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GIRLS' NIGHT IN? EFFECTS OF THE KENYAN COVID-19 LOCKDOWN ON WEB BROWSING

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ABSTRACT

We present the first objective evidence on how COVID-19 lockdowns affected internet browser usage in Africa, using detailed digital trace data on PC-based and mobile-based browsing patterns of 316 Kenyans who had access to a PC, covering the period before and during Kenya’s first national COVID-19 curfew that was declared on March 25, 2020. We find that total daily browser usage increased by 41 minutes, or 15 percent of average browsing time, after the curfew started. We find no significant differences in total browsing time during the curfew by gender or by residence in high-speed vs. low-speed broadband access areas. However, we do find gender differences in the content of browsing. Women’s time on YouTube and Netflix exceeded men’s from the start of our sample period, and the gender gap in Netflix browsing increased by 36 minutes daily, corresponding to almost twice the average daily Netflix time in the sample. Men’s browsing became less concentrated during the curfew, across both domains and topics, but women’s did not. The degree of overlap in browsing between men and women also increased, likely due to men visiting sites that were previously exclusively visited by women. Across the entire sample, browsing of Kenyan domains dropped significantly relative to that of non-Kenyan domains, indicating greater reliance on international content during this period of economic and social upheaval.

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1 Introduction

This paper studies the impact of the Kenyan COVID-19 lockdown on the total time that Kenyans devoted to internet browsing, and on changes in the distribution of internet content consumption between sub-populations and across web domains and topic areas. We do this by studying daily changes in browsing around the time of the March 25, 2020 declaration of the national "dusk-to-dawn" curfew, which was a key component of the containment and closure policies that comprised the Kenyan COVID-19 lockdown.[1]

Outside of pandemic policy, curfews have commonly been used in Kenya, principally as a means of maintaining civic order during episodes of terrorist attacks and civil violence – especially right before and after national elections. See, for example, McVeigh (2008) on the 2007-2008 Kenyan crisis following the December 2007 election; the UN Office for the Coordination of Humanitarian Affairs on the run-up to the 2013 election (OCHA, 2013); and Richardson (2017) on the response to violent attacks attributed to religious fundamentalists. We study the introduction of the curfew as a significant and sudden exogenous shock that increased the value of internet connectivity and digital activity. This differs from typical changes in Internet user behavior that transpire gradually and extend over long time periods. In the case of pandemic lockdowns, shifts in internet demand unfolded within a matter of weeks, with little to no room for short-run supply-side responses from the telecommunications industry and network operators.

We examine the curfew shock using novel data that combines survey responses from 316 Kenyans with their individual 90-day internet browser histories on PCs or mobile devices, ranging between March 14 and June 23, 2020. The browser records cover over 3.9 million unique website visits and provide a detailed and objective record of time use that is not only free from intentional misreporting or recall bias, but is also 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 that explore how pandemic policy affected digital divides in internet use. 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.

Our data provide a unique view on how people in Kenya responded to the increased value of internet access during COVID-19 lockdowns. The onset of the pandemic in early 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 examined some 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

[1] The lockdown provisions were gradually relaxed starting in July 2020, but most, including the curfew, remained in place for the next 18 months (Reuters, 2021). The curfew was enforced strictly, and Kenyan police were criticised for their heavy-handed and "brutal" approach (Human Rights Watch, 2020; Namu & Riley, 2020).

Tucker, 2020; Adams-Prassl, Boneva, Golin, and Rauh 2020). An important exception is Miller, Ramdas, and Sungu (2021), who study digital activity before and during the Indian lockdown. We are not aware of any prior studies on how the pandemic affected internet use in an African context.

Early studies of information and communication technologies in Africa measured the effects 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., Blumenstock, Cadamuro, and On 2015; Jack and Suri 2014). More recent research in Africa has examined the impact of expanded internet access on outcomes including employment and political mobilization (Hjort & Poulsen, 2019; Manacorda & Tesei, 2020), but researchers have been constrained by limited data availability on internet use. Data on time use have been gathered in Africa via mobile phone surveys before COVID-19 (Hoogeveen, Croke, Dabalen, Demombynes, & Giugale, 2014), but even phone-based data collection efforts suffered in many countries during COVID-19 lockdowns. Pandemic lockdowns hampered data collection even in developed nations, and the American Time Use Survey was suspended between March 19 and May 11, 2020.[2] Barriers to data collection were even greater in the developing world (Miller et al., 2021), making our detailed panel of digital time use during the lockdown even more unusual.

The first contribution of this paper is that it uses primary data on a sample of individuals in Kenya, observed during a period that spans the start of the COVID-19 national curfew, to document objectively measured changes in the levels and nature of internet activity. Consistent with expectations, we find significant increases in time online during the curfew, even relative to the immediately preceding time period, which followed the WHO pandemic declaration on March 11, 2020 and included the introduction of other lockdown measures in Kenya.

This study also contributes by examining the differential effects of the COVID-19 curfew shock on the internet activity of potentially disadvantaged groups. This allows us to comment on whether the increased demand for different online content amplified or diminished existing disparities. We consider two dimensions of potential disadvantage highlighted in prior policy and academic work related to the digital divide and pandemic lockdowns.

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 consider the Kenyan social context in which our analysis is conducted, which includes significant gender disparities. 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".[3] 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

[2] See https://www.bls.gov/tus/notices/2021/covid19.htm.

[3] The ranking is from least to greatest level of inequality. See https://hdr.undp.org/data-center/specific-country-data#/countries/KEN

71%, respectively. This is reflected in our sample too, with employment rates of 72% and 61% for men and women, respectively.

Despite this similarity, Table 1 shows that our sample of men and women who have access to an internet-connected PC (a prerequisite for participating in the study) is clearly not representative of the broader population, as 86 percent are college-educated. The female share in our sample is also 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) (Kenya National Bureau of Statistics, 2019a).[4]

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 curfew. Indeed, one motivation for our focus on gender is the widely expressed global concern that pandemic lockdown policies would impose particularly severe burdens on women (Alon, Doepke, Olmstead-Rumsey, & Tertilt, 2020; Burki, 2020; United Nations, 2020a), including in Kenya (Williams et al., 2022).

The second dimension of potential disparity that we investigate is 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 and mobile broadband speeds (which are Nairobi and Mombasa) and the rest of the country, according to the Speedtest.net speed checker.[5] It is not surprising that Nairobi, the capital city, has higher speed internet. Mombasa's higher speed may derive from that city being the site of all sub-sea cable landings (five by March 2020) in the country, as these play a critical role for fiber optic networks and carrying bandwidth inland, particularly to Nairobi.

An extensive prior literature has demonstrated the importance of internet connection speeds, in terms of value to consumers (Nevo, Turner, & Williams, 2016) as well as a range of economic (Akerman, Gaarder, & Mogstad, 2015; D'Andrea & Limodio, 2023; Forman, Goldfarb, & Greenstein, 2012, 2021; Goldfarb & Prince, 2008), social (Amaral-Garcia, Nardotto, Propper, & Valletti, 2021; Bhuller, Havnes, Leuven, & Mogstad, 2013), and political outcomes (Gavazza, Nardotto, & Valletti, 2019). Unlike prior literature focused on the impact of increased broadband access that exploits supply shocks triggered by technological investment, we consider local supply conditions to be fixed and instead study the differential impact of a demand shock across different areas. In that way, we most closely resemble Chiou and Tucker (2020), who document higher rates of compliance with COVID-19 stay-at-home orders among people with higher internet speeds in the US. Our analysis of internet browsing patterns

[4]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 (Kenya National Bureau of Statistics, 2019a). The low rate of computer access in rural areas is also reflected in the largely urban composition of our sample.

[5]See https://www.speedtest.net/global-index/kenya. Table TA1 in the Online Appendix reports average mobile broadband speeds for major cities in Kenya, along with each city's representation in our sample. Download speeds were on average (weighted by sample presence) 82 percent faster, and upload speeds were 54 percent faster, in our designated "high speed" locations.

goes beyond looking at the total quantity of data flows (Nevo et al., 2016), to focus on the content browsed. This is important because 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 curfew, 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 curfew on women (compared to men) and people with high speed (relative to low speed) broadband. Before delving into differentiated effects by gender, we note that in our sample women spent significantly more time online than did men, throughout the sample period. We find no significant relative changes in the total amount of browsing time between either pair of subgroups, but we do find some significant changes by gender in the content consumed. Our most striking finding is a substantial relative increase in women's time on Netflix – of over 35 minutes per day per person, which is nearly twice the sample average daily Netflix time.

The enormous shift in Netflix usage by women during the curfew 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 spent on health-related browsing. For the split by broadband speed, we find a relative increase in time on LinkedIn for people with faster broadband speeds, 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 time spent browsing top domains and topic areas, we next examine changes in the variety of content that people browsed each day, using the Herfindahl-Hirschman Index (HHI) as a measure of concentration, either across domains or across topics. We examine overall trends in the sample as well as differential changes by gender and broadband speed. We find a significant decrease in browsing concentration across both domains and topics, overall, and a similarly-sized relative increase in concentration for women. We find no significant relative changes in concentration between high-speed and low-speed areas. The increase in diversity of men's browsing, potentially coming from their starting to browse websites previously visited exclusively by women, is also associated with a convergence in the sets of domains and topics visited by men and women during the curfew, as measured by the Jaccard Index.

Finally, we consider how the COVID-19 curfew 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 on 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 COVID-19 lockdowns impacted browser usage in Africa, using an elite sample in Kenya. While our sample represents a small slice of Kenyan society, it constitutes 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 (Kenya National Bureau of Statistics, 2019a, Table 2.36). Reported internet usage among the population aged 3 and above was 22.6%, with the proportion rising to 42.5% in urban areas (Kenya National Bureau of Statistics, 2019a, 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 (Statista, 2022a).

2 Data, Sample and Empirical Approach

2.1 Browser Data Collection and Survey Design

We partnered with *PY Insights* and *Dynata* to field this study, using a method identical to that of Miller et al. (2021). Individuals from Dynata's marketing pools in Kenya were invited to participate in an online survey. The survey concluded with participants consenting to upload their browser data using *PY Insights* software. *PY Insights* uses a browser extension technology that captures retrospective data stored in the user's browser account history.[6] We essentially collect this internally saved data which is, effectively, the 'history' section of respondents' internet browsers. Once the data transfer process is completed, the *PY Insights* extension is automatically deleted and respondents are redirected back to the survey platform.

Note that although participants log into the study via a browser of their choice (e.g., Chrome or Firefox) from their personal computers, we observe their past browsing activities from multiple devices (e.g., tablet or smartphone), subject to some restrictions listed below. As an inbuilt functionality, browser apps connect a user's past activity from multiple devices 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 or private mode, as this activity is not saved on devices. Incognito mode is primarily used when using a public device or a borrowed computer, which is not our context. When using personal computers, internet users only switch to private browsing to complete a specific task (e.g., accessing a service that requires a login or consumption of adult content), and it is estimated that this type of browsing accounts for less than 4% of website visits (Habib et al., 2018).

The records encompass the respondent's browsing activity for a period of up to the prior 90 days, and include page URLs, web domains, time stamps, and page titles – which contain textual information about the URL such as the title of a Netflix movie or a Google search phrase. *PY Insights* utilizes this information to calculate the duration

[6] 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).

of each visit in seconds. A visit starts at the time of the click and then ends when another page is clicked from the same device, or after a period of inactivity. (This period of inactivity is web-domain specific – e.g., longer for video streaming websites). Importantly, *PY Insights* informed us that they validated their duration measurement approach on a hold-out sample, and were able to predict the true duration (measured via a time counter used for the purpose of their testing) with over 90 percent accuracy within minute-level precision.

Additionally, *PY Insights* employs a categorization scheme based on Google Cloud Platform's natural language processing algorithm to classify each website domain – implemented on the textual data of browsing history titles – into specific topics.[7] The data we collected via *PY Insights* thus includes the duration in seconds of each URL visit and the corresponding category of each site visited.

The study recruited 316 individuals, aged between 22 and 54 in Kenya, who had at least 30 days of browsing history data. Participants with valid survey data and a minimum of 30 days of uploaded browsing activity were compensated a fixed amount. 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 also omit from the analyses of gender gaps the three respondents (0.1% of our sample) who reported no information about their gender, leading to a sample size of 313.

We supplemented participants' browser history data with data from an online survey. Completing the survey required about 30 minutes of time, on average, from participants. 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 Period and Lockdown Policies

Our survey responses were collected between June 11 and 24, 2020, leading to a final sample period of browsing data from March 14 to June 23, 2020. We note that our entire sample period takes place after the WHO's declaration on March 11 of COVID-19 as a pandemic. This means that we are not able to observe browsing data before the pandemic announcement itself and are instead only able to study the incremental change associated with the adoption of the curfew policy on March 25, 2020.

We also note that the curfew was itself part of a broad-based set of policies comprising the Kenyan COVID-19 lockdown. The curfew is our empirical focus in this paper because of its severity and relatively later adoption date in our sample period. Because we use the timing of the curfew for our treatment, we describe our estimates in terms of the curfew while noting that we are limited in our ability to empirically isolate the impact of the curfew from other components of Kenyan COVID-19 lockdown provisions that were adopted around the same time, such as the international

[7] A complete list of topics is at https://cloud.google.com/natural-language/docs/categories.

travel ban that started on March 25 or the closure of schools and non-essential workplaces a few days earlier.[8] We consider it plausible that the effects of these other lockdown policies contribute to the changes we associate empirically with the curfew, in which case our estimates should be interpreted broadly as the impact of increasing the strictness of the lockdown, rather than narrowly as the impact of a curfew.[9]

The evolving strictness of the Kenyan lockdown is perhaps best measured by the Government Response Stringency Index, a composite measure based on 9 response indicators and scaled from 0-100, where 100 is the strictest response (McDade et al., 2020).[10] After Kenya's first case of the novel coronavirus was identified on March 12, 2020, the stringency index for the country jumped to 36.1 on March 13 and then 50.9 on March 15, gradually increasing to 68.5 shortly before the curfew announcement date, after which it jumped again to 87.0 by March 27, reaching a peak of 88.9 in April. The stringency of lockdown policies in Kenya in our sample period was comparable to stringency levels recorded in high-income countries (e.g., the UK peaked at 79.6 in that period, the US at 72.7, Italy at 93.5, and Singapore at 82.4) and countries in the Global South (e.g., India reached 100 and China peaked at 81.0). Despite the relatively low counts of confirmed cases (6,366 by the end of June 2020) and deaths (148) in the country (Hale et al., 2021), the Kenyan restrictions were maintained over several months and only relaxed after our sample period, starting in July 2020 (Reuters, 2021).

2.3 Sample Characteristics

Table 1 provides summary statistics for our full sample and for each of our subpopulations of interest. Column 1 shows that our sample was relatively young (mean age 31) and highly educated – 86% had a college education, relative to only 3.5% in the broader Kenyan population (Statista, 2020). The high education level is not surprising given that our data collection was restricted to Kenyans who owned an internet-connected PC they could use during the lockdown – PC-owners comprised only 3% of Kenya's population of 54 million in 2020 (Statista, 2022b).

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 population, according to Kenya National Bureau of Statistics 2019b).

In our select sample, we see no significant differences by gender in ethnic minority status or percent with a college education (see columns 2 and 3), quite different from the national demographic, where men significantly outnumber women both in completed university degrees as well as in current university enrollment (Kenya National Bureau of Statistics, 2019a). 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

[8]Kenyan COVID-19 lockdown policies also closed the borders with neighbouring countries; limited non-essential domestic movement into and out of the major cities; and banned all public gatherings, such as political rallies (McDade et al., 2020).

[9]This interpretation is supported empirically in our robustness analysis, which confirms the main findings after replacing the curfew indicator with a lockdown stringency index (described in the next paragraph) as our main explanatory variable. Our results are also robust to defining the curfew period as starting on March 27, when it went into effect. See Tables TA2 to TA7 in the Online Appendix for full results.

[10]The data are available by date and country at https://ourworldindata.org/covid-stringency-index.

Table 1 Demographic Summary Statistics

		Gender			Broadband Speed		
	All	Female	Male	diff.	High	Low	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	–	–	–
Has child	0.58	0.52	0.60	0.082	0.55	0.64	0.092
Other dependent	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
Tenured	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	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 were collected between June 11 and 24, 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*. 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. For columns 4 and 7, statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

find little variation in demographics between high-speed and low-speed broadband areas (see columns 5 and 6). The main exception is that among people in low-speed – possibly rural – areas, a smaller share of individuals in our sample is single, and almost twice as many are self-employed.

2.4 Empirical Approach

Our empirical analysis is focused on assessing how digital activity changed during the curfew period of our sample (from March 25 to June 23, 2020) compared to the sample period immediately preceding the curfew (from March 14 to 24, 2020).[11] We start with an individual level model, where the unit of observation is a person-day, and estimate a simple regression model that compares the curfew and pre-curfew periods:

$$Outcome_{it} = \alpha\ Curfew_t + \lambda_i + \omega_d + \varepsilon_{it} \tag{1}$$

The dummy variable $Curfew_t$ equals 1 for any date t after the adoption of the curfew, and 0 otherwise. λ_i is a set of individual fixed effects that account for the dispersion in the dates of data collection, which (because of the 90-day look-back window) causes

[11] Results are robust to defining the curfew period as starting on March 27, when it went into effect, or to using the lockdown stringency index instead. See Tables TA2 to TA7 in the Online Appendix.

variation in the start date of individuals and an unbalanced panel. ω_d is a set of fixed effects for 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 curfew was a shock to browsing activity that affected the entire population. To the extent that the exact timing was exogenous, α can be interpreted as the impact of the curfew, under the assumption that our browsing outcomes would have been stable within our narrow time period if not for the curfew.

Our analysis of sub-group differences goes beyond this before/after comparison to study changing variation within the sample over time. We use survey information on demographics to split the sample by gender and by broadband internet speeds and estimate differential changes in browsing during the curfew by sub-population. The model includes two-way fixed effects for individuals and dates:

$$Outcome_{it} = \beta \; Curfew_t \times Subgroup_i + \lambda_i + \tau_t + \varepsilon_{it} \tag{2}$$

The dummy variable $Curfew_t$ again equals 1 for any date t after the adoption of the curfew, 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 ω_d are replaced with τ_t, a set of date fixed effects. ε_{it} is the error term, clustered at the individual level.

The differential change in the outcome variable during the curfew, captured in the β coefficient, can be interpreted as the effect of the curfew on the relevant group difference under the assumption that the two sub-groups would have experienced parallel (though not necessarily flat) trends in the outcome over the horizon of the sample period, had the curfew not occurred. This is a weaker assumption than is needed to interpret α from Equation 1 as causal. Unfortunately, we are unable to rigorously examine either assumption empirically in our sample because we have only limited data (up to 10 days per person) before the curfew started and no data after it ended.[12]

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 each of the 10 major web domains in our sample and each of the 10 largest topic areas.[13] Additionally, we use the Herfindahl-Hirschman Index (HHI) to create daily measures of concentration at the level of web domains or topical areas and estimate Equation 2 using the individual-day level HHI measure as the outcome.

[12]We did conduct an exploratory analysis to test if browsing trends were smooth and constant over our sample period by using the Chow test for structural breaks. Although the test does not reject the null hypothesis of no structural break on the exact day of the national curfew announcement (March 25, 2020), it does detect a significant break a week later, on the 1st of April, with an F-test of 13.92, significant at a 1% level. This supports a change in trend associated with the curfew and likely in response to it and related lockdown policies. The lack of an immediate response on the curfew announcement day is consistent with a brief transition period in which people adjusted to the situation and adopted new browsing habits, as well as with the increasing severity of lockdown rules and enforcement after the initial curfew announcement.

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

We also examine a market-level aggregate measure of 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 is a measure between 0 and 1 that quantifies the degree of overlap between two sample sets. In our case, the sets are defined by demographics (gender, broadband speed). The higher the index, the more similar the two sets are deemed to be. In Equation 2 above, we compare domains (or topics) in each set, here referred to as M and F, to see which are shared and which are unique to each of the two 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 with the total number of unique categories, 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 elements (i.e., individuals) belonging to sets M and F, respectively, on the domain (topic) i.

Finally, we examine 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. We first estimate Equation 1 using a limited measure of browsing time only on local Kenyan domains as our outcome of interest. We then compare the changes in browsing time devoted to Kenyan and international domains by estimating an expanded version of Equation 1 of the form:

$$Outcome_{itk} = \gamma\ Curfew_t \times Local_k + \lambda_i + \tau_t + \eta_k + \varepsilon_{it} \tag{5}$$

This model is estimated on a transformed version of the data-set that contains two observations per person-day (for Kenyan and non-Kenyan browsing), where observations are indexed by individual i, date t, and Kenyan or non-Kenyan domains k. The additional fixed effect η_k is for Kenyan top-level domains and the coefficient of interest is γ, which measures the differential change in browsing of Kenyan domains relative to non-Kenyan domains during the curfew. We also estimate an expanded version of Equation 2 to test for differential effects for Kenyan domains across our main sample splits, by gender and broadband speed. This differential is captured by the δ coefficient on the triple-interaction term in the estimation equation:

$$\begin{aligned} Outcome_{itk} = {} & \delta\ Curfew_t \times Local_k \times Subgroup_i + \gamma\ Curfew_t \times Local_k + \\ & \beta\ Curfew_t \times Subgroup_i + \mu\ Subgroup_i \times Local_k + \lambda_i + \tau_t + \eta_k + \varepsilon_{it} \end{aligned} \tag{6}$$

The model also includes controls for the full set of pairwise interactions between subgroup, curfew, and Kenyan domain indicators as well as fixed effects for individuals, dates, and Kenyan domains.

The sample mean values for our individual-level outcome variables are presented in Table TA8 in the Online Appendix, overall and separately by gender and by broadband speed. While overall browsing time is significantly higher for women than for men and for people in high-speed than in low-speed areas, this pattern is not universal across all of the major domains and topic areas. In fact, men spend significantly more time on Google, Facebook, Yahoo, and Twitter, and on all topics other than Arts & Entertainment, Beauty & Fitness, and Computers & Electronics. People in low-speed areas spend slightly more time on Google and Yahoo, but much less time on Youtube and Netflix and in the Arts & Entertainment topic area.

The Jaccard indices are only computed for the full sample and are reported separately for each of the sample splits in Table TA9 in the Online Appendix. Even though each of the topic areas is visited by some people from each of the sub-populations over the course of the full sample period (see Table TA11 in the Online Appendix), it is not the case that every topic is visited by members of every sub-group on every day of the sample period. As a result, the Jaccard index by topic is also less than 1 on many days, and the average unweighted value of the index is 0.82 for gender and 0.87 by broadband speed.

3 Results

3.1 Effects of the Lockdown on Self-Reported Time Use

Before turning to the main analysis of browsing activity, we first briefly summarize the patterns in our survey data. We examine differential changes (by gender or internet speed) in self-reported measures of time use during the lockdown by asking people about current and retrospective (pre-pandemic): 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 the lockdown policies and one (contemporaneous) during the lockdown.

The results in Panel A of Table 2 show that the lockdown was associated with substantial increases in time devoted to home production and self-investment for both men and women. We find no significant differential effects 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 appears to have 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. This has the effect of cutting the significant pre-pandemic gender gap in this outcome almost in half. These results suggest that increasing gender disparities offline are unlikely to produce gender differences in online behavior within our sample.

Table 2 Effects of the Lockdown on Self-Reported Household Production and Self-Investment

	Hours managing household (1)	Hours on child-related activities (2)	Hours caring for dependent (3)	Self-investment activities (4)
Panel A. Gender				
Lockdown × Female	0.472	-0.047	-0.230	0.181**
	(0.343)	(0.403)	(0.736)	(0.079)
Female	0.307	0.518	0.145	-0.089*
	(0.284)	(0.335)	(0.561)	(0.050)
Lockdown	2.164***	1.589***	1.059**	0.319***
	(0.198)	(0.201)	(0.459)	(0.050)
Observations	620	420	206	618
Individuals	310	210	103	309
Panel B. Broadband Speed				
Lockdown × High Speed	0.037	-0.159	0.691	0.125
	(0.346)	(0.373)	(0.729)	(0.085)
High Speed	-0.044	-0.069	-0.604	-0.051
	(0.283)	(0.283)	(0.584)	(0.052)
Lockdown	2.283***	1.667***	0.571	0.295***
	(0.288)	(0.317)	(0.558)	(0.071)
Obs.	626	424	206	624
Individuals	313	212	103	312

Notes. This table shows estimation results of self-reported lockdown effect on variables as indicated in the 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. Sample sizes vary across outcomes because of varying non-response rates and also because only people with children were asked about childcare time and only people with other dependents were asked about time spent caring for them. Standard errors, shown in parentheses, are clustered at the individual level. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

We see from Panel B of Table 2 that the lockdown had no differential impacts by broadband speed on hours spent on managing the household, children or dependents, or time spent on self-improvement activities. This provides helpful 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 Curfew on Digital Time Use

Our first finding from estimating Equation 1 on our browser data is that total internet browsing time increased significantly during the Kenyan curfew. Table 3 shows an average increase of 41 minutes per day (column 1), corresponding to an increase of 0.15 log points (column 2), for the overall sample. The estimation model used to produce these coefficients includes individual fixed effects, to study within-person changes, accounting for the unbalanced panel, and day-of-week fixed effects to account for the strong within-week regular variation in browsing activity, evident in the raw data (e.g., as shown in Figure 1).

Table 3 Effects of the Curfew on Total Browsing Time

	Dependent Variable: Total browsing time					
	Level	Log	Level	Log	Level	Log
	(1)	(2)	(3)	(4)	(5)	(6)
Curfew	41.355***	0.152**				
	(9.386)	(0.076)				
Curfew × Female			18.011	0.025		
			(22.140)	(0.175)		
Curfew × High Speed					3.738	-0.191
					(18.959)	(0.160)
Observations	27699	27699	27426	27426	27699	27699
Individuals	316	316	313	313	316	316
Day FEs			✓	✓	✓	✓
Individual FEs	✓	✓	✓	✓	✓	✓
Day-of-week FEs	✓	✓	✓	✓	✓	✓

Notes. This table shows estimation results of the curfew effect on total browsing time. *Curfew* is a dummy variable that takes value 1 from 25 March 2020 onward, and zero otherwise. The unit of observation is a user-day. Standard errors, shown in parentheses, are clustered at the individual level. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

We present separate estimates by time of day in Panel A of Figure 2, after splitting the sample into 6 equal-duration time bins of 4 hours each. These estimates are also shown in Table TA10 in the Online Appendix, where Panel A matches the Figure and uses the full sample of individuals; Panel B drops observations from specific time bins for people who are never observed browsing during those hours in the data.

The first result of this split is the finding that the largest absolute increase in browsing time occurred late at night, between midnight and 4am, which coincides with (part of) the curfew time. The estimated increase is 11 minutes in the full sample and 14 minutes in the limited sample. We also find a significant increase during other curfew hours, between 8pm and midnight and between 4am and 8am, as well as during the day between 8am and 4pm. The only time period with no significant increase in browsing is the middle afternoon, from 4pm to 8pm. When compared to the average daily browsing times during the different time-of-day bins in Table TA8 in the Online Appendix, the proportional increases during the curfew periods between midnight and 8am are particularly large (39.5 and 43.5 percent, respectively). The significant increases in other time bins are smaller relative to their means, less than 15 percent. This pattern supports the idea that at least some of the effect we document comes from the curfew itself, although other lockdown policies likely contribute as well.[14] When we further

[14]Indeed, we find the same qualitative patterns for our results when we use the lockdown stringency index instead of the curfew announcement as our key explanatory variable. See Tables TA5-TA7 in the Online Appendix.

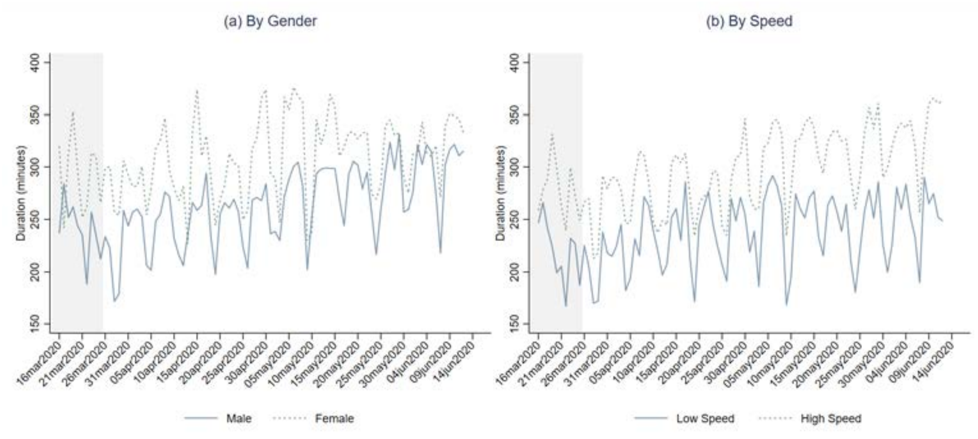

Fig. 1 Average Daily Internet Browsing Time. Fig. 1(a) shows average daily browsing time by gender. Fig. 1(b) shows average daily browsing time by broadband speed area. High-speed areas comprise Nairobi and Mombasa. The grey-shaded area indicates the pre-curfew period. Outcomes are reported in minutes. The unit of observation is a user-day

split the days into weekdays (Panel B of Figure 2) and weekends (Panel C), we find the largest increase is late at night on weekdays and the largest weekend increase is in the early morning hours. This overall pattern is also consistent with the characterization of internet traffic shifts across Europe and the US reported by Feldmann et al. (2021), who observed that traffic increased mainly during nontraditional peak hours.

Our next set of findings comes 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 2.3. 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 men are.

The remaining columns of Table 3 show the insignificant estimates for the interaction term between the curfew 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-curfew levels. As with gender, neither of these estimates is statistically significant.

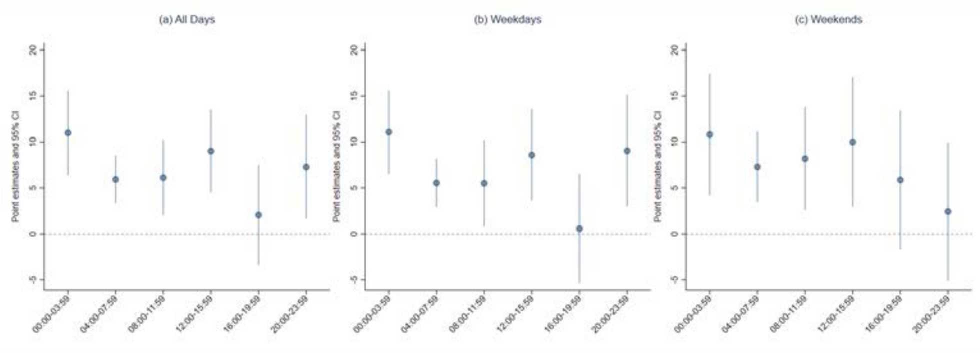

Fig. 2 Curfew Effects on Daily Browsing Time by Time of Day. The figures show coefficients and 95% confidence intervals from regressions of daily browsing time on a curfew dummy for each time of day bin. Each coefficient represents a separate regression. The sample in panel (b) is restricted to weekdays and in panel (c) to weekends. Other controls include user fixed effects and day-of-week fixed effects. Standard errors are clustered at the individual level. The unit of observation is a user-day-time-of-day bin

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. The 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). As context for this analysis, it is useful to note that some topics (Computers & Electronics, Email & Messaging, News, Online Communities) and domains (Google, YouTube, Facebook) have near-universal penetration among sub-groups in our sample, while others are less popular.[15]

[15] See Table TA11 in the Online Appendix for details. It is also notable that Instagram, Twitter, and Netflix are ever visited by about 10 percentage more of the sample in high-speed broadband areas than in low-speed broadband areas. Twitter and LinkedIn are more popular among male users than female users, while the opposite is true for Netflix. The most salient gender differences in topics are in Games, followed by Beauty and Fitness.

Table 4 Effects of the Curfew on Cross-Group Gaps in Browsing Time by Domain

	Google (1)	Youtube (2)	Facebook (3)	Yahoo (4)	Instagram (5)	Twitter (6)	LinkedIn (7)	Netflix (8)	PayPal (9)	WhatsApp (10)
Panel A. Outcome variable in level										
Curfew × 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										
Curfew × 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)
Observations	27426	27426	27426	27426	27426	27426	27426	27426	27426	27426
Individuals	313	313	313	313	313	313	313	313	313	313
Panel C. Outcome variable in level										
Curfew × 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										
Curfew × 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	27699	27699	27699	27699	27699	27699
Individuals	316	316	316	316	316	316	316	316	316	316
Day FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Individual FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes. This table shows estimation results of the curfew effect on browsing time on top domains, as indicated in the column headers. *Curfew* is a dummy variable that takes value 1 from 25 March 2020 onward, and zero otherwise. 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 * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

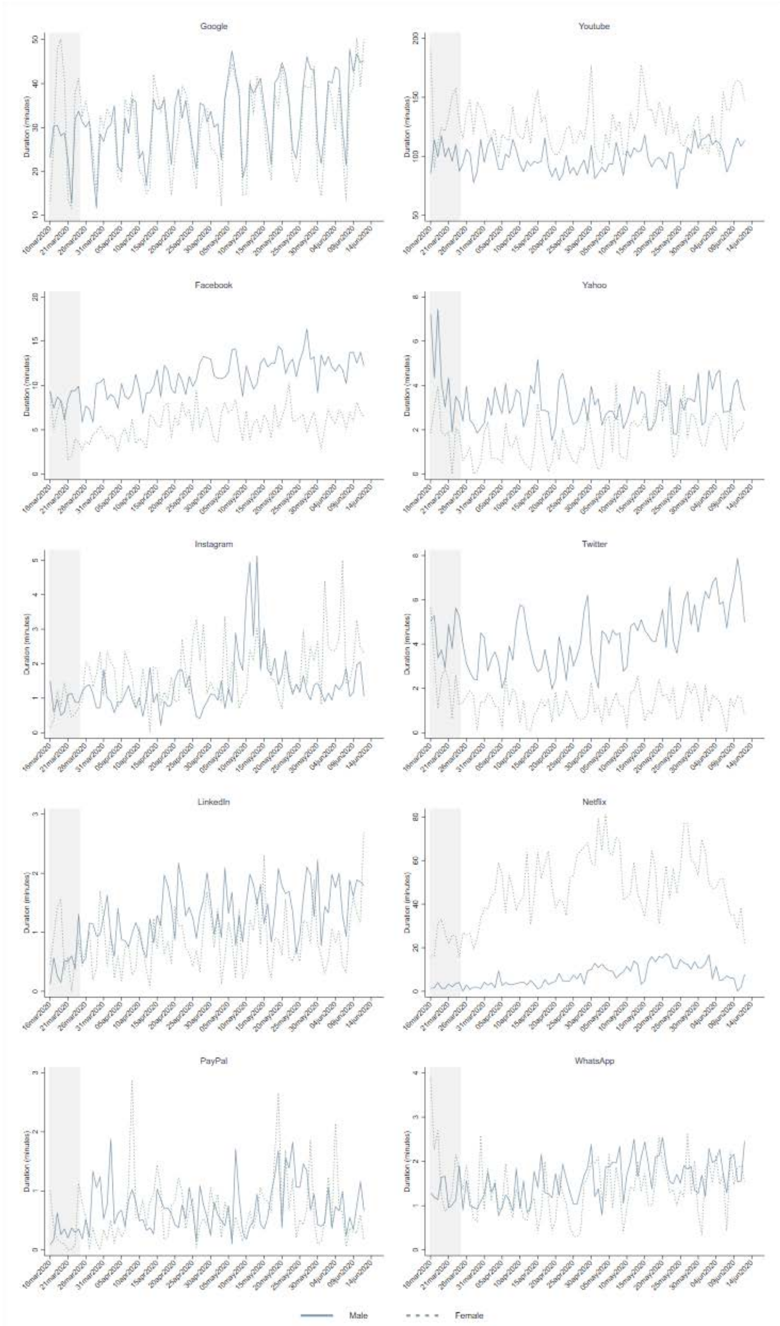

Fig. 3 Average Daily Time on Top Domains by Gender. Figures show average daily browsing time on top domains by gender. The grey-shaded area indicates the pre-curfew period. Outcomes are reported in minutes. The unit of observation is a user-day

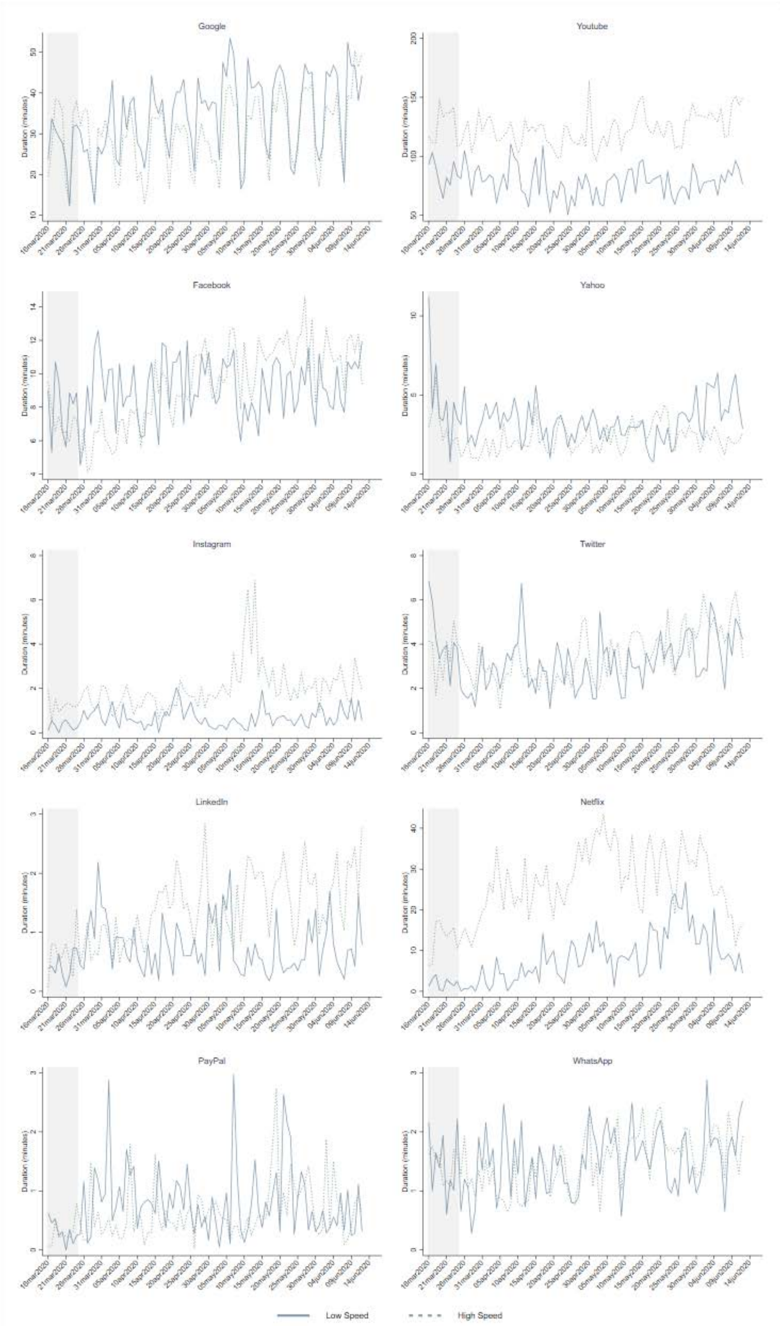

Fig. 4 Average Daily Time on Top Domains by Broadband Speed. Figures show average daily browsing time on top domains by broadband speed area. High-speed areas comprise Nairobi and Mombasa. The grey-shaded area indicates the pre-curfew period. Outcomes are reported in minutes. The unit of observation is a user-day

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 more minutes per day on average than men did during the curfew. 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 magnitude (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, which also presents other persistent gender differences in browsing across domains that were not affected by the curfew. Women spent more time than men on YouTube, but less time on Facebook and Twitter (and, to a lesser degree, Yahoo).

When we divide the sample by broadband speed, we also find some notable differences in time allocation across domains. Consistent with expectations, Figure 4 shows that people in areas with faster connection speeds spend more time on sites with significant video content such as YouTube and Netflix. They also appear to spend more time on LinkedIn and Instagram, particularly during the curfew period. In fact, the only statistically significant differences in browsing across domains that we find in apparent response to the curfew 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 a 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 changes in 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

This section explores how patterns of browser use across domains and topic areas changed during the curfew. We first examine concentration measures for individual browsing using HHI measures based on time allocation, where we assess overall changes

Table 5 Effects of the Curfew on Cross-Group Gaps in Browsing Time by Topic

	Arts & Entmt.	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										
Curfew × Female	34.238*	2.019	-2.940	-2.307	-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										
Curfew × 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)
Obs.	27426	27426	27426	27426	27426	27426	27426	27426	27426	27426
Individuals	313	313	313	313	313	313	313	313	313	313
Panel C. Outcome variable in level										
Curfew × High Speed	10.550	-1.637	-0.638	-4.080**	-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)	(2.534)	(1.885)	(2.903)
Panel D. Outcome variable log-transformed										
Curfew × High Speed	-0.094	-0.011	-0.138*	-0.172*	-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)
Obs.	27699	27699	27699	27699	27699	27699	27699	27699	27699	27699
Individuals	316	316	316	316	316	316	316	316	316	316
Day FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Individual FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes. This table shows estimation results of the curfew effect on browsing time on a sub-sample of topics, as indicated in the column headers. *Curfew* is a dummy variable that takes value 1 from 25 March 2020 onward, and zero otherwise. 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 * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

and differences between groups, defined by gender and broadband speed.[16] Next, we shift from the individual level unit of analysis to the group level and 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 (which is weighted) measures overlap based on time spent in the domain or topic.

Figure 5 plots daily variation in HHI across domains (left panels) and topics (right panels). The figures in Panel A are for the full sample; those in Panel B are split by gender; and those in Panel C are split by broadband speed. The consistent pattern across these figures is a decline in browsing concentration, across both domains and topics. Consistent across the two splits, it also appears that the group with higher average browsing levels (women, high speed) has more concentrated browsing overall. Table TA8 in the Online Appendix shows that these differences are highly statistically significant. It also shows that individual-level daily concentration levels are quite high: 0.51 by domain and 0.52 by topic.[17]

Comparisons between the curfew and prior period further show that women's browsing concentration, both by domain and by topic, increased significantly relative to men's during the curfew. The regression estimates in Table 6 of HHI measures show a relative increase of 0.043 for domains (column 3) and of 0.050 for topics (column 4).[18] The plots in Figure 5 show that these relative increases are coming from concentration dropping substantially among men and only modestly among women, which is confirmed in the regression models showing a significant overall reduction in browsing concentration in our sample, both by domain (0.046; column 1) and by topic (0.040; column 2), that is similar in magnitude to the relative drop for women. This suggests that the pandemic curfew significantly increased the amount of web exploration and time spent on less popular pages among men, but not among women. It is also possible that women's exploratory browsing of new domains and topics also increased somewhat during the curfew, similarly to men's, but that effect was overshadowed by their greater concentration in time spent on Netflix and other commonly-visited domains.

In contrast to these significant gender differences, we do not find significant differential changes in concentration by domain or by topic in high-speed versus low-speed areas (columns 3 and 4). Concentration measures are lower in low-speed areas throughout the sample period in Figure 5. While the drops in concentration appear larger for those areas as well, and the point estimates in Table 6 indicate the same pattern, they are not statistically different from zero.

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[16]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-curfew period. We also exclude from the analysis those websites classified as "Not Categorized". Overall, these account for about 8.3% of the observations.

[17]Market-level measures are lower by domain, ranging between 0.18 and 0.24 across subgroups, which would fall in the moderately concentrated category of the U.S. Department of Justice and Federal Trade Commission's Horizontal Merger Guidelines. Market-level concentration by topic 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.

[18]Another way of thinking of the magnitudes of these effects is that the relative drop in concentration of men's browsing, relative to women's, is equivalent to the reduction in market concentration from adding one fifth of a firm. This is shown in Table TA12 in the Online Appendix, which uses the inverse of the HHI, thought of as the effective number of firms, as the outcome variable.

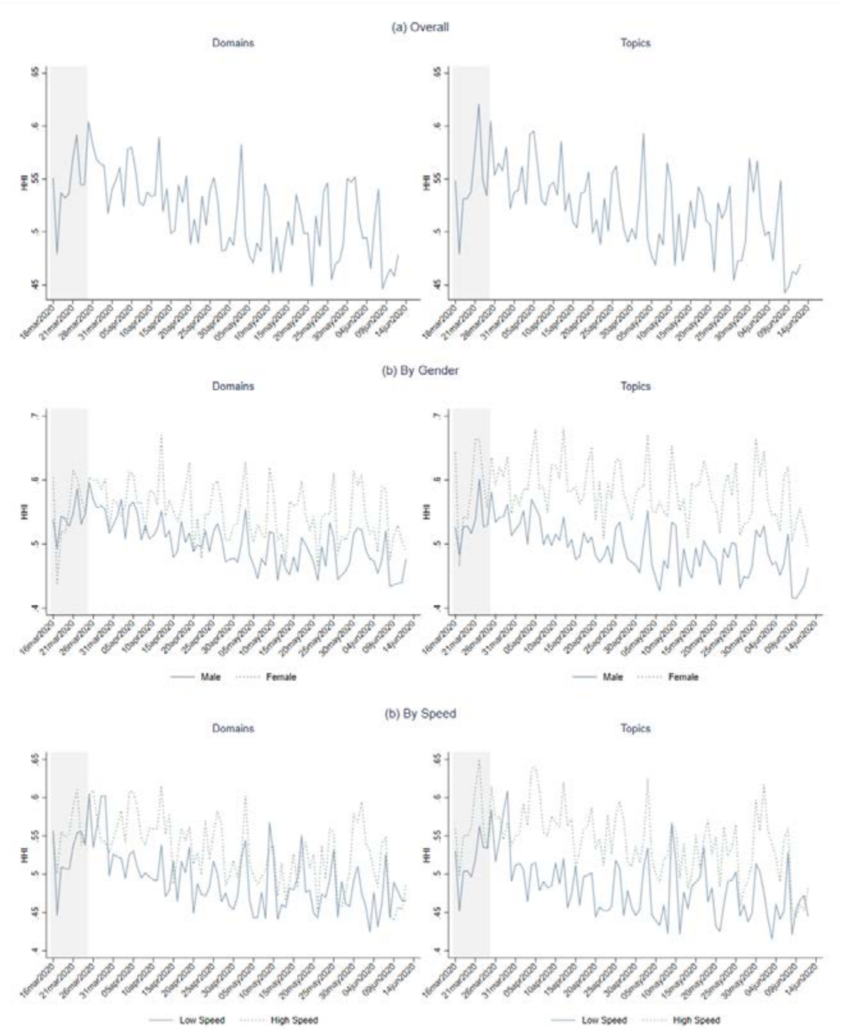

Fig. 5 Trends in Concentration Measures of Internet Domains and Topics. Figure shows concentration measures of daily browsing activities with respect to domains and topics. We measure concentration using the Herfindahl-Hirschman Index (HHI). A higher value of HHI indicates a convergent browsing mode. The unit of observation is the user-day aggregated at day level for panel (a) and at day-gender level and day-speed level for panels (b) and (c), respectively. The grey-shaded area indicates the pre-curfew period

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 2.4.

The results, in Table 7, show evidence of significant gender convergence in browsing habits by domain, particularly in the unweighted measure (showing a 12.4 percentage point increase in overlap) in column 1, but also in the measure that accounts

Table 6 Effects of the Curfew on Browsing Concentration

	Overall		By Gender		By Speed	
	Domains	Topics	Domains	Topics	Domains	Topics
	(1)	(2)	(3)	(4)	(5)	(6)
Curfew	-0.046***	-0.040***				
	(0.009)	(0.010)				
Curfew × Female			0.043**	0.050**		
			(0.020)	(0.022)		
Curfew × High Speed					0.012	0.013
					(0.018)	(0.020)
Obs.	23370	23370	23118	23118	23370	23370
Individuals	316	316	313	313	316	316
Day FEs			✓	✓	✓	✓
Individual FEs	✓	✓	✓	✓	✓	✓
Day-of-week FEs	✓	✓	✓	✓	✓	✓

Notes. This table shows the estimation results of the curfew effect on domain and topic concentration indices, measured by the Herfindahl-Hirschman Index. *Curfew* is a dummy variable that takes value 1 from 25 March 2020 onward, and zero otherwise. The unit of observation is a user-day. Standard errors, shown in parentheses, are clustered at the individual level. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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 curfew included additional 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

Table 7 Effects of the Curfew on Cross-Group Domain and Topic Similarity Indices

	By Gender				By 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)
Curfew	0.124***	0.040**	0.074**	0.032	0.115***	-0.022	0.041	-0.025
	(0.032)	(0.018)	(0.036)	(0.024)	(0.034)	(0.026)	(0.048)	(0.032)
Obs.	102	102	102	102	101	101	101	101

Notes. This table shows estimation results of the curfew effect on domain and topic similarity indices between subgroup pairs in the sample. *Curfew* is a dummy variable that takes value 1 from 25 March 2020 onward, and zero otherwise. The unit of observation is a day. While we always observe browsing activity for both male and female users in a single day, we only observe browsing activity for users in high-speed areas on June 23, the last day of our time period, resulting in slightly different sample sizes. Robust standard errors are shown in parentheses. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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 versus 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 shock in internet demand coming from the national curfew 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 relative effect of the curfew on Kenyan domains, using the model in Equation 5 with 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 report results from estimating Equation 6 to test for "triple-difference" interaction effects in the relative shift towards Kenyan content during the curfew by gender and browsing speed. None of these are 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 curfew, it is also possible that the source is on 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.[19]

[19]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.

Table 8 Effect of the Curfew on Browsing Time in Kenyan Top-Level Domains

	Level (1)	Log (2)	Level (3)	Log (4)	Level (5)	Log (6)	Level (7)	Log (8)
Curfew	0.554	0.108**						
	(1.999)	(0.050)						
Curfew × Kenyan TLD			-21.472**	-0.030	-24.130**	-0.031	-21.323	-0.011
			(10.040)	(0.087)	(11.762)	(0.108)	(14.869)	(0.145)
Curfew × Kenyan TLD × Female					7.740	0.015		
					(22.740)	(0.184)		
Curfew × Kenyan TLD × High Speed							2.231	-0.013
							(19.958)	(0.181)
Obs.	27699	27699	55398	55398	54852	54852	55398	55398
Individuals	316	316	316	316	313	313	316	316
Day FEs			✓	✓	✓	✓	✓	✓
Individual FEs	✓	✓	✓	✓	✓	✓	✓	✓
Day-of-week FEs	✓	✓	✓	✓	✓	✓	✓	✓
Kenyan TLD dummy			✓	✓	✓	✓	✓	✓
Curfew × Kenyan TLD					✓	✓	✓	✓
Curfew × Subgroup					✓	✓	✓	✓
Kenyan TLD × Subgroup					✓	✓	✓	✓

Notes. This table reports changes on browsing time in Kenyan top-level domains during curfew for the whole sample and for different sub-populations. *Curfew* is a dummy variable that takes value 1 from 25 March 2020 onward, and zero otherwise. 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 * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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-curfew 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 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 (Statista Market Insights, 2022). 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 (Statista, 2016).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-curfew gender gap on Netflix – is somewhat surprising given that 62% of subscription video-on-demand usage in Kenya is by men (Statista Market Insights, 2021).This difference may reflect the higher percentage of single women than single 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 (Netflix.com, 2021), 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 has a lower UN gender inequality index value (of 0.405 in 2021), as compared to Kenya (0.506) (United Nations Development Programme (UNDP), 2021), subscription video-on-demand has a longer history and higher penetration, and consumption is equal across men and women (Statista Market Insights, 2021).

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" (Moshiri & Nazanine, 2020). 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 curfew (Haynes, 2020). This spy-genre series based out of Johannesburg was shot in 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 curfews 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 COVID-19 curfew, which was announced on March 25, 2020. While our sample represents a select sub-population, the detailed and objective nature of our data enable us to provide a unique lens into how COVID-19 affected the digital activity of these Kenyan individuals.

Throughout our sample period of March to 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 than men to be employed, women in our Kenyan sample were twice as likely to be single, which may partially explain their greater time online.

We find a significant increase in overall browser usage during the first COVID-19 curfew, 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-curfew, went up by a remarkable 36 minutes relative to men's, after the curfew. 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. 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 (Deloitte, 2020)). Kenya is a nation with high gender disparities, and women around the world have been disproportionately hurt by COVID-19 (Alon et al., 2020; Burki, 2020; Goldin, 2022; United Nations, 2020b). It is also notable that our survey analysis showed women reporting a larger increase than men in self-investment activities during the curfew. The fact 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 (Chattopadhyay & Duflo, 2004; Iyer, Mani, Mishra, & Topalova, 2012).

The COVID-19 curfew increased the concentration of women's browser usage relative to men's, in terms of both domains and topics, 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 curfew 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 were clearly unique events, we suggest that the insights from this analysis can extend further to the consideration of other "market-deepening" demand shocks to online activity (in this case, occasioned by a curfew). 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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