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Girls' Night In? Effects of the Kenyan COVID-19 Lockdown on Web Browsing

Soledad Giardili (University of Edinburgh)
Sanjay Jain (niversity of Oxford)
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G²LM|LIC
c/o IZA – Institute of Labor Economics
Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Fax: +49-228-3894-510

Email: glm-review@iza.org

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ABSTRACT

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We present the first objective evidence on how Covid-19 affected browser usage in Africa, using detailed digital trace data on the PC-based and smartphone-based browsing patterns of 316 Kenyans who had access to a PC, covering the period before and during Kenya's first national lockdown in March 2020. We find that total daily browser usage increased by 41 minutes after the lockdown started, with no significant differences by gender or by residence in high-speed vs. low-speed broadband access areas. Women's usage of YouTube and Netflix exceeded men's throughout our sample period, and the gender gap in Netflix usage increased by 36 minutes post-lockdown. We find relatively more concentrated browsing by women post-lockdown, in terms of both domains and topics. Our analysis suggests that this is due to men visiting sites earlier exclusively visited by women. The browsing of Kenyan domains went down significantly post-lockdown, relative to that of non-Kenyan domains, indicating greater reliance on international content during this period of economic and social downturn.

JEL Classification:
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Keywords:
broadband access, brwoser history data, business concentration, COVID-19, gender, internet speed

Corresponding author:
Amalia R. Miller
Department of Economics
University of Virginia
P.O. Box 400182
237 McCormick Road
Charlottesville, VA 22904
USA
E-mail: armiller@virginia.edu

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Soledad Giardili, Sanjay Jain, Amalia R. Miller, Kamalini Ramdas, Alp Sungu*

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Abstract

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*Giardili: School of Economics, University of Edinburgh (soledad.giardili@ed.ac.uk); Jain: Department of Economics, University of Oxford (sanjay.jain@economics.ox.ac.uk); Miller: Department of Economics, University of Virginia, IZA and NBER (armiller@virginia.edu); Ramdas: Management Science and Operations, London Business School (kramdas@london.edu); Sungu: Management Science and Operations, London Business School (asungu@london.edu).

1 Introduction

This paper studies the effects of the initial COVID-19 lockdown in Kenya on the time that Kenyans devoted to internet browsing, and on lockdown-triggered changes in the distribution of internet content consumption. We focus on the lockdown as a significant exogenous shock that reduced access to in-person activities and therefore increased the value of internet connectivity and digital activity.

We examine novel data that we collected online during the lockdown that combines survey responses from 316 Kenyans with their individual internet browser histories covering the prior 90 days. The browser records cover over 3.9 million unique website visits and provide a detailed and objective record of time use that not only is free from intentional misreporting or recall bias, but also was easier to collect than subjective time use data – the collection of which was greatly hampered by the lockdown. Combining individuals' browser histories with their responses to survey questions allows us to accomplish several goals. First, it enables us to identify the key variables – gender and local broadband speed – that we use for our sub-population analyses and our estimates of differential impacts. Second, we are able to characterize the sample population along a wide range of attributes which can be compared with those of the overall Kenyan population.

These data provide a unique view on how people responded to the increased value of internet access during COVID-19 lockdowns. The onset of the pandemic in March 2020 was a significant global health shock that, both directly and through policy responses implemented by governments around the world, caused major social and economic disruptions. Previous research has extensively covered ways in which the pandemic increased digital activity, but much of the focus has been on production (e.g., work from home in the US and the UK) in high-income countries (Chiou and Tucker 2020, Adams-Prassl et al. 2020). An important exception is Miller et al. (2021), who study gender differences in digital activity in India.

The early studies of digital activity in Africa examined the impact of mobile phones – which may not have been connected to the internet – on different aspects of economic development, such as financial inclusion, access to market prices, poverty measurement, and access to other types of life-improving information (e.g., Jack and Suri 2014, Blumenstock et al. 2015). More recent research on digital activity in Africa has examined the effect of internet access on outcomes including employment and political mobilization (Hjort and Poulsen 2019, Manacorda and Tesei 2020). The limited research on digitization in Africa likely results from researchers being constrained by severe limitations on available data. Data limitations were greatly magnified during the Covid-19 pandemic, even in developed nations - for example, the American Time Use Survey was not fielded from March 19 until May 11, 2020.[1] These limitations were even greater in the developing world (Miller et al. 2021). While time use panel data has been gathered in Africa via mobile phone surveys pre-Covid-19 (Hoogeveen et al. 2014), even phone-based data collection suffered in many countries during pandemic lockdowns.

The first contribution of this paper is that it documents objectively measured changes in the levels and nature of internet activity on a sample of individuals in Kenya observed during

[1] Available at https://www.bls.gov/tus/covid19.htm

a period that spans the start of the initial Kenyan national lockdown. Consistent with expectations, we find significant increases in time online during the lockdown, even relative to the immediately preceding time period, which followed the WHO pandemic declaration on March 11, 2020.

This study also contributes by examining differential effects of the Covid-19 shock on the internet activity of two potentially disadvantaged groups. This allows us to comment on whether the increased demand for different online content amplified or diminished existing disparities.

The first dimension of disadvantage that we consider is gender. Although our sample is not representative of the population as a whole, it is useful to understand the social context in which our analysis is conducted. There are significant overall gender disparities in Kenya. The UN Human Development Report 2021 ranks Kenya 128th out of 170 countries on its Gender Inequality Index (GII), which "measures gender inequalities (the loss in human development due to inequality between female and male achievements) in three key dimensions – reproductive health, empowerment, and labour market".[2] By way of comparison, Kenya's 2021 GII score of 0.506 places it slightly below India, and above Bangladesh. Labour force participation - one of the components of the GII - is, however, quite similar for men and women: 75.6% and 71%, respectively. This is reflected in our sample too, with employment rates of 61% and 72% for women and men respectively.

Despite this similarity, our sample of relatively young and highly-educated men and women who own and access a computer at home is clearly not representative of the larger population. As Table 1 indicates, the female share in our sample is only 31%, possibly because of overall gender gaps in digital access. The extremely detailed Kenyan Population and Housing Census (KPHC) reports sizable gender disparities, even in urban areas, in both internet usage (40% of women, compared to 45% of men), and computer and tablet usage (19% and 24%, respectively) (KNBS 2019).[3]

Among our respondents, the proportions in full-time employment, white-collar jobs, and self-employment are actually higher among women than men. Hence, our analysis aims to observe whether, even among this relatively privileged group, there are gender disparities, and whether those disparities are exacerbated during the lockdown. Indeed, one motivation for our focus on gender is the widely expressed global concern that pandemic lockdowns and school closures would impose particularly severe burdens on women (Alon et al. 2020, United Nations 2020, Burki 2020).

The second dimension of potential disparity that we investigate is differential impacts in browser activity across geographic areas with higher and lower internet connection speeds. We do so by splitting the sample between the Kenyan counties with the fastest fixed broadband speeds (which are Nairobi and Mombasa according to Speedtest.net) and the rest of the country. Extensive prior literature has showed the importance of internet connection speeds, in terms of value to consumers (Nevo et al. 2016) as well as a range of economic (Goldfarb and Prince 2008, Forman et al. 2021, 2012, Akerman et al. 2015), social (Bhuller et al. 2013, Amaral-Garcia

[2]https://hdr.undp.org/data-center/specific-country-data/countries/KEN

[3]The national rates, including rural areas, are much lower, with 20% of women (and 25% of men) reporting internet usage and 9% of women (and 11.7% of men) reporting computer or tablet usage (KNBS 2019). The low rate of computer access in rural areas is also reflected in the largely urban composition of our sample.

et al. 2021), and political outcomes Gavazza et al. (2019). Unlike prior literature focused on the impact of increased broadband access that exploits supply shocks triggered by technological investment, we take variation in local supply conditions as fixed and instead study the differential impact of a demand shock across different areas. To do this, we go beyond looking at the total quantity of data flows (Nevo et al. 2016), to focus on the content browsed. This is important because the faster download speeds are likely most important for certain uses (e.g., streaming videos or transferring massive files).

We first document that browser time increased significantly during the lockdown for the overall sample (with a magnitude of 41 minutes per person-day in levels and of 0.15 points on a logarithmic scale). We then turn to estimating differential effects of the lockdown on women (compared to men) and people with high speed (relative to low speed) broadband. We find no significant differences in total amount of browsing time within either subgroup, but we do find significant changes in the content consumed. The most striking finding is a substantial increase in women's time on Netflix – of over 35 minutes per day per person – relative to men's. The enormous shift in Netflix usage by women post-lockdown is also reflected in the topical breakdown of content consumed, where women's time spent on topics associated with Arts & Entertainment increased by 34 minutes more than men's. We also find a smaller, but perhaps more surprising, relative drop in women's time on health-related browsing. For the split by broadband speed, we find a relative increase in time on LinkedIn for people with faster broadband speed, which could point to future differential effects on labor market outcomes. We also find a relative increase in browser time devoted to emails and messaging for people with slower speeds, relative to those with high-speed access, which may indicate that those with high internet connectivity migrated disproportionately towards video-based, and away from text-based, communication.

After documenting changes in top domains and topic areas using individual-day level data, we then take a market-level perspective and examine changes in how the full groups of men and women, or people with faster and slower broadband speeds, browsed the internet. There we find that the concentration of women's browsing, measured as the Herfindahl-Hirschman Index (HHI) across domains, increased relative to men's. Similarly, concentration of high-speed areas increased relative to low-speed areas – indicating an increasing diversity in internet surfing for men and individuals in slower broadband-speed areas. Further, we find a convergence in the sets of domains and topics visited by men and women, explained by men starting to browse websites exclusively visited by women before the lockdown.

Finally, we consider how the Covid-19 shock affected demand for local content, which we measure using visits to websites with Kenyan domain names. Despite the overall significant increase in browsing time, we find no increase in time spent in local Kenyan domains, implying the additional time went into international – most often US-based – websites.

Our results provide the first highly-granular view into how the initial Covid-19 lockdown impacted browser usage of an elite sample in Kenya. While our sample represents a small slice of Kenyan society, it represents a significant and growing sub-population. Even before the pandemic, 8.8% of households (and almost a fifth of urban households) owned a computer or tablet (KNBS 2019, Table 2.36).[4] Reported internet usage among the population aged 3 and above was 22.6%, with the proportion rising to 42.5% in urban areas (KNBS 2019, Table 2.33). The recent expansion in Kenyan internet usage is also reflected in the rapid growth of the market for computers. For example, revenues from Kenyan laptop sales trebled between 2015 and 2020.[5]

2 Data, Sample and Empirical Approach

The first national lockdown in response to Covid-19 in Kenya started on 25 March 2020, 14 days after the WHO's announcement on 11 March 2020, declaring that Covid-19 was a pandemic. The lockdown was implemented at national level and was as stringent as the lockdowns being imposed at the same time in high income countries (e.g., the UK, US, Italy, Singapore) or countries in the Global South (e.g., India, China, etc). The lockdown involved the limitation of domestic and international mobility, social gatherings and the closure of workplaces, schools and colleges.[6] Importantly, all of these policies remained in place during our study window and only began to be eased in July of 2020. Kenya's first case of the new coronavirus was identified on March 12, 2020. By the end of June, there were 6,366 confirmed cases and 148 deaths (University of Oxford 2020), which is much less than what was reported in many other countries.

2.1 Browser Data Collection and Survey Design

We partnered with *PY Insight* and *Dynata* to field this study, using a method identical to that of Miller et al. (2021). PY Insights uses a browser extension technology to parse the internet usage history from a PC browser.[7] A browsing history includes a timestamp, URL, and some text information about the websites visited. Every browser app saves past browsing activity. We essentially collect this internally saved data via PY Insights' browser extension technology. Effectively, we observe the 'history' section of respondents' internet browsers.

Participants log into the study via a browser of their choice (e.g., Chrome or Firefox) from their personal computers. As an inbuilt functionality, browser apps connect a user's past activity from multiple devices (e.g., tablet or smartphone) via a user account. For instance, if a participant has a Chrome account, her Chrome browsing history on her PC and on her smartphone will be synced, as long as she is logged in to the browser on both devices. Therefore, for those who use multiple devices (and also have a user account), while we parse the browser history on their PC, we also observe the URLs they visited through their smartphone browser app, provided they were logged in to their browser account on both their PC and their smartphone. We observe no data on browsing activities under Incognito mode.

[4] https://africacheck.org/infofinder/explore-facts/what-share-households-kenya-own-computer

[5] Available at https://www.statista.com/outlook/cmo/consumer-electronics/computing/laptops/kenya

[6] The lockdown involved the suspension of all international flights into and out if the country; closing of the borders with neighbouring countries; and the limitation of non-essential domestic movement into and out of the major cities. All schools, colleges and places of worship were shut down, and a harsh curfew was put into effect. In addition, all public gatherings, such as political rallies, were banned and workplaces were required to close or require workers to work from home (McDade et al. 2020).

[7] An extension/add-on is a small software module that is designed to be used in the browser (e.g., to block pop-up advertisements).

The study recruited 316 individuals aged between 22-54 in Kenya, who had at least 30 days of browsing history data. To avoid computer bots, we manually dropped all users with an average of more than 3,000 URL visits per day. Our total data consists of more than 3.9 million webpage visits, with their corresponding title and timestamp. Those URLs are segmented into 39,163 domains and domains are classified into 30 content categories or topics (e.g. mapping nation.co.ke to the "News" category).

We supplemented participants' browser history data with data from an online survey. Survey responses were collected between 11 and 24 of June, 2020 and the survey took, on average, about 30 minutes to fill in. We disregard respondents who failed a simple attention test question. Our survey included questions about participants' demographics, self-reported time use on various activities, and contextual information about their internet browsing patterns.

2.2 Sample Characteristics

Table 1 provides summary statistics for our full sample and for our subpopulations of interest. From column 1, we can see that our sample was relatively young (mean age 32) and highly educated – 89% had a college education, relative to only 3.5% in the broader Kenyan population.[8] The high education level is not surprising given that our data collection was restricted to Kenyans who owned a PC – who comprised only 3% of Kenya's population of 54 million in 2020.[9]

Our sample is about 31% female, partly reflecting lower access to computers and the internet among women. At the same time, our sample is representative in terms of religious affiliation, being predominantly (almost 90%) Christian (relative to about 78% in the national demographic).[10]

Interestingly, in our select sample, we see no significant differences in percent college education or ethnic minority status, by gender (see columns 2 and 3), quite different from the national demographic, where men outnumber women both in completed university degrees as well as in current university enrollment (KNBS 2019). On the other hand, the women in our sample are slightly younger than men, and are almost twice as likely to be single (56.3% vs. 33.2%). We find little variation in demographics in high-speed and low-speed broadband areas (see columns 5 and 6). In low-speed – possibly rural – areas, fewer individuals in our sample are single, and almost twice as many are self-employed.

2.3 Empirical Approach

Our empirical analysis is focused on assessing how digital activity changed during the lockdown period (from March 25 to June 23, 2020) compared to the sample period immediately preceding the lockdown (from March 14 to 24, 2020).

We start with an individual analysis, where the unit of observation is a person-day, and estimate a simple regression model that compares the lockdown and pre-lockdown periods:

[8] https://www.statista.com/statistics/1237796/distribution-of-population-in-kenya-by-highest-level-of-education-completed/

[9] https://www-statista-com.lbs.idm.oclc.org/outlook/dmo/digital-media/video-on-demand/video-streaming-svod/kenyakey-market-indicators

[10] https://en.wikipedia.org/wiki/Religion_in_Kenya

$$Outcome_{it} = \alpha \ Lockdown_t + \lambda_i + \tau_t + \varepsilon_{it} \tag{1}$$

The dummy variable $Lockdown_t$ equals 1 for any date t after the adoption of the lockdown, and 0 otherwise. λ_i is a vector of dummies for individual fixed effects that account for the dispersion in the dates of data collection, which (because of the 90-day look-back window) causes variation in the start date of individuals and an unbalanced panel. τ_t is a vector of dummies indicating days of the week and ε_{it} is the error term, clustered at the individual level.

This first model allows us to compare the two time periods, but lacks a control group to account for time trends. This is because the lockdown was a shock to browsing activity that affected the entire population. To the extent that the exact timing was exogenous, within our narrow time period, α can be interpreted as the impact of the lockdown.

Our main analysis goes beyond this simple comparison to study variation within the sample. We use survey information on demographics to split the sample by gender and by broadband internet speeds and estimate differential effects of the lockdown by population. The main panel data estimation uses two-way fixed effects for individuals and dates in the following form:

$$Outcome_{it} = \beta \ Lockdown_t \times Subgroup_i + \lambda_i + \delta_t + \varepsilon_{it} \tag{2}$$

The dummy variable $Lockdown_t$ again equals 1 for any date t after the adoption of the lockdown, and 0 otherwise. The dummy variable $Subgroup_i$ now equals 1 if the individual is female, or lives in a high broadband speed area, depending on the specification, and 0 otherwise. The day of week effects τ are replaced with δ_t, a vector of dummies indicating date fixed effects. ε_{it} is the error term, clustered at the individual level.

Our individual time use outcome variables, $Outcome_{it}$, for individual i on date t include total daily browser time as well as time spent browsing the 10 major web domains in our sample and the 10 largest topic areas.[11] We also measure time spent on local Kenyan vs. non-local browsing by identifying web domains that are registered in Kenya with the .ke ending or that include Kenya.com, Kenya.net, or Kenya.org.

In addition to the individual-level analyses, we also examine several market-level measures of concentration and overlap in browsing activity. We use the Herfindahl-Hirschman Index (HHI) to measure within-subgroup (by gender or broadband speed) daily measures of concentration at the level of web domains or topical areas.

We also measure the degree of similarity in browsing between each of the pairs of subgroups using Jaccard indices (J) for overlap in domains or topics:

$$J(M, F) = \frac{|M \cap F|}{|M \cup F|} \tag{3}$$

The Jaccard similarity index, which is a measure between 0 and 1, quantifies the similarities between two sample sets. In our case, the sets are defined by demographics like gender, or broadband speed in the county of residence. The higher the coefficient, the more similar the two sets are deemed to be. In equation (2) above, we compare domains (or topics) of each set,

[11] The domains, in order of number of visits, are: Google, YouTube, Facebook, Yahoo, Instagram, Twitter, LinkedIn, Netflix, PayPal, and WhatsApp.

here referred as M and F, to see which are shared and which are unique to each of the sets. We also employ a weighted Jaccard index. While the unweighted coefficient compares the number of categories (domains or topics) that are common to both sets, the weighted coefficient takes into consideration the browsing time spent in each category:

$$J(m, f) = \frac{\sum_i \min\{m_i, f_i\}}{\sum_i \max\{m_i, f_i\}} , \tag{4}$$

where i is a domain (topic) and m_i and f_i denote the amount of time spent by sets m and f, respectively, on domain (topic) i.

The sample mean values for our outcome variables are presented in Appendix Table 1A. The individual-level variables and HHI measures are presented separately by gender and by broadband speed, while Jaccard indices are only computed for the full sample.

3 Results

3.1 Effects of the Lockdown on Self-Reported Time Use

Before turning to the main analysis of browsing activity, we first examined the effects of the lockdown on several self-reported measures in our survey: hours spent managing the household, hours spent on child-related activities, hours spent taking care of dependents, and the extent of self-investment activities (including such activities as taking a course or learning a new skill, among others). For this analysis, we estimate a modified version of equation 2 where the unit of observation is a person and time period and each individual contributes two observations: one (retrospective) before and one (contemporaneous) during the lockdown.

The results are in Table 2. Panel A shows that the lockdown had no differential impact by gender on hours spent on managing the household, children or dependents, which could reflect the high representation of single women in the sample and their relatively advantaged status. Interestingly, the lockdown resulted in a significantly higher increase in the proportion of Kenyan women reporting frequent or very frequent self-investment time use, relative to their male counterparts.

From Panel B of Table 2, we see that the lockdown had no differential impact by broadband speed on hours spent on managing the household, children or dependents, or time spent on self-improvement activities. This provides some reassurance for attributing any relative changes in browsing activity as coming from broadband speed rather than other factors unrelated to the internet, that caused differential impacts of the pandemic lockdown across locations.

3.2 Effects of the Lockdown on Digital Time Use

Our first finding is that the Kenyan lockdown significantly increased total internet browser use time. Table 3 shows an average increase of 41 minutes per day (column 1), corresponding to an increase of 0.16 log points (column 2), for the overall sample. These coefficients are estimating equation 1 above, which includes individual fixed effects to account for the unbalanced panel and day-of-week fixed effects to account for within-week variation in browsing activity, evident in Figure 1.

Our next findings come from estimating equation 2 for differential impacts: the increase in total browser time was not significantly different by gender or by broadband speed. Figure 1 shows that, throughout the sample period, women and people in high-speed areas spent more time online than did their male and low-speed counterparts. While the greater browsing by people with faster speeds is consistent with the value of time online being higher for people with faster connections, the gender difference points to the unusual set of women in our sample, discussed above in Section 2.2. In particular, Panel B of Table 1 shows that women in our sample are more likely to be single and less likely to be employed than the men are. The remaining columns of Table 3 show the insignificant difference-in-differences estimates for the interaction term between the lockdown time period and the indicator female (columns 3 and 4) and with high speed (columns 5 and 6). The model includes a full set of individual fixed effects, as well as fixed effects for each date, and standard errors are clustered at the individual level. Although the increase in women's browsing time was higher in both levels and logs than men's, these differences are not statistically significant at conventional levels. For the interaction with broadband speed, the point estimate in levels indicates a greater increase in online time in faster areas, but the negative point estimates in logs suggests a smaller increase as a proportion of pre-lockdown levels. As with gender, neither of these estimates is statistically significant.

3.2.1 Individual Browser Time by Domain and Topic Area

Although we are unable to detect significant relative changes in the overall time spent online, we do find significant relative changes in the distribution of browsing time across the 10 most popular web domains in our sample.[12] The difference-in-difference regression estimates are in Table 4 and the corresponding raw daily average browsing time data are plotted in Figures 3 (by gender) and 4 (by speed).

The gender interactions by domain in Panels A and B of Table 4 reveal one significant divergence. Women increased their time on Netflix by 36 minutes more minutes per day on average than men did during the lockdown. This relative increase is comparable in magnitude to the total increase in daily browser time of 41 minutes reported in Table 3. Some of women's additional time on Netflix appears to be partially offset by relative drops in time spent on Google, Twitter, LinkedIn and WhatsApp, but these are all much smaller in magnitudes (under 6 minutes per day) and not statistically significant.

The substantial relative increase in women's time on Netflix is also shown dramatically in Figure 3. Figure 3 also presents other persistent gender differences in browsing across domains that were not affected by the lockdown. Women spent more time than men on YouTube, but less time on Facebook and Twitter (and, to a lesser degree, Yahoo). These overall differences in domain time by gender are also illustrated in the word cloud in Figure 2: Netflix and YouTube are more prominent in panel (a), while Facebook is larger in panel (b).

When we divide the sample by broadband speed, we also find some notable differences in time allocation across domains. Consistent with expectations, Figures 2 and 4 show that people in areas with faster connection speeds spend more time on sites with significant video content

[12] Figure 2 uses word clouds to depict the distributions of browsing time across the full set of website domains visited by the various sub-populations in our sample.

such as YouTube and Netflix. They also appear to spend more time on LinkedIn and Instagram, particularly during the lockdown period. In fact, the only statistically significant differences in browsing across domains that we find in the impact of the lockdown by broadband speed are for LinkedIn and Instagram. Although the relative increase in average time spent on each of these two domains is statistically significant (Table 4, Panel C, columns 5 and 7), they are quantitatively smaller (less than minute per day) and only the increase in LinkedIn time is statistically significant under the logarithmic transformation (in Table 4, Panel D, column 7).

We also explore changing time allocations across topic areas in Table 5. The largest relative change by gender is women's increase of over 34 minutes in the Arts & Entertainment category, which corresponds closely to the increase in Netflix time in the prior table. Despite this similarity, the breakdown by topic is not the same as the one by domain. This is because the topic split allows us to subdivide activities on major domains like Google that span multiple categories and because it allows us to group together the massive number of smaller domains into meaningful categories. The topic breakdown also shows a relative increase of 2.3 minutes in women's time consuming news and relative declines of 3.4 minutes in Finance and 0.3 minutes in Health. Of these gendered effects by topic, only the decline in Health is also statistically significant in the log specification.

The only significant effect we find in the split by broadband speed in Panel C of Table 5 is the relative drop in time spent (of about 4 minutes per day) on Email & Messaging among people in high speed areas. Although the point estimate for Arts & Entertainment is larger, it is estimated less precisely, and the sign on the log-transformed variable (in Panel D) is reversed.

3.2.2 Concentration and Overlap by Domain and Topic

In this section, we continue to examine patterns of browser use across domains and topic areas, but we shift from the individual level unit of analysis to the market level, where we define markets based on the sub-population breakdowns, separately by gender and broadband speed.[13] We first use the market level analysis to study measures of within group concentration, using an HHI measure based on based on time allocation. Next, we compare changes in two Jaccard measures of cross-group similarity. The first measures the share of visits to overlapping domains or topics, without regard to visit duration, while the second (weighted) measures overlap based on time spent in the domain or topic.

Figure 5 plots daily variation in HHI across domains (upper panels) and topics (lower panels). The figures on the left are split by gender and on the right by broadband speed. The consistent pattern across these splits is that the group with higher average browsing levels (women, high speed) is also the one with more concentrated browsing, by domain and (to a larger degree) by topic, during the lockdown. These differences are highly statistically significant, as shown in Table 1A. Average daily concentration levels by domain are between 0.18 and 0.24 across subgroups, which falls in the moderately concentrated category of the U.S. Department of Justice and Federal Trade Commission's Horizontal Merger Guidelines. Concentration by topic

[13] In this analysis, we consider the full set of web domains and 26 out of 30 topics, rather than just the top 10 for each. We disregarded 3 topics due to the lack of observations for at least one of the subgroups in the pre-lockdown period. We also exclude from the analysis those websites classified as "Not Categorized". Overall, these account for about 8.3% of the observations.

is higher (up to 0.43), likely because it is more common in the data to observe multiple domains offering competing content within a topic than to have domains that span a range of topics.

Comparisons between the lockdown and prior period further show that concentration gaps by domain increased significantly during the lockdown. The regression estimates in Table 6 of group-by-data HHI measures show a relative increase of 0.013 for women compared to men (column 1; a 6 percent increase relative to the male sample mean in Appendix Table 1A) and of 0.012 for high relative to low speed areas (column 3; a 7 percent increase relative to the low-speed mean). The plots in Figure 5 show that these relative increases in concentration for women and in high speed areas are coming from large drops in concentration among men and in low speed areas. This suggests that the pandemic lockdown increased the amount of web exploration and time spent on less popular pages among men and people in low speed areas, but not for women or people in high speed areas. It is also possible that women's exploratory browsing of new domains and topics also increased somewhat during the lockdown, similarly to men's, but that effect was overshadowed by their greater concentration in time spent on Netflix and other commonly-visited domains.

We find a larger increase in concentration for women relative to men when we examine the distribution of browsing time across topics, with a coefficient of 0.029 (column 2 of Table 6; a 12 percent increase over the male mean in Table 1A). However, the relative increase in concentration by domain in high speed areas (column 2) is not repeated for topic area concentration: the point estimate of -0.001 is much smaller and has the opposite sign (column 4). Taken together, these estimates suggest that people with slower broadband were more likely to explore less popular domains but slightly less likely to consume less popular categories of content.

In our final analysis of browsing patterns by domain and topic, we assess changes in the degree of overlap between the two sets of sub-populations using the Jaccard similarity indices described in Section 2.3.

The results, in Table 7, show evidence of significant gender convergence in browsing habits by domain, particularly in the unweighted measure (showing an 11.9 percentage point increase in overlap) in column 1, but also in the measure that accounts for time spent. This convergence of gender by domain, together with the relative decrease in concentration by domain for men, suggests that men's increasingly diverse browsing habits during the lockdown included addition visits to domains that were exclusively visited by women in the prior period. The greater gender convergence in the unweighted measure suggests that the increased likelihood in men and women visiting the same domains did not equally translate into an increase in the overlap in time spent across domains. Similarity by topic also increased by gender in the unweighted measure, but not in the weighted one (columns 3 and 4).

The remaining columns of Table 7 are for the split by broadband speed. There we find a significant increase in overlap across domains in the unweighted measure (column 5), but no significant effects by topic or in the weighted measures.

3.2.3 Visits to Kenyan and International Domains

In our final analysis, we consider another split based on domains, this time distinguishing between local content that originates in Kenya or is focused exclusively on the country and content that is based in other countries. The motivation for this analysis is the striking fact that the top domains that account for the majority of the time in the sample are all for companies based in the US, combined with the expectation that the demand shock in internet demand coming from the national lockdown might disproportionately increase demand for local content. This would happen, for example, if people devote significant amounts of time online to following local news coverage or local government information about the pandemic and policy responses or if they visit local business and job sites for production and job search.

This prediction is not borne out in the data. Instead, column 1 of Table 8 shows no significant increase in average daily time spent browsing Kenyan domains. The point estimate is small (30 seconds) and even the upper range of the 95% confidence interval is under 5 minutes. This is in stark contrast to the overall increase in browsing time of 41 minutes in Table 3. Column 2 of Table 8 does show a significant increase in Kenyan domains under the log specification, but this estimate (0.108) is smaller than the corresponding estimate for all content in Table 3 (0.151).

To compare the relative shifts in browsing time, we expand the sample to include two observations per person-day – for Kenyan and non-Kenyan domains – and estimate the difference-in-difference relative effect of the lockdown on Kenyan domains, including fixed effects for individuals, dates, and Kenyan top-level domains. We find a significant relative decrease, on the order of 21 minutes per day, in browsing of Kenyan domains (column 3 of Table 8), consistent with most of the additional browsing time going to international domains. The point estimate in the log model (column 4) is also negative but not statistically significant, which suggests that the relative increase in time at non-Kenyan domains was in proportion to the non-Kenyan browsing share overall. The remaining columns of the table test for triple-difference interaction effects in the relative shift towards Kenyan content during the lockdown by gender and browsing speed. None of these is statistically significant.

While it is possible that the lack of an increase in local content consumption in our data comes from supply constraints, where Kenyan domains were less equipped to handle the surge in demand during the lockdown, it is also possible that the source is the demand side. Here it is worthwhile to note a key feature of the top domains, which is that they operate as platforms or distribution sources for content (in many cases user-generated) rather than exclusive providers of content they develop and create.[14] That feature allows them to effectively dominate Kenyan browsing, despite the geographic, economic, and cultural distance.

4 Discussion

To interpret our findings of higher usage of Netflix and YouTube by women throughout our sample period and the stark relative increase in Netflix browsing by women post-lockdown in a broader context, we provide some industry background relevant to these results.

Faced with market saturation and high competition in their established markets, US-based providers of subscription video-on-demand have followed a strategy of international expansion in the last decade. Subscription video-on-demand penetration in Africa has been held back

[14]Netflix is the only exception in that they do produce original content, but they also distribute content produced elsewhere, including a significant volume of African movies and TV shows. See, e.g., https://www.netflix.com/browse/genre/100369.

by limited access to high-speed internet, and poor payment systems, which providers have counteracted by partnering with local telecom companies. Total revenues in this category in Kenya were almost USD 19 million in 2020, at an average revenue per user of USD 10.[15] Netflix started to serve the Kenyan market in 2016 and its demand is estimated to have grown seven-fold by 2020, to almost 30,000 users.[16] It was the main subscription video-on-demand platform in Kenya in 2020, with 45% of the Kenyan market, followed by ShowMax (owned by South African firm MultiChoice) at 20% and YouTube at 10%.

The greater time spent on YouTube and Netflix by women in our sample throughout our data collection period relative to men – and the even greater post-lockdown gender gap on Netflix – is somewhat surprising given that 62% of subscription video-on-demand usage in Kenya is by men.[17] This difference may reflect the higher percentage of single women than men in our select sample. It is also suggestive of the implications of the aggregation that is inevitable in national level industry statistics, which can fuel inaccurate stereotyping of specific population segments based on broad brush metrics. Indeed, although it happened after our sample period, Netflix introduced a free plan in Kenya in September 2021,[18] with the target of increasing viewership, perhaps particularly among less privileged – and more price sensitive – women than those in our sample. In South Africa, which ranks 19th on the World Economic Forum's Global Gender Gap (relative to Kenya's rank of 95),[19] subscription video-on-demand has a longer history and higher penetration, and consumption is equal across men and women.[20]

To increase viewership, the Netflix platform is increasingly showing African, and even Kenyan content. Local content producers explicitly aspire to "avoid the simplistic portrayals [in content made in the West] that African viewers often resent".[21] While Nigeria and South Africa were the main sources of African content on Netflix prior to 2020, Netflix aired its first Kenyan film, The Poacher, in 2020, and its first series fully produced in Africa – Queen Sono – on Feb 28, 2020, just prior to the lockdown.[22] This spy-genre series based out of Johannesburg was shot on 27 locations including Nairobi and Harare, and is sprinkled with many African languages, including Swahili. Netflix has also agreed content-licensing deals with other African markets including Senegal, Ghana, Zimbabwe, Angola and Mozambique.

5 Conclusion

We present the first objective evidence on how Covid-19 affected PC-based and smartphone-based browser usage in Africa. Our study is based on digital trace data on a sample of 316 Kenyans who had access to a PC during Kenya's first national lockdown which started on 25 March 2020. While our sample represents a select subpopulation, the detailed and objective

[15] https://www-statista-com.lbs.idm.oclc.org/outlook/dmo/digital-media/video-on-demand/video-streaming-svod/kenya?currency=USDlocale=enrevenue

[16] https://www.statista.com/statistics/607673/kenya-netflix-subscribers/

[17] https://www-statista-com.lbs.idm.oclc.org/outlook/dmo/digital-media/video-on-demand/video-streaming-svod/kenyausers

[18] https://about.netflix.com/en/news/netflix-launches-free-plan-in-kenya

[19] https://www3.weforum.org/docs/WEF$_GGGR_2$021.*pdf*

[20] https://www-statista-com.lbs.idm.oclc.org/outlook/dmo/digital-media/video-on-demand/video-streaming-svod/kenyausers

[21] https://www.reuters.com/article/ozatp-uk-africa-films-idAFKBN271181-OZATP

[22] https://time.com/5792339/queen-sono-netflix-africa/

nature of our data enable us to provide a unique lens into how Covid-19 affected the digital activity of the 316 individuals in our sample.

Throughout our sample period of March - June 2020, women and people in areas with high-speed internet spent substantially more time online. This finding is in stark contrast to those of Miller et al. (2021), drawn from a similarly gathered sample of PC users in India, where men spent significantly more time online. While the women in both of these samples were slightly less likely to be employed, in our sample women were twice as likely to be single, which may partially explain the higher time online.

We find a significant increase in overall browser usage after the first Covid-19 lockdown, with no significant differences in relative impact on men's vs. women's browsing, or on the browsing patterns of those residing in areas with high-speed vs. low-speed broadband. In contrast, in the Indian sample in Miller et al. (2021), which was subject to the same constraint of PC access but had a third fewer single women (at 40%), overall usage fell significantly for women relative to men after India's first Covid-19 lockdown, with the difference being driven by parents with children.

While there was no differential impact on overall usage by gender, our detailed data enabled us to identify some clear differences when we looked at specific domains. In particular, women's usage of Netflix, which was already higher than that of men's, pre-lockdown, went up by a remarkable 36 minutes relative to men's, after the lockdown. While some of this gender gap in Netflix usage can be explained by the higher proportion of single women than men in our sample, it is still a noteworthy finding, considering that Netflix content is largely entertainment – which men may have had more time for during Covid-19.[23] Further, it is an expensive subscription service relative to free content (e.g., women in the US cut Netflix subscriptions during Covid-19 to cut costs).[24] As discussed earlier, Kenya is a nation with high gender disparities, and women around the world have been disproportionately hurt by Covid-19. It is also heartening that our survey-analysis showed that women engaged more in self-investment activities than men, post-lockdown. That the relatively younger, unmarried women in our select sample were pursuing their own advancement portends well for the future of women's progress in Kenya. Such progress in the upper echelons of Kenya's economy could spark wider progress, as has been seen in other countries, where, for example, elected female political leaders have benefited women in their constituencies (Iyer et al. 2012).[25]

The Covid-19 lockdown increased the concentration of women's browser usage relative to men's, in terms of both domains and topic, due to both women's increased Netflix time and men visiting sites previously visited only by women. Which specific sites grew their usage, and whether such changes in concentration will continue long term, are interesting areas for future research. The lockdown reduced consumption on Kenyan domains, relative to non-Kenyan domains. Why this happened, and whether this migration initiated a more permanent shift in demand, is also worth exploring further.

While the pandemic, and associated lockdowns, might be considered to be somewhat unique

[23]https://deloitte.wsj.com/articles/a-closer-look-at-the-media-subscription-gender-gap-01604952130

[24]https://deloitte.wsj.com/articles/a-closer-look-at-the-media-subscription-gender-gap-01604952130

[25]These authors found that the reporting of crimes against women was higher in Indian constituencies with women political leaders.

events, we suggest that the insights extend further, to the consideration of other 'market-deepening' demand shocks to online activity (in this case, occasioned by a lockdown). Future research might look at the effects of these sorts of market shifts, with more detailed and more representative data, on gender and spatial inequality in particular.

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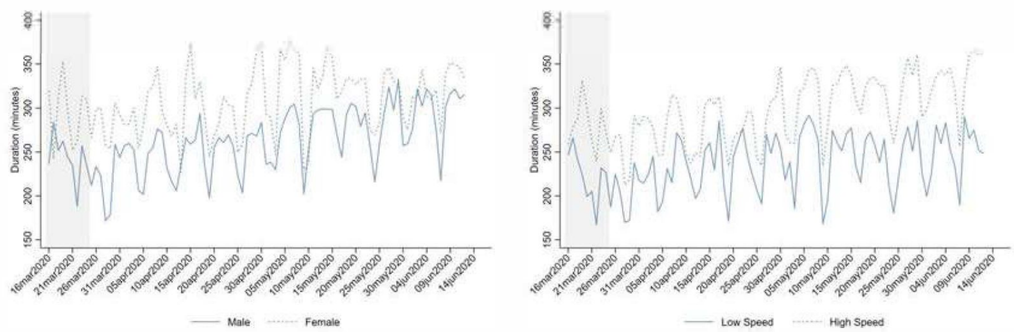
FIGURES AND TABLES

Figure 1. Average Daily Internet Browsing Time

(a) by Gender | (b) by Broadband Speed



Notes: Figure 1(a) shows average daily browsing time by gender. Figure 1(b) shows average daily browsing time by broadband speed area. High-speed areas comprise Nairobi and Mombasa. The grey-shaded area indicates the pre-lockdown period. Outcomes are reported in minutes. The unit of observation is a user-day.

Figure 2. Domains Word Cloud

by Gender

(a) Female

(b) Male

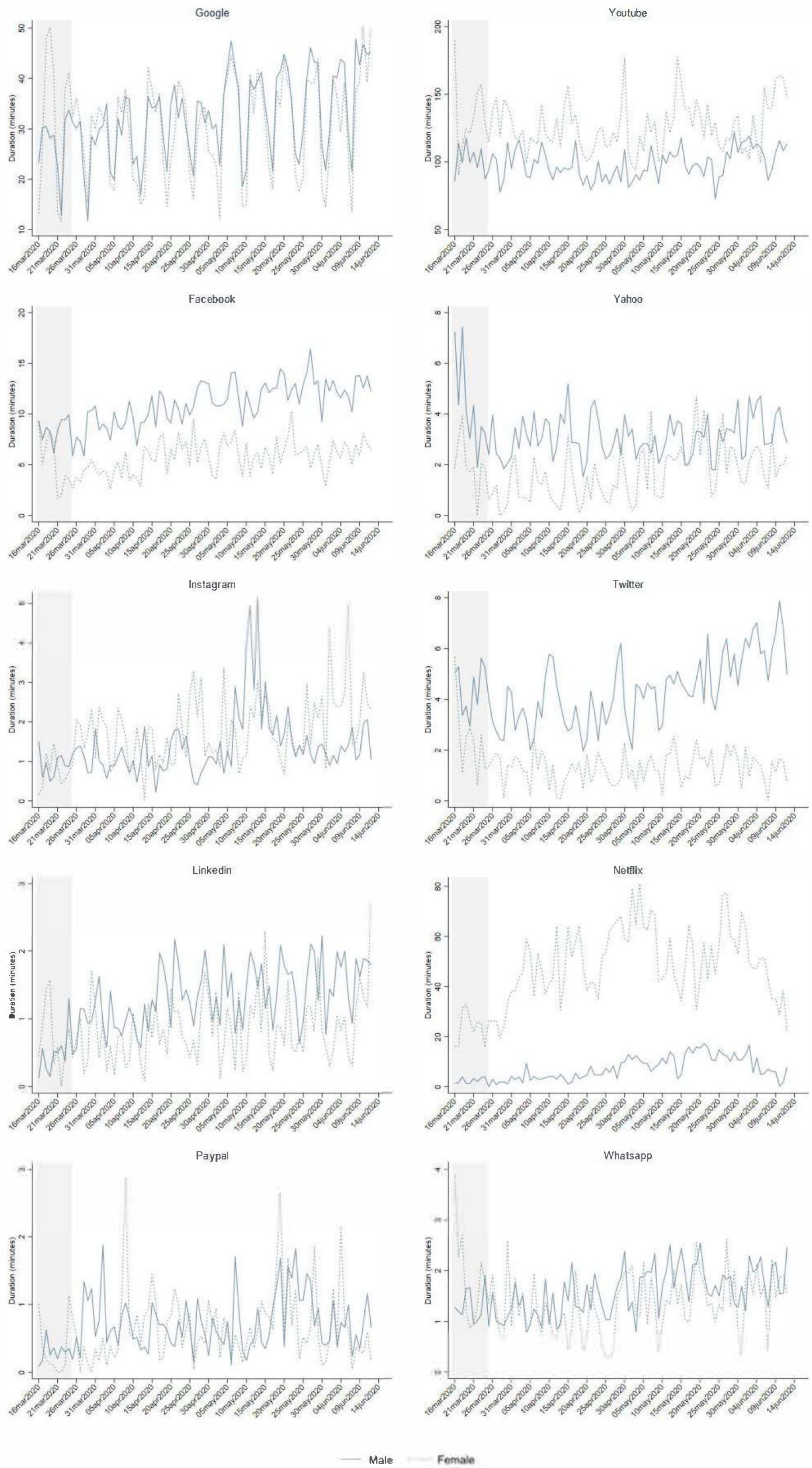
by Broadband Speed

(c) High-speed

(d) Low-speed

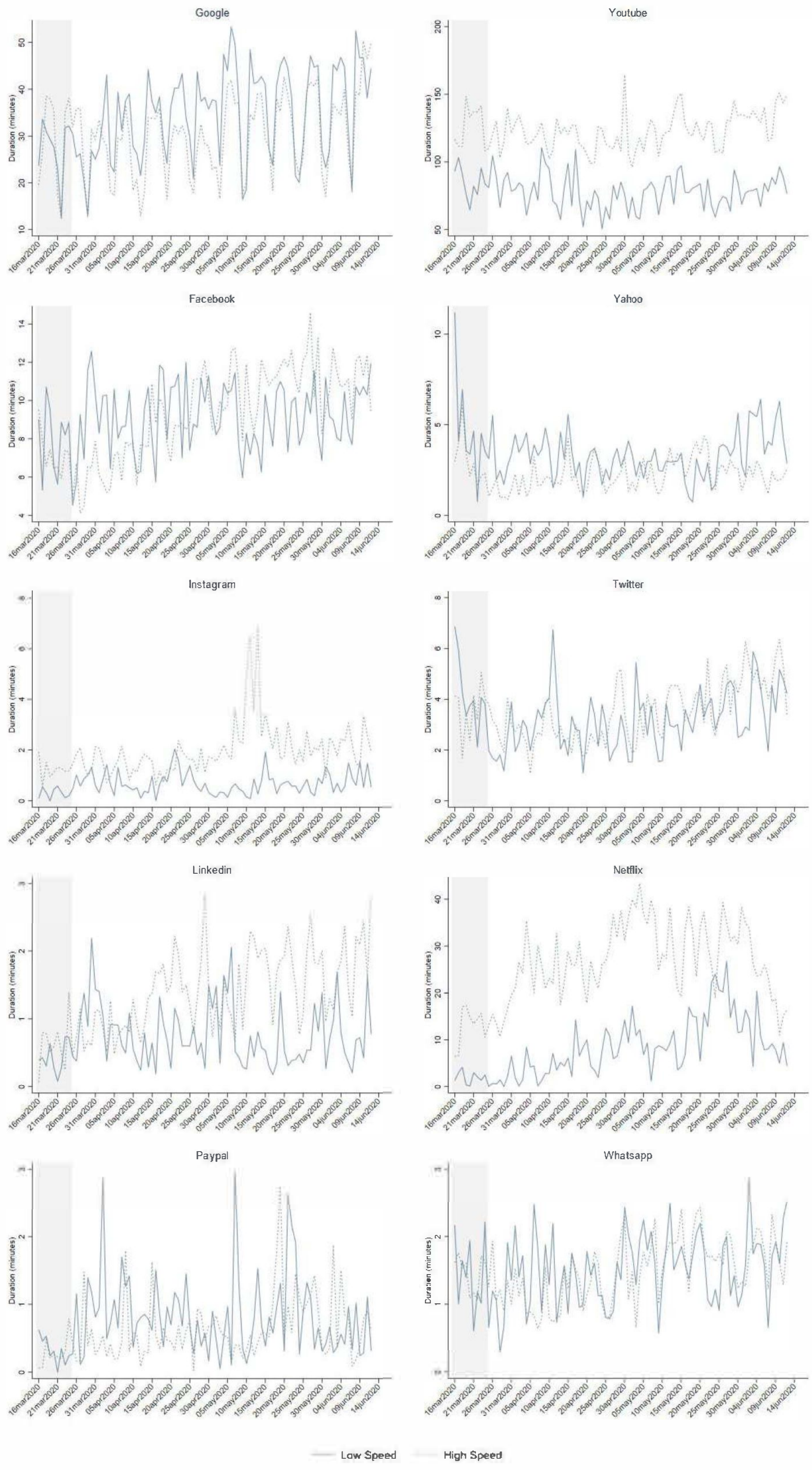
Notes: Figures show a word cloud visualization of frequently visited domains. The size of the words is determined by the number of visits, so larger words are more frequently browsed. The unit of observation is a user-day-url.

Figure 3. Average Daily Time on Top Domains by Gender



Notes: Figures show average daily browsing time on top domains by gender. The grey-shaded area indicates the pre-lockdown period. Outcomes are reported in minutes. The unit of observation is a user-day.

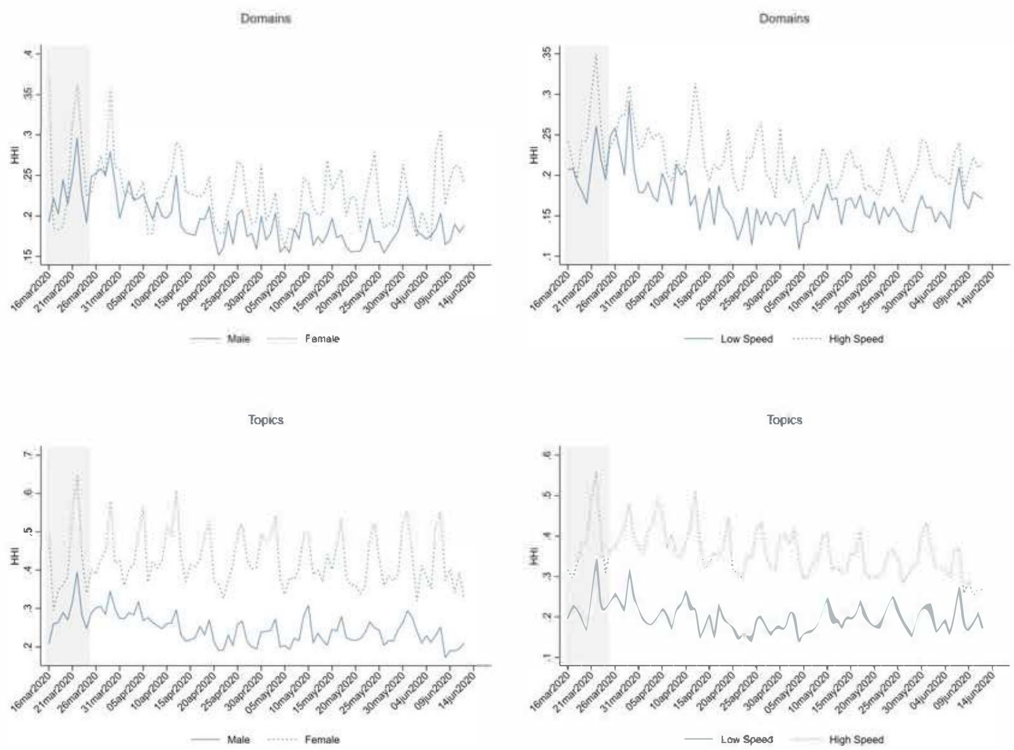
Figure 4. Average Daily Time on Top Domains by Broadband Speed



Notes: Figures show average daily browsing time on top domains by broadband speed area. High-speed areas comprise Nairobi and Mombasa. The grey-shaded area indicates the pre-lockdown period. Outcomes are reported in minutes. The unit of observation is a user-day.

Figure 5. Trend in Concentration Measures of Internet Domains and Topics

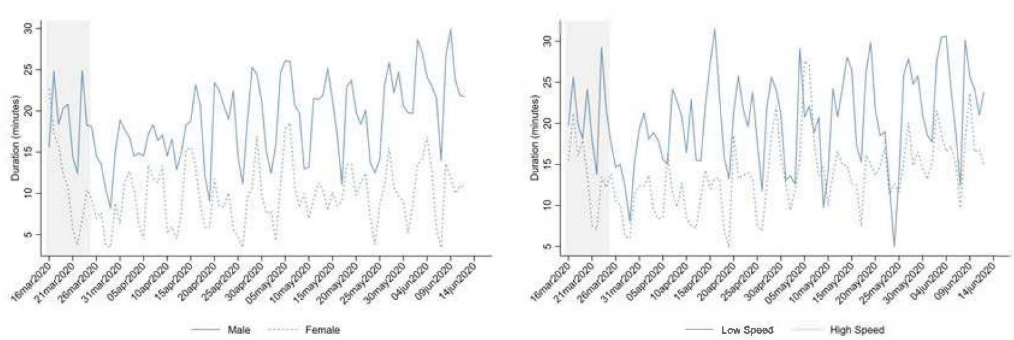
(a) by Gender (b) by Broadband Speed



Notes: Figure shows concentration measures of daily browsing activities with respect to domains and topics. We measure concentration using the Herfindahl-Hirschman Index (HHI). A higher value of HHI indicates a convergent browsing mode. The unit of observation in (a) is a gender-day, while in (b) the unit of observation is the broadband speed area-day. The grey-shaded area indicates the pre-lockdown period.

Figure 6. Average Daily Internet Browsing Time in Kenyan Top-level Domains

(a) By Gender (b) By Broadband Speed



Notes: Figure 6(a) shows average daily browsing time in kenyan top-level domains by gender. Figure 6(b) shows average daily browsing time in kenyan top-level domains by broadband speed area. Kenyan top-level domains comprise domain name extensions like .ke, kenya.com, kenya.org, and kenya.net. High-speed areas comprise Nairobi and Mombasa. The grey-shaded area indicates the pre-lockdown period. Outcomes are reported in minutes. The unit of observation is a user-day.

Table 1. Demographic Statistics

		Gender			Broadband Speed		
	All	Female	Male	diff.	High-Speed	Low-speed	diff
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	0.31				0.32	0.28	-0.035
Age	31.06	29.72	31.61	1.890*	31.55	30.21	-1.343
College	0.86	0.86	0.87	0.002	0.86	0.86	-0.003
Ethnic minority	0.19	0.18	0.19	0.013	0.18	0.21	0.031
Christian	0.89	0.91	0.89	-0.018	0.89	0.89	-0.006
Single	0.40	0.56	0.33	-0.231***	0.44	0.34	-0.104
Nairobi	0.59	0.60	0.58	-0.024			
Number of children up to 18 y.o. at home	1.24	1.11	1.29	0.175	1.18	1.35	0.179
Other dependent at home	0.33	0.36	0.32	-0.045	0.30	0.38	0.070
Employed	0.70	0.61	0.73	0.114	0.69	0.71	0.017
Working full-time	0.53	0.54	0.53	-0.017	0.54	0.50	-0.043
Worked on current job for more than 3 years	0.18	0.15	0.19	0.043	0.18	0.16	-0.021
Essential worker	0.66	0.69	0.65	-0.046	0.64	0.69	0.047
White collar worker	0.27	0.27	0.26	-0.012	0.28	0.24	-0.039
Self-employed	0.20	0.22	0.20	-0.024	0.15	0.28	0.128*

Notes. This table shows summary statistics for our internet users sample comprising 316 individuals between 22 and 54 years old. Survey responses where collected between 11 and 24 of June, 2020. Columns 1-3 and 5-6 present mean values. Columns 4 and 7 present the difference in means. All variables are dummy variables except for Age and Number of children. Ethnic minority respondents were defined to include any group except those belonging to the most populous and politically influential ethnicities: Kikuyu, Luo, Luhya, Kamba and Kalenjin. The mean values for the last five work-related variables in the table are conditional on being employed. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2. Effects of the Lockdown on Household Production Time and Self-investment

	Hours managing household	Hours on child-related activities	Hours taking care of dependent	Self-investment activities
	(1)	(2)	(3)	(4)
Panel A. Gender				
Lockdown × Female	0.472	-0.047	-0.230	0.181**
	(0.343)	(0.402)	(0.734)	(0.078)
Panel B. Broadband Speed				
Lockdown × High Speed	0.037	-0.159	0.691	0.125
	(0.346)	(0.373)	(0.727)	(0.085)
Observations	626	424	206	624
Individuals	313	212	103	312
Post dummy	✓	✓	✓	✓
Individual FEs	✓	✓	✓	✓

Notes. This table shows estimation results of self-reported lockdown effect on variables as indicated in column headers. For columns 1 to 3, we re-scaled the original values reported in hours intervals by choosing the middle value of each interval. Self-investment, in column 4, is a dummy variable taking value 1 if the respondent indicated having done self-investment activities (such as taking a course, teaching yourself a new skill, etc.) frequently or very frequently, and 0 otherwise. Standard errors, shown in parentheses, are clustered at the individual level. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3. Effects of the Lockdown on Cross-group Gaps in Total Browsing Time

	Dependent Variable: Total browsing time					
	Level	Log	Level	Log	Level	Log
	(1)	(2)	(3)	(4)	(5)	(6)
Lockdown	41.336***	0.151**				
	(9.386)	(0.076)				
Lockdown × Female			18.015	0.026		
			(22.140)	(0.175)		
Lockdown × High Speed					3.745	-0.191
					(18.959)	(0.160)
Observations	27714	27714	27428	27428	27701	27701
Individuals	316	316	313	313	316	316
Day FEs			✓	✓	✓	✓
Individual FEs	✓	✓	✓	✓	✓	✓
Day-of-week FEs	✓	✓	✓	✓	✓	✓

Notes. This table shows estimation results of lockdown effect on gender and broadband area gaps. The outcome variable is the total browsing time. The unit of observation is a user-day. Standard errors, shown in parentheses, are clustered at the individual level. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4. Effects of the Lockdown on Cross-group Gaps in Browsing Time by Domain

	Google	Youtube	Facebook	Yahoo	Instagram	Twitter	Linkedin	Netflix	Paypal	Whatsapp
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A. Outcome variable in level										
Lockdown × Female	-5.536	2.191	-0.880	0.028	0.550	-0.278	-0.412	35.964***	-0.235	-0.658
	(4.033)	(11.498)	(1.908)	(0.813)	(0.713)	(0.984)	(0.275)	(12.863)	(0.189)	(0.411)
Panel B. Outcome variable log-transformed										
Lockdown × Female	-0.156	-0.047	0.009	0.012	0.045	-0.025	-0.045	0.462***	-0.018	-0.079
	(0.123)	(0.160)	(0.112)	(0.049)	(0.046)	(0.061)	(0.040)	(0.153)	(0.024)	(0.051)
Panel C. Outcome variable in level										
Lockdown × High Speed	-4.681	4.935	-0.652	0.049	0.951*	1.201	0.550**	9.184	-0.270	-0.024
	(3.114)	(10.178)	(2.066)	(0.688)	(0.567)	(1.462)	(0.234)	(7.703)	(0.233)	(0.281)
Panel D. Outcome variable log-transformed										
Lockdown × High Speed	-0.155	-0.005	-0.031	-0.019	0.032	0.003	0.075**	0.100	-0.004	0.001
	(0.125)	(0.161)	(0.110)	(0.043)	(0.036)	(0.062)	(0.032)	(0.104)	(0.027)	(0.040)
Observations	27699	27699	27699	27699	27701	27701	27699	27701	27701	27701
Individuals	316	316	316	316	316	316	316	316	316	316
Day FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Individual FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes. This table shows estimation results of lockdown effect on browsing time on top domains, as indicated in column headers. The unit of observation is a user-day-domain. Standard errors, shown in parentheses, are clustered at the individual level. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5. Effects of the Lockdown on Cross-group Gaps in Browsing Time by Topic

	Arts & Entertainment	Beauty & Fitness	Computers & Electronics	Email & Messaging	Finance	Games	Health	Jobs & Education	News	Online Communities
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A. Outcome variable in level										
Lockdown × Female	34.236*	2.019	-2.940	-2.306	-3.437*	-1.814	-0.324*	0.754	2.321*	-1.538
	(19.657)	(1.960)	(2.606)	(2.163)	(2.078)	(2.332)	(0.189)	(2.058)	(1.288)	(2.636)
Panel B. Outcome variable log-transformed										
Lockdown × Female	0.158	0.016	-0.065	-0.088	-0.024	-0.052	-0.052*	-0.027	0.105	-0.016
	(0.198)	(0.013)	(0.087)	(0.115)	(0.062)	(0.061)	(0.031)	(0.099)	(0.067)	(0.125)
Panel C. Outcome variable in level										
Lockdown × High Speed	10.548	-1.637	-0.638	-4.078**	-0.015	0.909	0.085	-2.787	0.577	2.979
	(14.769)	(1.531)	(2.502)	(1.710)	(2.156)	(3.393)	(0.242)	(2.533)	(1.885)	(2.903)
Panel D. Outcome variable log-transformed										
Lockdown × High Speed	-0.094	-0.011	-0.138*	-0.171*	-0.037	0.005	0.014	-0.181*	0.038	0.022
	(0.184)	(0.010)	(0.079)	(0.103)	(0.058)	(0.067)	(0.035)	(0.099)	(0.080)	(0.122)
Observations	27701	27701	27701	27701	27701	27701	27701	27701	27701	27701
Individuals	316	316	316	316	316	316	316	316	316	316
Day FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Individual FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes. This table shows estimation results of lockdown effect on browsing time on a sub-sample of topics, as indicated in column headers. The unit of observation is a user-day-topic. Standard errors, shown in parentheses, are clustered at the individual level. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6. Lockdown Effects on Cross-group Gaps in Browsing Concentration

	Gender		Broadband Speed	
	HHI (domains)	HHI (topics)	HHI (domains)	HHI (topics)
	(1)	(2)	(3)	(4)
Lockdown × Female	0.013***	0.029***		
	(0.000)	(0.000)		
Lockdown × High Speed			0.012***	-0.001***
			(0.000)	(0.000)
Observations	204	204	202	202

Notes. This table shows estimation results of the lockdown effect on domain and topic concentration indices. The unit of observation for HHI is a subgroup-day. Estimations for HHI control for date fixed effects and subgroup fixed effects. Robust standard errors are shown in parentheses. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7. Effects of the Lockdown on Cross-group Domain and Topic Similarity Indices

	Gender				Broadband Speed			
	Domains		Topics		Domains		Topics	
	Jaccard	Jaccard (weighted)	Jaccard	Jaccard (weighted)	Jaccard	Jaccard (weighted)	Jaccard	Jaccard (weighted)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lockdown	0.119***	0.040**	0.065*	0.032	0.104***	-0.022	0.022	-0.025
	(0.033)	(0.018)	(0.037)	(0.024)	(0.035)	(0.026)	(0.050)	(0.032)
Observations	103	102	103	102	103	101	103	101

Notes. This table shows estimation results of the lockdown effect on domain and topic similarity indices between subgroup pairs in the sample. The unit of observation is a day. Robust standard errors are shown in parentheses. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8. Effect of Lockdown on Browsing Time in Kenyan Top-Level Domains

	Level	Log	Level	Log	Level	Log	Level	Log
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lockdown	0.550	0.108**						
	(1.999)	(0.050)						
Lockdown × Kenyan TLD			-21.331**	-0.028	-23.938**	-0.029	-21.014	-0.007
			(10.047)	(0.087)	(11.772)	(0.108)	(14.886)	(0.145)
Lockdown × Kenyan TLD × Female					7.548	0.012		
					(22.747)	(0.184)		
Lockdown × Kenyan TLD × High Speed							1.922	-0.018
							(19.972)	(0.181)
Observations	27714	27714	55428	55428	54882	54882	55428	55428
Individuals	316	316	316	316	313	313	316	316
Day FEs			✓	✓	✓	✓	✓	✓
Individual FEs	✓	✓	✓	✓	✓	✓	✓	✓
Day-of-week FEs	✓	✓	✓	✓	✓	✓	✓	✓
Kenyan TLD dummy			✓	✓	✓	✓	✓	✓
Lockdown × Kenyan TLD					✓	✓	✓	✓
Lockdown × Female					✓	✓	✓	✓
Kenyan TLD × Female					✓	✓	✓	✓

Notes. This table reports changes on browsing time in Kenyan top-level domains during lockdown for the whose sample and for different sub-populations. The unit of observation is a user-day-domain type. Kenyan top-level domains comprise domain name extensions like .ke, kenya.com, kenya.org, and kenya.net. Standard errors, shown in parentheses, are clustered at the individual level. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

APPENDIX

Table 1A. Browser Activity

		Gender			Broadband Speed		
	All	Female	Male	diff.	High-Speed	Low-speed	diff
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Total duration	273.57	305.52	261.45	-44.063***	296.82	233.81	-63.009***
Domains							
Google	32.15	30.70	32.82	2.116**	30.87	34.33	3.457***
Youtube	105.95	126.14	97.89	-28.255***	122.77	77.15	-45.617***
Facebook	9.14	5.59	10.85	5.254***	9.28	8.90	-0.383
Yahoo	2.61	1.63	3.09	1.461***	2.23	3.27	1.045***
Instagram	1.46	1.74	1.36	-0.387**	1.92	0.68	-1.244***
Twitter	3.35	1.29	4.32	3.023***	3.46	3.16	-0.299
Linkedin	1.14	0.84	1.29	0.457***	1.37	0.75	-0.618***
Netflix	19.19	46.55	7.16	-39.396***	25.66	8.13	-17.528***
Paypal	0.67	0.64	0.69	0.053	0.62	0.77	0.155*
Whatsapp	1.53	1.40	1.61	0.206**	1.55	1.51	-0.036
Topics							
Arts & Entertainment	141.39	194.37	119.05	-75.320***	169.80	92.82	-76.984***
Beauty & Fitness	1.11	3.54	0.04	-3.505***	0.05	2.93	2.879***
Computers & Electronics	9.83	11.65	9.10	-2.548***	10.37	8.91	-1.456***
Email & Messaging	20.16	17.25	21.50	4.255***	18.89	22.33	3.442***
Finance	4.97	3.24	5.82	2.583***	4.61	5.59	0.983*
Games	3.55	0.91	4.79	3.874***	3.33	3.93	0.608*
Health	1.56	0.68	1.98	1.298***	0.44	3.47	3.037***
Jobs & Education	12.17	9.54	13.32	3.779***	11.04	14.10	3.062***
News	3.94	2.01	4.85	2.846***	3.30	5.03	1.735***
Online Communities	17.48	11.67	20.32	8.653***	18.82	15.19	-3.634***
Domain Concentration and Similarity Indices							
HHI		0.24	0.21	-0.033***	0.22	0.18	-0.041***
Jaccard		0.44			0.48		
Jaccard (weighted)		0.19			0.21		
Topic Concentration and Similarity Indices							
HHI		0.43	0.25	-0.176***	0.35	0.21	-0.142***
Jaccard		0.81			0.85		
Jaccard (weighted)		0.22			0.25		
Kenyan top-level domains	15.96	9.46	18.94	9.478***	13.54	20.12	6.582***

Notes. This table shows summary statistics of our main outcome variables related to browsing activities. Columns report mean values, except for columns 4 and 7 that report difference in means by sub-population. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.