accessing the internet, as reflected in the higher average number of sessions per device—around 76.3 sessions per week—than in 2019. By 2019, the number of sessions per device for home computers had dropped to about 60.9, suggesting that internet usage had shifted, with mobile devices becoming a more prominent means of access. This shift is evidenced by the Mobile 2019 dataset, where the number of sessions averaged about 208 sessions per week—more than three times the number for home computers in 2019. This substantial session per device difference between home and mobile data is consistent with our theoretical framework, which suggests that the transaction costs associated with using mobile devices are lower for a subset of sites than those for laptops and desktops, facilitating more frequent site visits.

[Table 1 about here]

Table 2 provides an overview of demographic information for our device users across each dataset. Here we see that our datasets skew towards non-Hispanic, middle-aged, and high-income individuals. The predominant family size is characterized by having two children, with nearly two-thirds of households in our sample devoid of any children. Moreover, the sex distribution among household heads in the Mobile 2019 data is relatively balanced. In both the Home 2008 and Home 2019 datasets, the skew towards middle-aged, high-income users remains consistent. However, the skewness towards high-income and middle-age is less pronounced in the Mobile 2019 dataset, where the distribution is more balanced across these demographics.

[Table 2 about here]

Table 3 presents the weekly time observations in minutes for Home 2008, Home 2019, and Mobile 2019, including both the total time per device and the average time per session. We calculate the total time as follows. For a given household j and week t, let $i \in N_{jt}$ denote website

i visited by household j during week t, from among the full set of websites visited by household j during week t, N_{jt}. Let x_{ijt} denote the time (in minutes) devoted to website i by household j during week t. We then calculate the total time spent online by household j during week t as x_{jt}, where $x_{jt} = \sum_{i \in N_{jt}} x_{ijt}$. The overall distribution of time across weeks is fairly consistent for both Home 2019 and Mobile 2019, with Home 2008 being somewhat higher in March than in May, suggesting a slight variation in activity over time. Here we see that the total time (per week, per device) for desktops and laptops has fallen over a decade, but the increase in total time for mobile is much larger—roughly captured by the time per device, which was virtually zero in 2008. However, caution is warranted because the samples do not directly match the same household to each other.[2]

[Table 3 about here]

We conclude this section with summary statistics of session level observations across demographics. Table 4 presents the average frequency of sessions visited per household for each week, broken down by income and age groups, highlighting how digital engagement patterns within households evolved from home devices in 2008 to home and mobile devices in 2019. For income, the frequency of visits across each income group remained consistent across all datasets. In 2008, the average sessions visited per household/week ranged from 75.78 for those earning less than $25,000 to 75.97 for those earning $100,000 or more. This pattern persisted in Home 2019

[2] One concern with our data is the measurement of time spent at a site. If a household in the data leaves a browser open, we do not know if the user is calmly consuming its content or whether the user has left the room. ComScore ends such sessions after a period of inactivity, but this is a limitation of the data that biases total attention expenditure and average expenditure per site visit upwards. This may lead to an overestimation of time spent on certain websites, potentially for home devices compared to mobile.

(58.18 to 60.94) and Mobile 2019 (195.64 to 208.36). However, over time, there was a shift towards reduced home usage in 2019 (60.80) and increased mobile engagement (208.08). For age, there was greater variation. In Home 2008, younger generations of aged 18-24 had higher average visits at 85.56 compared to 69.44 for those aged 65 and older, reflecting greater Internet adoption among younger users. This pattern was similar in Mobile 2019, with youngest user group averaging 258.86 visits per device/week compared to 187.89 for oldest groups. However, in Home 2019, this trend reversed, as older generations averaged 71.15 visits compared to 49.95 for the 18-24 age group. This indicates that older users became relatively more active on home devices when younger users shifted more toward mobile platforms.

[Table 4 about here]

4. Measure of Variety

In Section 3, we described our data and provided summary statistics pertaining to online sessions and time on home and mobile devices. Analyses of these variables (in Section 5) allow us to address our first three predictions. Our last prediction concerns a measure of variety, to which we now turn. In this section, we consider ways of measuring variety and present summary statistics for those measures in our data; we then examine our fourth prediction concerning these measures in Section 5. We consider two different ways of measuring variety, one focused on frequency and the other focused on intensity. In particular, we construct one measure, V, which is a measure of variety across *visits*, and another measure, H, which is a measure of variety across *time*. Intuitively, changes in V are driven by movements on the extensive margin while changes in H are a mix of changes to the extensive and intensive margins.

There is no consensus on how to measure variety. For illustrative purposes, we will discuss in detail one such measure, and in our empirical analysis, we will use multiple alternatives to test for robustness. The primary measure we utilize is the Herfindahl-Hirschman Index (HHI), or the HHI index, which quantifies the degree of concentration of a household's visit or time allocation to various sites. We first consider concentration in visits, $HHI(Visits)$. Let y_{ijt} denote the number of visits to website i by household j during week t. We then calculate the total number of website visits by household j during week t as y_{jt}, where $y_{jt} = \sum_{i \in N_{jt}} y_{ijt}$. Next, we define q_{ijt} as the share of visits allocated to each website i by household j during week t, calculated as $q_{ijt} = y_{ijt}/y_{jt}$. Our measure of $HHI(Visits)$ for online content consumption by household j during week t is the sum of the squared website shares:

(1) $HHI(Visits)_{jt} = \sum_{i \in N_{jt}} q_{ijt}^2$

The advantage of using the *HHI* metric for online consumer behavior is that it is simple, scale-free, and deeply grounded as a market concentration measure. In applying it to online activity, a higher HHI implies less variety (more concentration). To align this metric with our other scale-free indices and to make it easily interpretable as a variety measure, we also construct $V = 1 - HHI(Visits)$, which is one of the measures of variety we use in our analyses. This function of HHI is such that a higher value implies more variety (less concentration).

We also consider concentration in time, $HHI(Time)$. Recall from Section 3 that x_{ijt} is the time devoted to website i by household j during week t and x_{jt} is the total time spent online by household j during week t. We define p_{ijt} as the share of time allocated to each website i by household j during week t, calculated as $p_{ijt} = x_{ijt}/x_{jt}$. Our measure of $HHI(Time)$ for online content consumption by household j during week t is the sum of the squared website shares:

(2) $HHI(Time)_{jt} = \sum_{i \in N_{jt}} p_{ijt}^2$

$HHI(Time)$ declines with increased variety. So, we use $H = 1 - HHI(Time)$, which increases with variety, as another variety measure.

The difference between *V* and *H*, if any, comes from heterogeneity in the intensive margin across visited sites. For example, if a household visits all sites for the exact same amount of time per visit (e.g., ten minutes), *V* and *H* for that household will be the same. Broadly speaking, *V* will tend to be greater than *H* if the count of visits across sites is more balanced than the amount of time spent across sites. For example, if during a given week a household visits three sites, four times each, but spends one hour per visit for one site while spending only ten minutes per visit for the other two, we'll have *V* > *H*, i.e., there is greater variety in visits than in time. In contrast, *H* will tend to be greater than *V* if the time spent across sites is more balanced than the count of site visits. For example, if during a given week a household visits one site six times, spending ten minutes per visit, and two other sites once each, spending one hour per visit, we'll have *H* > *V*, i.e., there is greater variety in time than in visits.

Given what drives any difference between *V* and *H*, we next turn to examining differences in how *V* and *H* change with total time online, i.e., *V'(TT)* and *H'(TT)*. Consider an increase in a household's total time online (*TT*) for a given week. The effect on *V'* and *H'* will depend on some specifics of how this new time is allocated. If that additional time is spent at a new site (for that week), both *V* and *H* will increase (more variety in visits and more variety in where time is spent).

If the additional time is an extension of a site visit (e.g., the household extends a visit to Amazon from ten to fifteen minutes), *V* will remain unchanged; *H* will increase if that site had a low share of the household's time that week, and vice versa. Lastly, if the additional time is spent as an additional visit to a site already visited that week, *V* will increase if that site had a low share of the household's visits that week and vice versa; and again, *H* will increase if that site had a low share of the household's time that week, and vice versa.

A second measure of variety that we examine is equivalent to an entropy index, frequently used in information theory to measure levels of uncertainty and disorder (Singh 1997; Maasoumi 1993; Mishra et al. 2009). It uses the same components (q and p) as our *HHI* measures in equations (1) and (2). For each household *j* and week *t*, the entropy index E_{jt} (in time) is defined as:

$$(3)\ E_{jt} = -\sum_{i \in N_{jt}} p_{ijt}\, log(p_{ijt})$$

where $p_{ijt}log(p_{ijt}) < 0$ for $p_{ijt} > 0$, and $p_{ijt}log(p_{ijt}) = 0$ when p_i equals 0 or 1. Note that this index rises with greater variety. When the entropy measure is zero (representing the minimum value of entropy), it implies that a household's consumption behavior is entirely predictable – it either exclusively dedicates all of its time to a single site or does not engage with any sites. In contrast, our entropy index reaches its highest value when a household evenly distributes its time, achieving a uniform and balanced distribution of online usage across various activities. Note that *V* and *H* also reach their maximum under these circumstances. Our entropy measure in visits is defined analogously, replacing p with q.

Our third variety metric measures the proportion of time a household dedicates to its most frequented sites.Specifically, we use *FC3*, which represents the fraction of total time allocated to the top three sites by a household within a given week. To compute this variety index, for each household *j* during each week *t*, we identify the names of the top 3 sites visited by that household based on time spent. Using these top 3 site names, we calculate the fraction of the household's total time spent on these sites. Specifically, following our methodology, let Top^3 denote the top 3 sites for household *j* in week *t*. Then, we define the fraction of time spent at these top 3 sites by household *j* during week *t* as:

$$(4)\ FC3_{jt} = \sum_{i \in Top^3} \left(x_{ijt} / x_{jt} \right)$$

We also calculate this measure for visits by replacing x with y. Similar to *HHI*, *FC3* decreases as variety increases. To ensure that an increase in the measure consistently reflects greater variety, we use *1-FC3* in our analyses.

Table 5provides a summary of our various variety metrics—*Entropy*, *1-HHI*, and *1-FC3*—calculated separately for visits and time spent on sites. In 2008, households showed greater variety in their online activity with higher *Entropy* and *1-HHI* values for both visits and time. This indicates that activity was more evenly spread across multiple sites. By 2019, home internet usage became more concentrated with lower *Entropy* and *1-HHI* values. Additionally, *1-FC3*, which reflects the proportion of activity beyond the top three sites, was also slightly higher in 2008, further showing that online behavior was more varied. Comparing the first three columns of "visits" (*Entropy, 1-HHI, 1-FC3*) to the last three columns of "time," we can see that the variety in how time is spent is consistently lower than the variety in visits. For example, in 2008, the mean *Entropy* for visits is 2.769, while for time it is much lower at 1.966. This shows that visits are spread across more sites, but time is focused on fewer. Similarly, in 2019, the *1-FC3* for visits for mobile is

52.94, compared to only 29.43 for time, meaning households spent a much larger proportion of their time on just their top three sites. This trend is consistent across both years and platforms, with visits showing more variety and time showing greater concentration.

[Table 5 about here]

5. Results

5.1. Main Findings

In this section, we test the predictions from Section 2. We begin by testing Prediction #1: Given total sessions, average session length (and also total time) is declining in *f*. Here we can use income as a proxy for the utility of the outside option (*f*) and so test this prediction by testing the relationship between average session length (and total time) and income, controlling for total sessions. We show the results in Table 6.

[Table 6 about here]

In Table 6, we see a clear negative relationship between income and both average session length and total time spent online for both home PC datasets (2008 and 2019). Higher income brackets consistently show shorter average session lengths with the $100k+ income group having the steepest declines in Home 2008 and Home 2019. For example, in the Home 2019 dataset, the average session length for the $100k+ group is 1.21 minutes shorter than for those earning less than $25k. Given that the average session length for Home 2019 is 11.42 minutes (as shown in Table 3), this translates to a 10.59% reduction in average time spent per session for the highest income group. Despite the fact that various income groups engage in the similar number of sessions visited on average (in Table 4), higher-income individuals spend significantly less time per each session. For Mobile 2019, the negative relationship initially holds but then there is an increase for the highest two income groups. Nonetheless, given the average session length for mobile is 3.72 minutes, the highest income group spends 0.532 minutes less per session than the lowest income group, a 14.3% reduction.

Similar to session lengths, the total time spent online also decreases with income for both Home PC datasets, though the magnitude of this decline varies by dataset. For instance, in Home 2008, the total time per week for those earning \$100k+ is 90.432 minutes lower than for those earning less than \$25k, whereas in Home 2019, this difference is smaller at 54.103 minutes. Even with the variation in these level differences, there is a relationship where total time monotonically decreases as income increases. In the Mobile 2019 dataset, we again see an initial decline followed by a modest increase for the highest two income groups. Even so, the reduction in total time for the highest income group versus the lowest is even more pronounced, with the \$100k+ group spending 119.213 fewer minutes online than the lowest income group.

Overall, our data provide some support the prediction (#1) that as income increases, individuals allocate less time per session, possibly reflecting a greater value placed on their time or a higher utility of outside options (*f*). The slight discrepancy in mobile data may reflect greater ability to multitask and/or higher rates of usage for work.

Next, Prediction #2 states: There will be higher proportion of short sessions for mobile compared to desktops/laptops. Testing this hypothesis is straightforward in the data. Namely, we can test it by plotting the distribution of session lengths for our datasets. Figure 1 presents these distributions.

[Figure 1 about here]

Figure 1 clearly validates Prediction #2, as there is a much higher proportion of short sessions in the mobile data compared to the two home PC datasets (which have quite similar-looking distributions despite the time difference).

Lastly, Prediction #3 states: The slope of variety (measured in both of our ways, *V* and *H*) with respect to time will be lower for mobile than for laptops/desktops. This leads to our results concerning *V'* and *H'* for the home PC and mobile. We test this prediction by examining how our variety measures change in relation to total time. Tables 7a and 7b contain regressions of our different variety measures (*V* and *H*, respectively) on total time for all three datasets (2008 Home, 2019 Home, 2019 Mobile), including household fixed effects. Hence, these regressions show, on average, for a given access method and year, how the variety of online consumption by a given household changes with its total consumption after controlling for persistent household-level differences in online consumption variety.

[Tables 7a and 7b about here]

There are several main takeaways from the results in Tables 7a and 7b. First, the results in Table 7a focus on the extensive margin of online consumption. We observe that variety increases significantly with total consumption for both home devices in 2008 and 2019. This is evident across all three variety metrics, entropy, *1-HHI*, and *1-FC3*, indicating that as users spend more time online via home devices, they explore a broader range of websites, as evidenced by positive and significant coefficients on total time for all three. For example, for *Entropy (visits)* in 2008 Home, a one standard deviation increase in total time (0.876) increases entropy by about 0.359. Since the standard deviation of entropy (visits) is 0.795, this means the increase in entropy is equivalent to about 0.452 standard deviations. For *1-HHI (visits)* in column (2), the change is approximately 0.256 standard deviations, and for *1-FC3 (visits)* in column (3), it is about 0.243 standard deviations. Similar patterns are observed in the 2019 Home dataset, where the one standard deviation increase in total time results in 0.447, 0.209, and 0.343 increase in *Entropy*, *1-HHI*, and *1-FC3*, respectively.

In contrast, the results for Mobile 2019 generally show a weaker positive relationship between total time and (extensive margin) variety. The coefficients for entropy and *1-HHI* for Mobile 2019 are only about half that of home devices, indicating that mobile users are more limited in their variety expansion as time increases. Specifically, for Mobile 2019, a one standard deviation increase in total time leads to changes of 0.268 standard deviations for *Entropy* and 0.077 standard deviations for *1-HHI*, compared to 0.452 and 0.256 standard deviations, respectively, for 2008 Home. The contrast is also evident for our third variety measure, *1-FC3*. For Mobile 2019, a one standard deviation increase in total time leads to a change of 0.170 standard deviations, whereas the change is 0.243 standard deviations for 2008 Home and 0.343 standard deviations for 2019 Home. This reinforces the finding that mobile users exhibit smaller increases in visits variety as their total time increases compared to home device users. Overall, the generally smaller magnitudes for mobile are consistent with Prediction #3.

For our time variety measures, Table 7b further emphasizes the contrast between home computers/laptops and mobile by examining changes in variety that incorporate the intensive margin of consumption. Here, we see that for all three time measure of *Entropy* , *1-HHI*, and *1-FC3* variety continues to increase for home devices in both 2008 and 2019, as users not only visit more websites but also distribute their time more evenly across them. For Mobile 2019, the relationship is not only less positive, but is actually reversed: as users spend more time on their mobile devices, their consumption becomes more concentrated, as evidenced by negative coefficients on *Entropy*, *1-HHI*, and *1-FC3*.[34]

These results highlight an important distinction of online consumption patterns between mobile and home device users, particularly when viewed through the lens of our theoretical framework. The reduced variety observed in Mobile 2019 can be interpreted in the context of how users derive utility from different types of websites. Specifically, long sessions tend to be associated with websites that offer relatively high utility per visit—users are unlikely to spend extended periods on websites that provide little value. Conversely, the ability to derive utility from multiple separate visits in a single day is typically limited to websites whose optimal visit length is shorter. For mobile users, the nature of mobile interaction encourages shorter, more frequent sessions (as evidenced by the higher frequency of sessions and shorter session lengths than home

[3] Here's an illustrative example of the 2019 mobile pattern for the three metrics of time variety (H). Assume a user initially spends 1 hour online, distributing 20 minutes each to Websites A and B, and 10 minutes each to Websites C and D. Under this allocation, Entropy is calculated as 1.329 and 1-*HHI* is 694. Now, suppose the user increases their total time to 2 hours, allocating 70 minutes to Website A, 20 minutes to Website B, 10 minutes each to Websites C and D, and 5 minutes each to two new websites, E and F. As a result of this shift, Entropy decreases to 1.293 and 1-*HHI* to 614. Although the user visits a broader set of websites, their online activity becomes more concentrated, with a huge disproportionate amount of time allocated to a primary site. This behavior is indicative of concentrated consumption patterns as total time increases, where the marginal utility of new website exploration diminishes compared to the time spent on familiar, high-utility sites.

[4] To ensure the robustness of our findings, we also tested alternative measures such as *1-FC1* and *1-FC5*. These measures provide additional perspectives on the distribution of activity beyond the top 1 and top 5 visited sites, respectively. The results, presented in Tables A1a (for visit variety *V*) and A1b (for time variety *H*), remain strongly consistent with our main findings and reinforce the robustness of the observed patterns with different thresholds.

devices in Table 3). These shorter sessions are often concentrated on apps or websites where quick interactions are sufficient to derive utility—such as social media platforms, messaging apps, or quick searches. As a result, even as the total time spent online increases, the variety of websites visited may not expand significantly. Instead, users may allocate additional time to a limited set of high-utility websites that support shorter, repeatable interactions, rather than diversifying their consumption. Mobile users, faced with limited screen size, simpler navigation interfaces, and the app-centric structure of mobile platforms, may prioritize familiar and highly frequented sites over broader exploration. As total time rises, the marginal benefit of exploring new websites on mobile diminishes, leading users to allocate their increased time to a smaller, more focused set of websites or apps.

This stands in contrast to home devices, where longer sessions facilitate engagement with content that requires extended time to derive high utility—such as media streaming, online research, or complex tasks. On home devices, users are more likely to explore a broader range of websites, as the larger screen and multitasking capabilities encourage longer, deeper sessions, which naturally lead to higher variety in consumption.

Thus, the reduced variety seen in Mobile 2019 reflects a behavioral optimization where users concentrate their time on high-utility, short-interaction websites, reinforcing the idea that mobile platforms, while facilitating frequent access, do not support the same breadth of content exploration as home devices. This behavior aligns with our theoretical assumption that utility is more easily derived from multiple short visits, particularly on platforms optimized for quick, frequent interactions.

5.2. Additional Analyses of Variety

Given the striking difference between the variety/time relationship for home PCs vs. mobile, we conduct additional analyses to try and better assess whether this difference is driven by a difference in transaction costs or by other factors. We focus our additional analyses on the negative relationship between total time and variety (in time) in smartphones, as this is the most striking finding.

We begin by considering several possible alternative explanations. First, we assess whether the simple linearity assumption is driving the result. In Table 8 we allow for the relationship between variety and time to be quadratic. We find that the negative relationship persists. For *1-FC3*, there is a significant linear and quadratic term. For *1-HHI* there is a neagive linear term but positive and significant quadratic term. This suggests that variety in terms of how time is distributed across websites initially declines as total time increases, but eventually starts to increase. However, the turning point for this relationship occurs at nearly 5,000 minutes of weekly usage, a threshold that is extremely rare (around 0.04%) in our dataset. Entropy follows a similar pattern, with a near-zero linear term and a significant negative quadratic term, indicating a steady decline in the evenness of time distribution across websites as total time increases. As a result, the overall trend remains negative for the vast majority of users, reinforcing the idea that increased mobile usage tends to lead to more concentrated consumption patterns.

[Table 8 about here]

Next, we consider whether the difference may be driven by demographics. To check this, we examine if the relationship we find between variety and time is operating on any particular demographic dimension. We conduct our analysis with respect to income and age, and the results are in Tables 9 and 10, respectively. We find little evidence of any specific demographic subgroup being a driver of the negative relationship between variety and time. While there are some variations across income groups in Table 9, the overall relationship between total time and variety remains negative, supporting our broader findings. Table 10 provides more robust evidence when considering age as the key demographic factor. The negative relationship between total time and variety is consistent across all age groups, with significant coefficients for the youngest group (-178.55) and the second oldest group (-226.01). This suggests that the negative relationship between total time and variety holds strong across age demographics, reinforcing our primary conclusion that increased total time leads to more concentrated consumption patterns, regardless of age.

[Tables 9 and 10 about here]

We also examine whether our variety findings for mobile are driven entirely by certain types of consumption that may tend towards longer sessions, namely video, social media, and music. To do this, we run our analysis from Table 7b again, but removing top sites in all three categories.[5] Tables 11, 12, and 13 present these results, respectively. In all three tables, our primary variable of interest, *1-HHI*, continues to show a significant negative relationship with total time. This reaffirms that even after excluding video, social media, and music sites, increased time spent online is associated with more concentrated usage patterns. For example, in Table 11, which excludes video sites, the *1-HHI* coefficient is -560.4, indicating that users tend to focus their time on fewer websites as total time increases. This pattern is consistent in Table 12, where social media

[5] The specific name of the sites and apps removed are listed in Table A2.

sites are excluded, with a *1-HHI* coefficient of -525.6, and in Table 13, where music sites are excluded, with a coefficient of -431.9.

[Tables 11, 12, and 13 about here]

Considering that our search for alternative explanations has turned up little, we finish by seeking corroborative evidence for transaction costs being the driver of our main finding. To do this, we hypothesize that, if there is a difference in transaction costs between laptops/desktops and smartphones, a source of this difference could be the app-centered feature of smartphones, where users download apps that they can later access by simply touching their screen. In Tables 14a and 14b, we split our mobile sample according to whether users were heavy or light app users, splitting them according to whether they were above or below the median proportion of time spent on apps. Here, we see that the results differ notably between heavy and light app users. In Table 14a, which focuses on time variety across time (*H*), we observe that variety reduces for both groups as total time increases, but the reduction is less pronounced for light app users. Even the coefficient of Entropy measure shows significantly positive for light app users, showing that their browsing behavior exhibits greater variety when lower reliance on apps. This suggests that heavy app users, who rely more on apps for their interactions, experience a stronger decline in variety as their time online grows, likely due to the concentrated nature of app usage. In contrast, light app users show a more gradual reduction in variety, indicating that they may engage with a broader range of content, particularly through websites. In Table 14b, the results for time variety (*V*) offer an interesting contrast. Here, we see that low app users—assumed to be primarily mobile web users—

exhibit a pattern of increasing variety with total time, which is strikingly similar to the patterns we observed for home users in the Home 2008 and Home 2019 datasets. For low app users, the increase in variety is substantial. Specifically, a one standard deviation increase in total time leads to a 0.331 standard deviation increase in *Entropy*, which is more than four times the corresponding increase for high app users, at just 0.085. Similarly, for *1-HHI*, the increase for low app users is 0.182 standard deviations, which is significantly larger than the 0.041 increase for high app users. A similar pattern is observed for *1-FC3*, where low app users see an increase of 0.078 standard deviations compared to only 0.043 for high app users. The pronounced increase in variety for low app users suggests that mobile web usage, like home computer usage, encourages broader exploration and interaction with a diverse set of websites. On the other hand, high app users display a more concentrated usage pattern, suggesting that app-based interaction leads to more focused and repetitive consumption.

[Table 14a and 14b about here]

6. Discussion and Conclusions

Our findings highlight several key distinctions in online consumption behavior between mobile devices and home computers. The shift from home computers to mobile platforms has fundamentally altered how users engage with online content, resulting in more frequent but shorter sessions, coupled with a reduction in the diversity of websites visited. Specifically, as users spend more time on mobile devices, they tend to focus on a smaller number of high-utility apps or websites, resulting in a more concentrated consumption pattern. In contrast, on home computers, longer sessions promote broader exploration and more diverse content consumption.

The implications of these results suggest that mobile platforms, due to lower transaction costs (e.g., easy access to apps), encourage repeated interactions with familiar sites, reinforcing concentrated consumption behavior. This reduction in variety on mobile platforms may also point toward a shift in digital markets, where a smaller group of content providers could dominate user attention and time. In essence, as users dedicate more time to a few well-established apps or websites, the market for online content may experience increased concentration, potentially reducing competition and content diversity.

In contrast, home devices, which facilitate longer, more varied sessions, continue to support broader content consumption. Users on home devices distribute their time across a wider array of websites, allowing for more extensive online exploration. This suggests that the higher transaction costs associated with home devices—such as more complex navigation or multi-tasking—encourage users to allocate their time more broadly across different content providers.

The robustness of our findings is further supported by additional analyses, including tests for unobserved factors like income, functional forms, and the exclusion of major content categories like video, social media, and music. The persistence of our results across these robustness checks underscores the importance of device-specific factors, particularly the app-centric structure of mobile platforms, in driving the observed reduction in variety.

These insights carry significant implications for the future of digital markets and competition policy. If mobile consumption trends continue to favor concentrated engagement with a limited number of platforms, this may increase market power among dominant content suppliers, presumably leading to much reduced content diversity. Policymakers should remain attentive to these trends, as they may affect market competition and diversity, making it important to consider these dynamics in the enforcement of antitrust regulations and in shaping policies to encourage more competitive digital ecosystems.

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Tables and Figures

Table 1
Weekly Session Observations

	Home 2008		Home 2019		Mobile 2019	
Week	Total sessions	Sessions/device	Total sessions	Sessions/device	Total sessions	Sessions/device
March - 1	2,607,834	83.1	1,821,165	57.3	1,139,709	210.0
March - 2	2,581,204	82.1	1,924,417	58.8	1,139,851	209.6
March - 3	2,544,385	81.2	2,024,104	61.1	1,129,132	207.7
March - 4	2,455,366	78.2	2,048,167	61.7	1,131,716	208.3
April - 1	2,308,956	73.7	2,038,233	61.1	1,192,767	209.5
April - 2	2,401,826	76.1	2,103,573	62.7	1,200,302	210.4
April - 3	2,334,006	73.8	2,033,251	61.2	1,192,461	209.2
April - 4	2,357,160	74.4	2,028,319	61.3	1,186,538	208.0
May - 1	2,353,126	74.6	1,993,674	60.3	1,120,843	207.9
May - 2	2,336,145	74.4	1,943,945	59.5	1,133,022	209.9
May - 3	2,297,406	73.8	2,081,366	63.5	1,110,018	205.7
May - 4	2,171,036	70.6	1,990,244	61.9	1,080,122	200.4
Total	28,748,450	76.3	24,030,458	60.9	13,756,481	208.1

Table 2
Demographic Distribution across Datasets

	Home 2008	Home 2019	Mobile 2019
Income			
Less than $25,000	6,897	7,699	1,575
$25,000 - $39,999	3,024	4,997	771
$40,000 - $59,999	3,362	5,830	965
$60,000 - $74,999	7,399	3,153	487
$75,000 - $99,999	5,115	4,273	1,033
$100,000 or more	6,662	8,351	937
Age			
18-24	777	2,032	786
25-34	4,026	3,792	1,092
35-44	8,306	5,234	1,027
45-54	10,528	7,566	1,073
55-64	5,487	7,579	988
65 +	3,335	8,100	802
Ethnicity			
Hispanic	6,934	5,620	991
Non-Hispanic	25,525	28,683	4,777
Race			
Asian	414	2,607	-
Black	2,709	4,011	-
Other	1,201	5,194	-
White	28,135	22,491	-
Household size			
1	2,137	5,714	-
2	11,004	11,605	-
3	8,084	6,972	-
4	5,968	4,626	-
5 +	5,266	5,386	-
With children			
Yes	10,085	13,253	-
No	22,374	21,050	-
Sex			
Female	-	-	3,074
Male	-	-	2,694
Total	32,459	34,303	5,768

Table 3
Weekly Time Observations (in minutes)

	Home 2008		Home 2019		Mobile 2019	
Week	Time/device	Time/session	Time/device	Time/session	Time/device	Time/session
March - 1	843.3	10.15	654.7	11.43	778.2	3.71
March - 2	831.2	10.12	668.1	11.35	781.9	3.72
March - 3	834.2	10.28	699.5	11.45	774.9	3.73
March - 4	807.9	10.33	698.5	11.32	776.9	3.72
April - 1	772.6	10.49	693.4	11.35	773.1	3.49
April - 2	796.2	10.47	714.7	11.40	774.2	3.68
April - 3	766.9	10.39	688.6	11.26	776.9	3.71
April - 4	773.7	10.40	688.3	11.23	773.3	3.72
May - 1	735.8	9.86	676.8	11.24	767.2	3.69
May - 2	736.8	9.89	683.2	11.48	786.2	3.75
May - 3	733.5	9.94	744.2	11.72	768.4	3.74
May - 4	714.9	10.13	734.6	11.86	756.1	3.77
Total	779.0	10.21	695.4	11.42	774.0	3.72

Table 4
Average Number of Sessions Visited per Household/Week
across Income/Age Groups (units)

	Home 2008	Home 2019	Mobile 2019
Income			
Less than $25,000	75.78	58.18	195.64
$25,000 - $39,999	77.47	60.06	205.54
$40,000 - $59,999	77.69	62.68	215.88
$60,000 - $74,999	75.94	62.39	214.46
$75,000 - $99,999	75.26	62.38	218.20
$100,000 or more	75.97	60.94	208.36
Age			
18-24	85.56	49.95	258.86
25-34	77.30	53.52	236.26
35-44	78.52	53.23	209.19
45-54	77.42	56.91	181.20
55-64	71.94	65.21	182.60
65 +	69.44	71.15	187.89
Total	76.13	60.80	208.08

Table 5
Variety Metrics Summary Statistics

	Entropy (Visits)	1-HHI (Visits)	1-FC3 (Visits)	Entropy (Time)	1-HHI (Time)	1-FC3 (Time)
2008 Home						
Mean	2.769	8,824	62.23	1.966	7,451	31.98
Sd	0.795	1,171	19.90	0.674	1,753	17.71
Min	0	0	0	0	0	0
Max	6.667	9,983	99.48	5.728	9,932	96.40
Count	376,507	376,507	376,507	376,507	376,507	376,507
2019 Home						
Mean	2.413	8,328	52.52	1.622	6,531	23.14
Sd	0.827	1,621	22.64	0.699	2,206	16.64
Min	0	0	0.00	0	0	0.00
Max	7.846	9,996	99.80	7.709	9,995	99.52
Count	394,732	394,732	394,732	394,732	394,732	394,732
2019 Mobile						
Mean	2.574	8,480	52.94	1.905	7,046	29.43
Sd	0.654	1,156	18.03	0.738	2,071	17.45
Min	0	0	0	0	0	0
Max	5.746	9,950	97.32	4.793	9,789	83.31
Count	66,113	66,113	66,113	66,113	66,113	66,113

Table 6
Average Session Length and Total Time as Function of Total Sessions and Income

Dep. Var.	Average Session Length/Week (in minutes)			Total Time/Week (in minutes)		
Sample	Home 2008	Home 2019	Mobile 2019	Home 2008	Home 2019	Mobile 2019
Total Sessions	0.001***	-0.002***	-0.003***	9.785***	10.755***	2.938***
	(0.000)	(0.000)	(0.000)	(0.011)	(0.013)	(0.010)
Income						
(Base: less than $25k)						
$25k-39.99k	-0.249***	-0.271***	-0.776***	-38.930***	-15.491***	-167.830***
	(0.043)	(0.052)	(0.055)	(3.310)	(2.719)	(6.724)
$40k-59.99k	-0.289***	-0.918***	-0.666***	-45.496***	-41.458***	-166.189***
	(0.042)	(0.050)	(0.051)	(3.190)	(2.597)	(6.236)
$60k-74.99k	-0.571***	-1.250***	-1.032***	-61.530***	-45.187***	-188.316***
	(0.033)	(0.060)	(0.065)	(2.539)	(3.160)	(7.904)
$75k-99.99k	-0.736***	-1.170***	-0.541***	-67.708***	-49.021***	-121.666***
	(0.037)	(0.055)	(0.050)	(2.798)	(2.853)	(6.115)
$100k+	-0.911***	-1.210***	-0.532***	-90.432***	-54.103***	-119.213***
	(0.034)	(0.045)	(0.051)	(2.607)	(2.366)	(6.289)
Constant	10.547***	12.492***	5.439***	82.512***	73.303***	270.182***
	(0.026)	(0.036)	(0.036)	(2.008)	(1.859)	(4.347)
Count	376,507	394,732	66,113	376,507	394,732	66,113
R-square	0.002	0.003	0.027	0.680	0.647	0.555

Table 7a: Time Variety (V) as a Function of Total Time

	2008 Home			2019 Home			2019 Mobile		
Dep. Var.	Entropy	1-HHI	1-FC3	Entropy	1-HHI	1-FC3	Entropy	1-HHI	1-FC3
Total Time (‘000 min.)	0.410***	341.9***	5.520***	0.422***	525.9***	6.515***	0.200***	181.5***	3.386***
	(0.002)	(2.9)	(0.047)	(0.002)	(4.2)	(0.048)	(0.004)	(8.3)	(0.131)
Constant	2.451***	8558.5***	57.950***	2.120***	7962.9***	47.992***	2.419***	8339.5***	50.319***
	(0.001)	(2.7)	(0.044)	(0.002)	(3.5)	(0.047)	(0.003)	(6.9)	(0.109)
Household Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Count	376,507	376,507	376,507	394,732	394,732	394,732	66,113	66,113	66,113
R-square	0.161	0.038	0.038	0.134	0.041	0.037	0.037	0.008	0.011

Table 7b: Time Variety (H) as a Function of Total Time

	2008 Home			2019 Home			2019 Mobile		
Dep. Var.	Entropy	1-HHI	1-FC3	Entropy	1-HHI	1-FC3	Entropy	1-HHI	1-FC3
Total Time (‘000 min.)	0.257*** (0.001)	440.7*** (4.3)	5.151*** (0.040)	0.205*** (0.002)	436.0*** (5.7)	3.837*** (0.039)	-0.079*** (0.004)	-409.1*** (13.9)	-3.018*** (0.113)
Constant	1.766*** (0.001)	7109.1*** (3.9)	27.985*** (0.037)	1.480*** (0.001)	6227.9*** (4.5)	20.477*** (0.033)	1.966*** (0.004)	7362.7*** (11.540)	31.762*** (0.094)
Household Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Count	376,507	376,507	376,507	394,732	394,732	394,732	66,113	66,113	66,113
R-square	0.084	0.030	0.045	0.045	0.018	0.026	0.005	0.014	0.012

Table 8: Time Variety (H) as a Quadratic Function of Total Time

	2019 Mobile		
Dep. Var.	Entropy	1-HHI	1-FC100
Total Time (‘000 min.)	-0.000 (0.009)	-639.9*** (28.5)	-2.517*** (0.233)
Total Time squared	-0.024*** (0.002)	71.102*** (7.7)	-0.154** (0.063)
Constant	1.934*** (0.005)	7456.1*** (15.3)	31.559*** (0.125)
Household Fixed Effects	✓	✓	✓
Count	66,113	66,113	66,113
R-square	0.007	0.016	0.012

Table 9
Mobile 2019 1-HHI as a Function of Total Time, by Income

Dep. Var.	1-HHI	1-HHI	1-HHI	1-HHI	1-HHI	1-HHI
Income Group	Lowest	2nd Lowest	3rd Lowest	3rd Highest	2nd Highest	Highest
Total Time ('000 min.)	-306.788***	-46.905*	-179.307***	61.684*	-222.600***	-23.244
	(19.791)	(27.791)	(27.078)	(36.543)	(24.549)	(27.620)
Age						
(Base: 18-24)						
Age 25-34	402.522***	278.248***	593.279***	833.376***	291.282***	53.632
	(46.843)	(89.308)	(84.286)	(122.280)	(68.556)	(80.770)
Age 35-44	84.210*	82.152	299.225***	561.927***	177.611**	95.633
	(49.661)	(91.485)	(83.150)	(115.866)	(70.582)	(80.022)
Age 45-54	20.940	-76.153	144.637*	291.565**	-55.391	126.931*
	(53.542)	(90.858)	(83.810)	(115.251)	(70.339)	(73.694)
Age 55-64	-49.114	-100.221	88.696	340.110***	64.636	109.566
	(56.947)	(96.008)	(84.796)	(115.363)	(69.682)	(73.213)
Age 65 and over	105.951	-10.606	143.059*	421.667***	236.313***	287.340***
	(65.983)	(97.943)	(85.539)	(118.685)	(73.909)	(76.898)
Gender						
(Base: Female)						
Male	-677.432***	-579.030***	-475.100***	-283.560***	-329.531***	-231.644***
	(32.323)	(43.187)	(40.578)	(53.838)	(37.244)	(42.019)
Ethnicity						
(Base: Hispanic)						
Non-Hispanic	513.533***	374.614***	346.912***	-123.803	207.199***	202.859***
	(38.096)	(59.883)	(63.341)	(78.531)	(49.993)	(56.372)
Region Controls	✓	✓	✓	✓	✓	✓
Count	17,954	8,784	11,112	5,603	11,856	10,804
R-sq	0.066	0.045	0.037	0.029	0.024	0.017

Table 10
Mobile 2019 1-HHI as a Function of Total Time, by Age

Dep. Var.	1-HHI	1-HHI	1-HHI	1-HHI	1-HHI	1-HHI
Age Group	Youngest	2nd Youngest	3rd Youngest	3rd Oldest	2nd Oldest	Oldest
Total Time ('000 min.)	-178.556***	-166.543***	-141.920***	-231.227***	-226.011***	-93.040***
	(22.678)	(21.553)	(25.788)	(28.651)	(27.963)	(32.571)
Income						
(Base: less than $25k)						
$25k-39.99k	574.126***	358.159***	469.337***	341.421***	461.039***	286.288***
	(85.056)	(51.530)	(63.706)	(64.443)	(73.841)	(74.677)
$40k-59.99k	270.945***	412.899***	457.524***	315.531***	370.605***	144.651**
	(73.142)	(52.083)	(59.934)	(63.223)	(65.360)	(66.465)
$60k-74.99k	450.763***	598.470***	740.551***	443.612***	609.779***	488.320***
	(107.609)	(75.056)	(74.262)	(74.828)	(76.264)	(80.811)
$75k-99.99k	401.838***	208.151***	485.009***	259.464***	497.074***	395.700***
	(61.547)	(49.501)	(61.241)	(62.564)	(62.737)	(68.716)
$100k+	403.414***	-133.001**	248.109***	319.283***	399.143***	314.434***
	(61.696)	(59.558)	(68.743)	(62.412)	(63.521)	(67.865)
Gender						
(Base: Female)						
Male	-690.991***	-641.865***	-515.643***	-530.328***	-284.971***	-118.065***
	(42.504)	(36.295)	(41.047)	(39.125)	(39.773)	(43.253)
Ethnicity						
(Base: Hispanic)						
Non-hispanic	320.198***	359.557***	293.563***	425.191***	301.111***	209.756***
	(49.473)	(44.030)	(52.063)	(53.494)	(61.275)	(70.158)
Region Controls	✓	✓	✓	✓	✓	✓
Count	8,824	12,425	11,764	12,315	11,501	9,284
R-square	0.055	0.065	0.046	0.037	0.024	0.025

Table 11
Time Variety (H) as a Function of Total Time, Absent Top Video Sites

	2019 Mobile		
Dep. Var.	Entropy	1-HHI	1-FC3
Total Time ('000 min.)	-0.099*** (0.005)	-560.4*** (16.9)	-6.192*** (0.170)
Constant	1.978*** (0.004)	7465.6*** (10.9)	37.990*** (0.110)
Household Fixed Effects	✓	✓	✓
Count	66,012	66,012	66,012
R-square	0.006	0.018	0.022

Table 12
Time Variety (H) as a Function of Total Time, Absent Top Social Media Sites

	2019 Mobile		
Dep. Var.	Entropy	1-HHI	1-FC3
Total Time ('000 min.)	-0.104** (0.005)	-525.6** (15.2)	-5.338*** (0.137)
Constant	1.929*** (0.004)	7281.8*** (11.2)	35.009*** (0.101)
Household Fixed Effects	✓	✓	✓
Count	65,998	65,998	65,998
R-square	0.008	0.020	0.025

Table 13
Time Variety (H) as a Function of Total Time, Absent Top Music Sites

	2019 Mobile		
Dep. Var.	Entropy	1-HHI	1-FC3
Total Time ('000 min.)	-0.068** (0.005)	-431.9** (14.9)	-3.484*** (0.130)
Constant	1.933*** (0.004)	7314.2*** (11.3)	33.204*** (0.099)
Household Fixed Effects	✓	✓	✓
Count	65,979	65,979	65,979
R-square	0.003	0.014	0.012

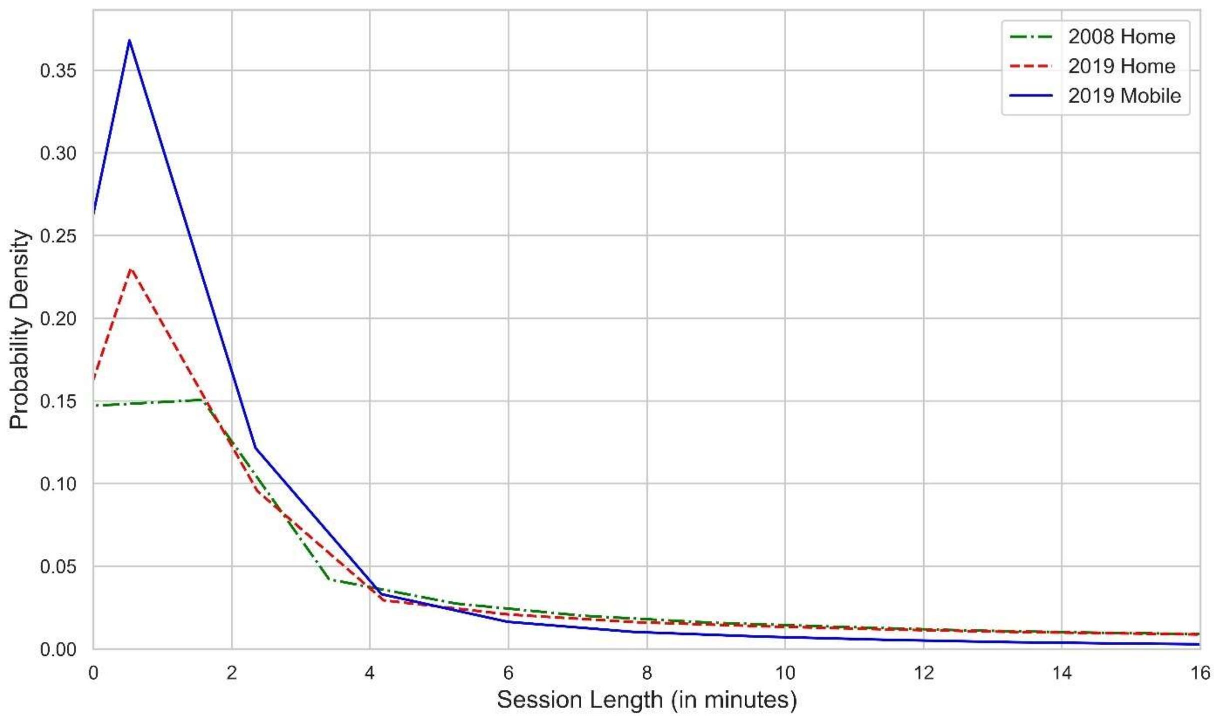
Table 14a
Mobile 2019 Time Variety (H) as a Function of Total Time, High-App vs. Low-App Users comparison (Only iOS users)

	High App users (> median)			Low App users (<median)		
Dep. Var.	Entropy	1-HHI	1-FC3	Entropy	1-HHI	1-FC3
Total Time ('000 min.)	-0.109***	-308.2***	-2.890***	0.221***	-213.5***	-3.751***
	(0.004)	(14.8)	(0.126)	(0.016)	(54.8)	(0.889)
Constant	1.970***	7204.4***	27.298***	1.723***	7035.2***	32.032***
	(0.007)	(22.3)	(0.190)	(0.006)	(19.9)	(0.323)
Household Fixed Effects	✓	✓	✓	✓	✓	✓
Count	26,853	26,853	26,853	27,871	27,871	27,871
Num. of Household	2,376	2,376	2,376	2,377	2,377	2,377
R-square	0.026	0.018	0.022	0.008	0.001	0.001

Table 14b
Mobile 2019 Time Variety (V) as a Function of Total Time, High-App vs. Low-App Users comparison (Only iOS users)

	High App users (> median)			Low App users (<median)		
Dep. Var.	Entropy	1-HHI	1-FC3	Entropy	1-HHI	1-FC3
Total Time ('000 min.)	0.067***	58.19***	1.175***	0.933***	976.1***	9.395***
	(0.004)	(7.18)	(0.159)	(0.015)	(35.3)	(0.872)
Constant	2.565***	8528.9***	45.931***	2.095***	8025.2***	43.566***
	(0.006)	(10.7)	(0.240)	(0.006)	(12.8)	(0.317)
Household Fixed Effects	✓	✓	✓	✓	✓	✓
Count	26,853	26,853	26,853	27,871	27,871	27,871
Num. of Household	2,376	2,376	2,376	2,377	2,377	2,377
R-square	0.014	0.003	0.002	0.130	0.031	0.005

Figure 1
Densities of Session Counts by Session Lengths



Appendix

Table A1a: Time Variety (V) as a Function of Total Time (other thresholds)

	2008 Home		2019 Home		2019 Mobile	
Dep. Var.	1-FC1	1-FC5	1-FC1	1-FC5	1-FC1	1-FC5
Total Time ('000 min.)	3.129***	6.924***	4.075***	7.856***	2.011***	3.787***
	(0.035)	(0.050)	(0.047)	(0.055)	(0.126)	(0.123)
Constant	80.365***	44.492***	73.613***	34.030***	75.043***	36.912***
	(0.032)	(0.046)	(0.040)	(0.046)	(0.105)	(0.102)
Household Fixed Effects	✓	✓	✓	✓	✓	✓
Count	376,507	376,507	394,732	394,732	66,113	66,113
R-square	0.023	0.053	0.020	0.054	0.004	0.015

Table A1b: Time Variety (H) as a Function of Total Time (other thresholds)

	2008 Home		2019 Home		2019 Mobile	
Dep. Var.	1-FC1	1-FC5	1-FC1	1-FC5	1-FC1	1-FC5
Total Time ('000 min.)	4.219***	5.018***	3.663***	3.300***	-4.504***	-1.529***
	(0.045)	(0.032)	(0.053)	(0.028)	(0.151)	(0.089)
Constant	57.685***	16.035***	49.164***	10.881***	59.435***	20.244***
	(0.042)	(0.030)	(0.045)	(0.024)	(0.125)	(0.074)
Household Fixed Effects	✓	✓	✓	✓	✓	✓
Count	376,507	376,507	394,732	394,732	66,113	66,113
R-square	0.025	0.066	0.013	0.036	0.015	0.005

Table A2
Mobile 2019 App/websites Dropped in Top 100 list

Video			Social Media			Music		
Name	Rank	Time Share	**Name**	Rank	Time Share	**Name**	Rank	Time Share
YouTube (App)	1	17.90	Snapchat (App)	3	4.78	Pandora Radio (App)	4	3.58
Netflix (App)	7	1.95	Pinterest (App)	9	1.45	Spotify (App)	5	2.99
Hulu (App)	14	0.92	Facebook (App)	11	1.25	iTunes (App)	17	0.62
Tik Tok (App)	19	0.55	facebook.com	12	1.19	iHeartRadio (App)	18	0.58
xvideos.com	22	0.43	Twitter (App)	16	0.79	SoundCloud (App)	23	0.42
pornhub.com	28	0.37	Tik Tok (App)	19	0.55	Musi - Unlimited Free Music for YouTube (App)	41	0.29
xnxx.com	29	0.36	WhatsApp Messenger (App)	50	0.23	YouTube Music (App)	42	0.27
youtube.com	31	0.35	Tinder (App)	56	0.20	Apple Music (App)	54	0.21
Amazon Prime Video (App)	36	0.32	Tumblr (App)	59	0.20	Simple Radio by Streema (App)	84	0.14
The Walt Disney Company	43	0.27	Facebook Messenger (App)	63	0.18	SiriusXM (App)	85	0.13
youporn.com	72	0.16	GroupMe (App)	64	0.18	Amazon Music with Prime Music (App)	100	0.12
			Instagram (App)	78	0.14			
			Discord (App)	89	0.13			