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 on 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 several predictions concerning the concentration of online consumption and the distribution of session lengths across devices, which we test 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 a reduced variety than desktops 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 (Statista, 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 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. We also expect that the variety of more data-intensive applications will fall when users face data charges on smartphones.

The data comes from ComScore's panel of browser and app usage. The first sample comes from over thirty (after cleaning, or fifty before cleaning) 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 online material 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.

While the comparison between devices in 2019 is the focus of the investigation, the comparison across time serves a valuable purpose. For desktop and laptop online consumption, we show that the total time spent on devices varies systematically with income, age, and ethnicity. The total time on desktops and laptops varies a little between our time periods. This is surprising considering the rise and widespread adoption of substitutes for laptops and desktops by 2019, and we consider several explanations. In contrast, the relationship between total time and variety of consumption is strongly positive and invariant over time. We conclude that the determinants of using laptops and desktops primarily operate through changes in the total time devoted to the device. More to the point, our findings are consistent with the view that the relationship between variety and time for a user is device-specific and comparatively constant over time, with the most significant changes coming from the youngest generation of users.

We next compare the variety of consumption between smartphones and desktops. Again, we break it into two parts, comparing the total time in each device and the relationship between demographics and total time. Then, we show that the variety of consumption on the smartphone varies systematically with demographics, and this relationship differs sharply from the relationship found with laptops and desktops in the same year. We find considerable heterogeneity in our variety/time relationships. It differs across consumers of different incomes, ages, and ethnicities.

Finally, and most notably, we show that the variety/time relationship for smartphones fundamentally differs from what we find for laptops and desktops. Whereas for desktops and laptops we found variety increasing with time spent online (both in 2008 and 2019), we find a decrease in variety with time spent online for smartphones.

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 interfaces, and quicker, more frequent sessions, encourage users to spend time on a limited set of websites or apps. As the total time spent on mobile increases, users appear to consolidate their time on a smaller group of familiar, high-utility sites, rather than exploring new content. This behavior likely reflects the way mobile platforms streamline interactions, reducing the need for users to engage in more diverse or exploratory browsing activities.

In contrast, home devices, such as desktops and laptops, support longer, deeper sessions, allowing users to engage in more diverse online activities. Larger screen sizes and more flexible interfaces encourage users to visit a broader range of websites, supporting more expansive exploration over time. As total time spent online increases for home device users, they are more likely to diversify their web browsing and content consumption, driven by the convenience and multitasking capabilities of these devices. Home users allocate their time across a wider array of websites, which naturally leads to increased variety compared to mobile platforms.

These results suggest that the key difference between mobile and home platforms is rooted in how transaction costs shape online consumption. The lower transaction costs associated with mobile devices—such as ease of access to apps with a single tap—reduce the incentive to explore new websites. Users focus on familiar apps or high-frequency websites that provide reliable value in shorter bursts, reinforcing patterns of concentrated consumption. In contrast, higher transaction costs on home devices—such as navigating across multiple browser tabs or engaging with more complex content—encourage broader exploration when users commit to longer online sessions. The findings from our robustness test reassure these conclusions. When we exclude major content categories like video, social media, and music, the relationship between total time and variety remains largely unchanged. This highlights that the app-centric structure of mobile platforms, rather than specific content types, drives the reduction in variety.

This shift toward more concentrated consumption on mobile devices raises important questions about the future of digital markets. If mobile users continue to focus on a limited set of apps or websites, this could drive a trend toward greater market concentration among a smaller group of content providers. Policymakers and practitioners should take note of these dynamics, as they have important implications for competition, market entry strategies, and the enforcement of antitrust regulations in the digital space.

1.1.Literature Review

What is the relationship between the time spent on a consumer-oriented electronics device and the consumption of variety? This question arose several times before the focal era in this study. Technological advances in information and communications technologies (ICTs led to dramatic changes in how people accessed and consumed online content and the volume they consumed. Among the significant technological changes that increased the variety of consumptions, screens grew larger,[1] operating systems gained multitasking functionality,[2] and developers introduced new apps and games to take advantage of ever-growing capabilities. The laptop and tablet eventually

[1] The earliest IBM personal computers had an 11.5-inch screen when measured diagonally. New monitors today for desktops have screens that measure between 15 and 21 inches, while laptops typically have screens between 13 and 15 inches.
[2] The Windows operating system introduced multitasking in the early 1990s.

dominated the desktop,[3] and the replacement of dial-up with broadband connections for home internet access[4] increased the ability of the device to support a greater variety of online applications. The smartphone deployment represented additional changes and a significant change in users' consumption behavior.

Such changes motivated research on 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 been deployed, so we see a more comprehensive set of demographics.

[3] This is generally dated to Intel's embrace of laptop architectures, and the introduction of Centrino brand in 2003.
[4] By 2008 half of the adults in the US had a broadband connections. https://www.pewresearch.org/internet/fact-sheet/internet-broadband/

Though we lack a direct comparison of the same households, we can compare households with similar characteristics.

Survey data show that young consumers have shifted most of their time toward mobile for higher volume uses (Pew, 2019). In contrast, our dataset is much larger and enables analysis of the correlations of more time and consumed variety. We also borrow from extensive economics literature on the elasticity of variety in consumers' budgets. Such analyses indicate how increasing wealth and income can, per se, affect market concentration by telling us whether more wealth leads to more consumption of popular goods or niche goods. One can address a similar question in online consumption, except the budget is temporal rather than monetary in this context. Economics literature has also examined how consumer choices (variety?) change with the medium of consumption.

We measure the relationship between the variety of online consumption and 1) access method (mobile vs. home PC) and 2) the amount of time dedicated online. For the latter analysis, we measure the time elasticity of online variety. The relevance of this question is a bit different compared to priced markets; here, we are assessing how the concentration of online markets changes as people dedicate more time to online consumption.

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. This means high-income households have a wider choice than low-income households because high-income households can spend more on high-hierarchy commodities (e.g., health, clothing, and transportation). Instead, low-income and high-income households purchase an indifferent number of low-hierarchy commodities (e.g., food, alcohol and tobacco, and education). Here, the quality of expenditure can be larger than a simple comparison of the items consumed between two groups because the products purchased by low-income households may include interior goods or complementary to interior goods.

Considerable attention has been brought to the relationship between income and consumption diversity because policymakers and authorities are concerned about the malnutrition of their low-income population. 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.

Just as enough food consumption was essential in the 1970s, internet consumption – website surfing and mobile app usage – is the new basic necessity of life in the 21st century. However, little is known about a person's taste or distaste for various online consumption. Furthermore, online users' heterogeneity in different website preferences makes it more challenging to answer even a simple question – is surfing on Facebook/Meta popular goods or niche goods?

A handful of research studied online users' utility on different websites. Using the mobile usage data, Han et al. (2016) examined how consumers chose apps of numerous categories and estimated the baseline utility levels across different categories. They found that the highest baseline utility for regular apps – alarm clock and schedule – indicates they are a popular market, while the lowest baseline utility for irregular apps – personal finance and map/navigation – indicates they are a niche market.

2. Theory

We begin with some basic theory to fix ideas. The data, described in detail in Section 3, track users in 2008 and 2019. The commercial browser had existed for fifteen years by 2008, and 2019 (which unlike 2008 has mobile online usage) was a dozen years after the deployment of the iPhone. This makes a full-information model plausible. We begin with a benchmark laptop/desktop browsing model in which the marginal cost of additional data and time from a provider is zero, so the primary constraint on usage is total time.

We posit that a household has many consumption goods. Consider L, M, and O, where L stands for the laptop (also including desktop), M is the mobile device, and O is the outside good. Each set has many 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 is the number of options in each set (for simplicity, we make the inconsequential assumption that the number of options across sets is equal). Suppliers provide these different options, and we assume there is a large number of them, i.e., n is large. For simplicity, we assume each good is continuous in time, so we ignore discrete consumption like ten-minute movies. We also assume consumption is additive in seconds, the first second of consumption results in weakly positive utility, and the user experiences diminishing marginal returns in every additional second. In addition, we assume the opportunity cost of a minute of time is f for the outside good.

Theory sketch from here…

- Allow for transaction costs when visiting another site. For L, there is a cost, c. For M, users can choose a subset of sites where the cost is 0, and the rest have cost, k > c. This captures the prevalence of app icons and touch-based favorites on the mobile. This structure implies a subset of apps/sites with low transaction/switching costs (c), which jumps up when moving outside of favorites. This dynamic is to a much lesser degree on PC & laptop.

- Assume that long sessions implies relatively high utility from the visit (i.e., no visits where you stay a long time and get little utility) and that the ability to get utility from multiple, separate visits in a day is predominantly, or exclusively, limited to sites whose optimal length of visit is short. Some possible support here.

Within this framework, we solve for the relationship between our two key parameters (*c* and *f*) and observable outcomes, thus generating empirically testable predictions.

From the model, we can see that the utility of the first minute of consumption on one good must be higher than the cost of initiating use of that good (c) plus the opportunity cost (f). Otherwise, the user would not visit the site (and we ignore the search cost or the possibility of a failed search). Leads to first prediction:

Prediction #1: Given total time, total sessions is declining in f (which is likely higher for people with higher incomes). That will be true on BOTH L and M.

Examine the model to show intuition for second prediction:

Prediction #2: Given total sessions, average session length (and also total time) is declining in f. Again, BOTH L and M ought to show that.

Examine the model to show intuition for third prediction. (Show this by considering distribution of utilities from optimal time allocation to sites. In such a scenario, low-time sites are more likely to be visited when transaction cost is zero vs. when it is not.)

Prediction #3: There will be higher proportion of short sessions for M compared to L.

Show frequency distributions according to session length bins and elasticity regressions

Examine the model to show intuition for fourth prediction. (Idea is that, for mobile, there will be high incentive to allocate that time within the c=0 set; less so for PC. As time online increases, mobile users will more likely cram it into the zero cost group, making variety go up less (or even decrease in time) vs home PC).

Prediction #4: The slope of variety (measured in both of our ways) with respect to time will be lower for M than for L. This leads to our results concerning V' and H' for PC and mobile.

3. Data

The data we utilize for this study come from three separate datasets, all from ComScore. Each dataset contains information on online activity by users at the device level for a given period; 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. 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.

The information collected for our home PC data includes the name of the sites (which includes apps 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 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 online 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 engaged 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 operating 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 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 session 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 the 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. 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 further evidenced by the Mobile 2019 dataset, which shows more than three times the number of sessions per device compared to home computers, with mobile devices averaging about 208 sessions per week. 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 than those for laptops and desktops, facilitating more frequent consumptions in online.

[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]

We conclude this section with summary statistics concerning total and average time spent on the devices. We calculate 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 $x_{jt} = \sum_{i \in N_{jt}} x_{ijt}$.

Table 3 shows 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. 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.[5]

[5] One concern with the data is our 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 overstating engagement for home devices compared to mobile.

In addition, a clear polarization between desktop/laptop and mobile usage is evident in 2019. While the average time per session for home devices in 2008 was 10.21 minutes, it increased to 11.42 minutes in 2019, suggesting that users are engaging in longer sessions for tasks that require extended attention, such as online banking, document editing, or video streaming. In contrast, the average time per session for mobile devices in 2019 is much shorter, at 3.72 minutes, reflecting their usage for quick tasks such as social media checks, messaging, navigation, or brief web searches. This contrast points to the different transaction costs associated with each device. Home devices, with higher setup and navigation costs, lead to fewer but longer sessions, while mobile devices, with lower transaction costs, allow for more frequent, shorter interactions. These patterns are consistent with our theoretical prediction, which suggests that the lower transaction costs of mobile devices promote more frequent, yet shorter, online sessions, while home devices, with higher costs, encourage longer but less frequent usage.

[Table 3 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 below, 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 primary measure 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 time online for a given week (TT). 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 captures the fraction of time allocated to the top sites. The measure we use is *FC100*, which measures the fraction of time allocated to the top 100 sites. To compute this variety index, we first aggregate all activities across households and identify the names of the top 100 sites. Subsequently, for each household *j* during each week *t*, we assess the names of sites used by the household and calculate the fraction of time spent at these top 100 sites. Specifically, following our methodology, let Top^{100} denote the top 100 sites. Then, we define the fraction of time spent at top-100 sites by household *j* during week *t* as:

$$(4)\ FC100_{jt} = \sum_{i \in Top^{100}} \left(x_{ijt} / x_{jt} \right)$$

We also calculate this measure for visits by replacing *x* with *y*.

Table 4 contains summary stats for our various variety metrics.

[Table 4 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 time, total sessions is declining in ***f***. In other words, for a given amount of total time, total sessions will be lower for users with higher utility for the outside option (*f*). To test this prediction, consistent with Goldfarb and Prince (2008), we posit that *f* is likely increasing in income. This supposition leads to a simple empirical test of Prediction #1, namely a test of the relationship between total sessions and income, controlling for total time. We show the results of such a test in Table 5.

[Table 5 about here]

In Table 5 we see that… we got the opposite result that total number of sessions is increasing in income. My interpretation of table 5 is, controlling for time, the total number of sessions actually rises in income. This might be because total sessions is increasing as one's c is lower (total sessions decline as f increases, but they also decline as c increases, if I understand it correctly). This means, for a fixed amount of total time, users with lower search costs will have a higher frequency of visits. If we can use income as a proxy for individuals' search costs (since education is not usable in our data), the result in Table 5 seems to be consistent with theory.

Prediction #2 states that: Given total sessions, average session length (and also total time) is declining in *f*. Here again 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, across all three datasets. Higher income brackets consistently show shorter average session lengths with the $100k+ income group having the steepest declines in Home 2008 and Home 2019, and more modest declines in Mobile 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 engaging in the same number of total sessions, higher-income individuals spend significantly less time per session. Similarly, in Mobile 2019, where the average session length is 3.72 minutes, the highest income group spends 0.532 minutes less per session, a 14.3% reduction. This suggests 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), consistent with Prediction #2.Similarly, the total time spent online also decreases with income, 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, the reduction is more pronounced, with the $100k+ group spending 119.213 fewer minutes online than the lowest income group, further reinforcing the idea that higher-income individuals may have more attractive alternatives than online activities, particularly on mobile platforms where quick, short interactions are more common.

Prediction #3 states that: There will be higher proportion of short sessions for M compared to L. 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 #3, 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 #4 states that: The slope of variety (measured in both of our ways) with respect to time will be lower for M than for L. This leads to our results concerning *V'* and *H'* for 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, with our primary measure of interpretation being 1-*HHI*. 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 *FC100*, indicating that as users spend more time online via home devices, they explore a broader range of websites. The coefficients on 1-*HHI* metric for Home 2008 (341.9) and Home 2019 (525.9) demonstrate that as time spent online increases, users visit a more diverse set of websites. FC100 further reinforces this, as a decrease in this metric implies that users are spending less time on the top 100 websites and more time exploring niche content. All three metrics—Entropy, 1-HHI, and FC100—are consistent in showing that increased time online leads to more varied consumption for home devices.

In contrast, the results for Mobile 2019 show a weaker positive relationship between total time and variety. While variety still increases with time on mobile devices, the effect is much smaller compared to home devices. The 1-HHI coefficient for Mobile 2019 is only 181.5, much lower than for home devices, indicating that mobile users are more limited in their variety expansion as time increases. FC100 similarly decreases, suggesting that mobile users do venture the visits beyond the top 100 websites as they spend more time online, but the decrease in FC100 is less pronounced than for home devices, given the baseline FC100 is much higher for mobile. This pattern suggests that mobile users, constrained by the app-based nature of mobile platforms and smaller screens, tend to engage in more focused sessions, revisiting a narrower set of websites or apps as their total time increases.

Table 7b further emphasizes this contrast by examining changes in both the extensive and intensive margins of consumption. Here, we see that 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. The 1-HHI coefficients for Home 2008 (440.7) and Home 2019 (436.0) confirm that longer online sessions promote more balanced and diversified content consumption. However, for Mobile 2019, the relationship is reversed: as users spend more time on their mobile devices, their consumption becomes more concentrated. The negative coefficient on 1-*HHI* (-

409.2) suggests that mobile users tend to focus their time on a smaller set of apps, likely due to the more task-oriented nature of mobile usage, which encourages longer interactions with a limited number of apps or websites. Additionally, while the extensive margin of variety (i.e., the number of websites visited) increases, the measure that captures both extensive and intensive margins decreases, indicating that intensive margins are declining more steeply. This suggests that although mobile users may visit more websites, they allocate a disproportionate amount of time to a few key apps or sites, reinforcing concentrated consumption patterns as total time increases.[6]

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 demonstrated by the higher frequency of sessions and shorter session lengths in Table 3). These shorter sessions are often concentrated on apps or websites where brief interactions are sufficient to derive utility—such as social media platforms, messaging apps, or quick searches. As a result,

[6] Here's an illustrative 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, 1-*HHI* is 694, and FC100—which reflects the fraction of time on the top 4 websites in this case—is 1.0. 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, 1-*HHI* to 614, and FC100 to 0.916. 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.

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 more 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 Analysis 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 FC100, there is a positive but insignificant linear term, and for 1-HHI there is a 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 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. However, 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 (-178.542) and the second oldest group (-225.997). 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.[7] 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 -560.6, 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 sites are excluded, with a 1-HHI coefficient of -525.7, and in Table 13, where music sites are excluded, with a coefficient of -432.1.

[7] The specific name of the sites and apps removed are listed in Table A1.

[Tables 11, 12, and 13 about here]

Given 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 Table 14, 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. 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. 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

Implications/Conclusions from our findings…

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
Variety Metrics Summary Statistics

	Entropy (Visits)	**1-HHI (Visits)**	**FC100 (Visits)**	**Entropy (Time)**	**1-HHI (Time)**	**FC100 (Time)**
2008 Home						
Mean	2.769	8,824	43.40	1.966	7,451	55.53
Sd	0.795	1,171	19.97	0.674	1,753	26.06
Min	0	0	0	0	0	0
Max	6.667	9,983	100	5.728	9,932	100
Count	376,507	376,507	376,507	376,507	376,507	376,507
2019 Home						
Mean	2.413	8,328	48.25	1.622	6,531	58.76
Sd	0.827	1,621	23.13	0.699	2,206	29.58
Min	0	0	0	0	0	0
Max	7.846	9,996	100	7.709	9,995	100
Count	394,732	394,732	394,732	394,732	394,732	394,732
2019 Mobile						
Mean	2.574	8,480	60.75	1.905	7,046	66.25
Sd	0.654	1,156	19.80	0.738	2,071	25.73
Min	0	0	0	0	0	0
Max	5.746	9,950	100	4.793	9,789	100
Count	66,113	66,113	66,113	66,113	66,113	66,113

Table 5
Total Sessions as Function of Total Time and Income

Dep. Var.	Total Number of Sessions Visited								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sample	Home 2008	Home 2008	Home 2008	Home 2019	Home 2019	Home 2019	Mobile 2019	Mobile 2019	Mobile 2019
Total Time ('000 min.)	64.750***	64.749***	64.721***	55.423***	55.394***	55.391***	137.540***	137.512***	137.565***
	(0.080)	(0.080)	(0.080)	(0.074)	(0.074)	(0.074)	(0.615)	(0.616)	(0.616)
Income									
(Base: less than $25k)									
$25k-39.99k	3.176***	3.266***	3.134***	1.659***	0.796	0.664	15.577***	16.402***	14.547***
	(0.772)	(0.773)	(0.771)	(0.557)	(0.552)	(0.552)	(4.489)	(4.504)	(4.478)
$40k-59.99k	3.649***	3.839***	3.579***	4.128***	2.408***	2.289***	19.908***	21.904***	21.052***
	(0.745)	(0.747)	(0.746)	(0.532)	(0.532)	(0.532)	(4.142)	(4.174)	(4.166)
$60k-74.99k	4.060***	4.268***	4.105***	4.224***	2.902***	2.744***	27.383***	30.095***	29.385***
	(0.593)	(0.597)	(0.595)	(0.648)	(0.647)	(0.647)	(5.264)	(5.297)	(5.274)
$75k-99.99k	4.233***	4.501***	4.226***	4.448***	2.956***	2.793***	18.119***	19.923***	19.327***
	(0.653)	(0.660)	(0.658)	(0.585)	(0.585)	(0.584)	(4.352)	(4.367)	(4.348)
$100k+	5.961***	6.311***	6.001***	4.140***	3.379***	3.142***	13.055***	16.284***	17.133***
	(0.608)	(0.621)	(0.620)	(0.484)	(0.484)	(0.484)	(4.256)	(4.293)	(4.296)
Constant	22.229***	25.235***	19.582***	19.161***	12.547***	9.858***	88.839***	86.517***	76.196***
	(0.431)	(1.304)	(1.352)	(0.353)	(0.719)	(0.797)	(2.788)	(4.439)	(6.963)
Control Var.									
Age		✓	✓		✓	✓		✓	✓
Gender			✓			✓			✓
Ethnicity			✓			✓			✓
Region			✓			✓			✓
Count	376,507	376,507	376,507	394,732	394,732	394,732	66,113	66,113	66,113
R-square	0.680	0.680	0.681	0.647	0.652	0.653	0.554	0.558	0.567

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

Dep. Var.	Average Session Length (in minutes)			Total Time (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	FC100	Entropy	1-HHI	FC100	Entropy	1-HHI	FC100
Total Time ('000 min.)	0.410***	341.9***	-1.621***	0.422***	525.9***	-0.655***	0.200***	181.5***	-0.773***
	(0.002)	(2.9)	(0.039)	(0.002)	(4.2)	(0.048)	(0.004)	(8.3)	(0.109)
Constant	2.451***	8558.5***	44.661***	2.120***	7962.9***	48.705***	2.419***	8339.5***	61.352***
	(0.001)	(2.7)	(0.036)	(0.002)	(3.5)	(0.041)	(0.003)	(6.9)	(0.090)
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	0.005	0.134	0.041	0.001	0.037	0.008	0.001

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

	2008 Home			2019 Home			2019 Mobile		
Dep. Var.	Entropy	1-HHI	FC100	Entropy	1-HHI	FC100	Entropy	1-HHI	FC100
Total Time ('000 min.)	0.257** (0.001)	440.7** (4.3)	0.178** (0.050)	0.205** (0.002)	436.0** (5.7)	1.260** (0.06)	-0.079** (0.004)	-409.2** (13.9)	-0.063** (0.15)
Constant	1.766*** (0.001)	7109.056*** (3.933)	55.389*** (0.050)	1.480*** (0.001)	6227.978*** (4.500)	57.884*** (0.054)	1.966*** (0.004)	7362.690*** (11.540)	66.300*** (0.129)
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	0.001	0.045	0.020	0.007	0.005	0.007	0.014

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

	2019 Mobile		
Dep. Var.	Entropy	1-HHI	FC100
Total Time (‘000 min.)	-0.000 (0.009)	-640.314*** (28.504)	0.470 (0.318)
Total Time squared	-0.024*** (0.002)	71.166*** (7.666)	-0.164* (0.085)
Constant	1.935*** (0.005)	7456.299*** (15.319)	66.084*** (0.171)
Household Fixed Effects	✓	✓	✓
Count	66,113	66,113	66,113
R-square	0.007	0.016	0.000

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.)	-306.819***	-46.878*	-179.287***	61.778*	-222.900***	-23.164
	(19.791)	(27.791)	(27.078)	(36.541)	(24.549)	(27.620)
Age						
(Base: 18-24)						
Age 25-34	402.563***	278.221***	593.328***	833.389***	291.157***	53.514
	(46.843)	(89.307)	(84.286)	(122.275)	(68.558)	(80.769)
Age 35-44	84.207*	82.088	299.169***	561.972***	177.445**	95.599
	(49.662)	(91.484)	(83.150)	(115.862)	(70.583)	(80.021)
Age 45-54	20.987	-76.282	144.662*	291.203**	-55.107	126.648*
	(53.543)	(90.857)	(83.810)	(115.247)	(70.340)	(73.693)
Age 55-64	-49.481	-100.862	88.728	340.073***	64.578	109.558
	(56.948)	(96.007)	(84.796)	(115.359)	(69.683)	(73.212)
Age 65 and over	106.089	-10.603	142.711*	421.768***	237.331***	287.498***
	(65.984)	(97.942)	(85.539)	(118.681)	(73.910)	(76.897)
Gender						
(Base: Female)						
Male	-677.316***	-578.822***	-475.035***	-283.766***	-329.466***	-231.758***
	(32.324)	(43.187)	(40.578)	(53.836)	(37.245)	(42.018)
Ethnicity						
(Base: Hispanic)						
Non-hispanic	513.408***	374.583***	346.864***	-123.173	206.719***	202.949***
	(38.097)	(59.882)	(63.341)	(78.528)	(49.994)	(56.371)
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.)	-178.542***	-166.579***	-141.906***	-231.258***	-225.997***	-93.338***
	(22.678)	(21.553)	(25.788)	(28.651)	(27.963)	(32.571)
Income						
(Base: less than $25k)						
$25k-39.99k	574.197***	358.118***	469.346***	341.432***	460.837***	286.347***
	(85.056)	(51.530)	(63.705)	(64.441)	(73.841)	(74.678)
$40k-59.99k	270.981***	412.901***	457.464***	315.617***	371.058***	143.930**
	(73.142)	(52.083)	(59.934)	(63.222)	(65.361)	(66.466)
$60k-74.99k	450.787***	598.425***	740.564***	443.341***	610.129***	488.141***
	(107.609)	(75.056)	(74.261)	(74.826)	(76.264)	(80.812)
$75k-99.99k	401.858***	208.098***	485.018***	259.927***	497.507***	396.569***
	(61.547)	(49.501)	(61.240)	(62.562)	(62.737)	(68.717)
$100k+	403.472***	-133.156**	248.102***	319.081***	399.490***	314.117***
	(61.696)	(59.558)	(68.742)	(62.410)	(63.522)	(67.866)
Gender						
(Base: Female)						
Male	-690.939***	-641.840***	-515.648***	-530.751***	-284.708***	-117.654***
	(42.504)	(36.295)	(41.047)	(39.124)	(39.773)	(43.253)
Ethnicity						
(Base: Hispanic)						
Non-hispanic	320.205***	359.562***	293.572***	424.843***	300.853***	210.018***
	(49.473)	(44.030)	(52.062)	(53.492)	(61.276)	(70.159)
Region Controls	✓	✓	✓	✓	✓	✓
Count	8824	12425	11764	12315	11501	9284
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	FC100
Total Time (‘000 min.)	-0.099*** (0.005)	-560.6*** (16.9)	-2.394*** (0.206)
Constant	1.978*** (0.003)	7465.8*** (10.9)	61.072*** (0.133)
Household Fixed Effects	✓	✓	✓
Count	66,012	66,012	66,012
R-square	0.006	0.018	0.002

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

	2019 Mobile		
Dep. Var.	Entropy	1-HHI	FC100
Total Time (‘000 min.)	-0.104** (0.005)	-525.7** (15.2)	0.529** (0.173)
Constant	1.929*** (0.004)	7281.9*** (11.2)	62.280*** (0.128)
Household Fixed Effects	✓	✓	✓
Count	65,998	65,998	65,998
R-square	0.008	0.020	0.001

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

	2019 Mobile		
Dep. Var.	Entropy	1-HHI	FC100
Total Time (‘000 min.)	-0.069** (0.005)	-432.1** (14.9)	-0.775** (0.171)
Constant	1.933*** (0.004)	7314.4*** (11.3)	64.743*** (0.130)
Household Fixed Effects	✓	✓	✓
Count	65,979	65,979	65,979
R-square	0.003	0.014	0.001

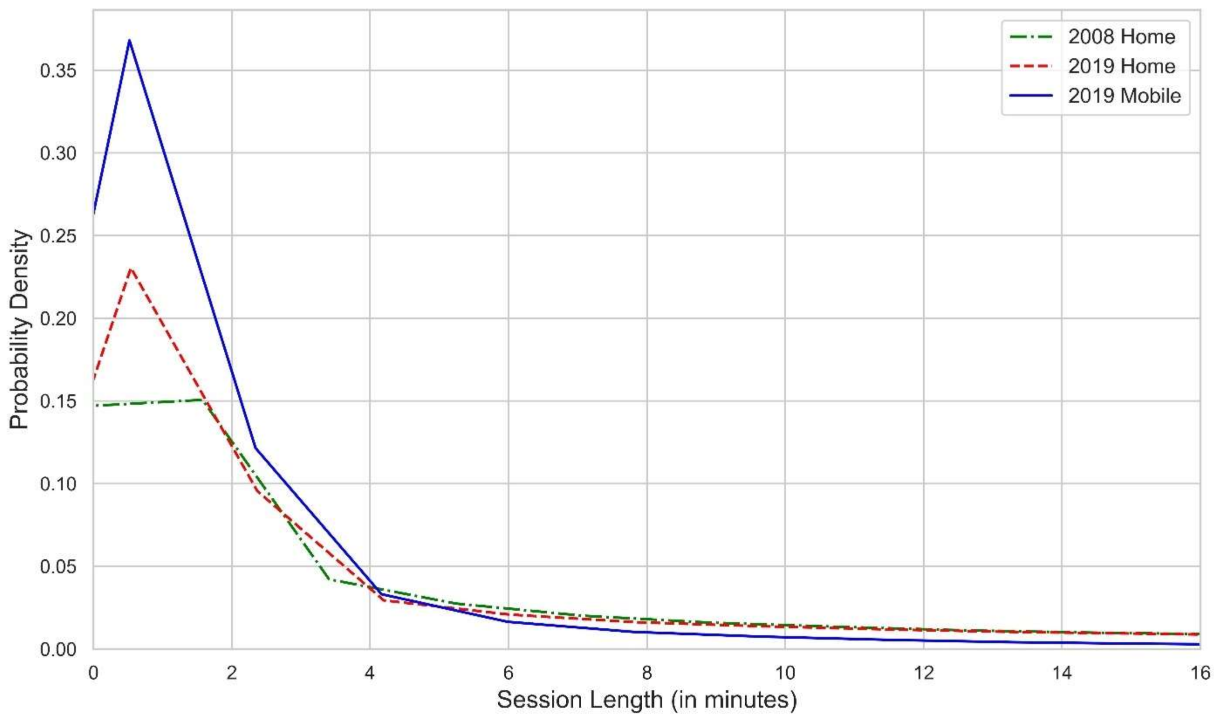
Table 14a
Mobile 2019 Time Variety (H) as a Function of Total Time, High-App vs. Low-App Users comparison (Only iOS users)

	High App users (> median)			Low App users (<median)		
Dep. Var.	Entropy	1-HHI	FC100	Entropy	1-HHI	FC100
Total Time ('000 min.)	-0.110***	-311.121***	-0.005	0.223***	-212.175***	-0.533
	(0.004)	(14.782)	(0.153)	(0.016)	(55.004)	(0.631)
Constant	1.971***	7208.654***	74.347***	1.723***	7034.308***	67.709***
	(0.007)	(22.255)	(0.230)	(0.006)	(19.940)	(0.229)
Household Fixed Effects	✓	✓	✓	✓	✓	✓
Count	26,944	26,944	26,944	27,780	27,780	27,780
Num. of Household	2,376	2,376	2,376	2,377	2,377	2,377
R-square	0.026	0.018	0.000	0.008	0.001	0.000

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	FC100	Entropy	1-HHI	FC100
Total Time ('000 min.)	0.067***	57.7***	-0.323***	0.936***	978.5***	-6.077***
	(0.004)	(7.1)	(0.103)	(0.016)	(35.3)	(0.457)
Constant	2.565***	8529.6***	67.787***	2.094***	8024.4***	63.723***
	(0.006)	(10.6)	(0.155)	(0.006)	(12.8)	(0.166)
Household Fixed Effects	✓	✓	✓	✓	✓	✓
Count	26,944	26,944	26,944	27,780	27,780	27,780
Num. of Household	2,376	2,376	2,376	2,377	2,377	2,377
R-square	0.014	0.003	0.000	0.130	0.031	0.007

Figure 1
Densities of Session Counts by Session Lengths



Appendix

Table A1
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			