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BROWSERS DON'T LIE?
GENDER DIFFERENCES IN THE EFFECTS OF
THE INDIAN COVID-19 LOCKDOWN ON DIGITAL ACTIVITY AND TIME USE

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ABSTRACT

We measure the impact of the initial Indian national COVID-19 lockdown on digital activity using browser histories of 1,094 individuals, spanning over 31.5 million website visits on computers and mobile devices. Reflecting the predicted increase in the value of online activity, both men and women in our sample dramatically increased their internet browsing during the lockdown. However, men’s browsing increased by significantly more, causing gender gaps overall and in key browsing categories, and in browsing on mobile devices. Our browser data showed significant relative reductions in women’s online job search, corroborated in aggregate data obtained from a major Indian online job platform, indicating potentially persistent harms to women’s employment. Consistent with increased childcare obligations driving the observed gender gaps, we find that gaps were greatest among parents. Men and women in our sample had similar browsing levels and trends pre-pandemic, which diverged during the lockdown. Our primary findings therefore shed new light on determinants of digital time use, while also highlighting the importance of considering both extensive and intensive margins of digital activity to track the digital divide. In our secondary analysis of time devoted to childcare, we find conflicting survey responses between fathers (who report an increase relative to mothers) and mothers (who report no such increase). While our data cannot directly resolve this conflict, they do show fathers having larger increases in time spent online, with no relative increase in childcare-related browsing. This secondary result demonstrates the value of complementing survey data with digital trace data.

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Keywords: computer and mobile browsing activity, COVID19 lockdown, digital time use, gender and digital divide, data privacy.

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1. Introduction

This paper studies the effects of the first Indian national COVID-19 pandemic lockdown on internet browsing by adult men and women. The lockdown started on March 25, 2020 and abruptly curtailed offline leisure and business activities, closed schools and blocked non-essential workers from leaving home (MHA 2020). We measure the extent to which people adapted to these restrictions by increasing their activity online, across a range of leisure and production uses. Our particular focus is on measuring gender differences in the effects of the lockdown to test if the severe time burdens imposed on women (United Nations 2020a; Alon et al. 2020; Burki 2020; Deshpande 2020) limited their digital activity.

Our empirical analysis draws on primary data we collected during the lockdown using a brief online survey of respondents followed by consensual sharing of internet browser histories, including activity on their PCs and mobile devices and going back 90 days. Gathered at a time when traditional survey methods were infeasible, these data provide a unique view into the impact of the lockdown on people's daily lives. Despite the costs of recruiting participants and of obtaining individual consent for each browser history upload, we were able to obtain data from over a thousand people, covering over 30 million website visits between February 22 and May 10, 2020.

We find that people in our sample had significantly higher browser use during the lockdown, compared to the preceding period, both in total (66 minutes, which is 35.7% of the pre-lockdown mean) and across a range of activities that includes production (23.7 minutes, 34.6%) and leisure (33.9 minutes, 37.2%). This supports a greatly amplified value of digital access during the first Indian lockdown, and a capacity to substitute for a range of offline activities with online alternatives. However, despite browsing time being higher among both men and women, we estimate a significantly larger increase for men, both in total (25.3%), and across a range of categories (e.g., 28.6% for production and 27,8% for leisure), and for browsing on mobile devices (33.1% across categories). This is particularly striking in light of the fact that men and women in our sample had comparable browsing levels and trends before the pandemic declaration by the World Health Organization (WHO) on March 11, 2020, and in the two weeks between the WHO declaration and the start of the first Indian lockdown. We therefore interpret our data as showing that the pandemic and its attendant restrictions on social and economic activity caused a new gender gap in internet activity to emerge among people with established digital access. This highlights the importance of examining variation in both extensive and intensive margins of internet access. Consistent with the hypothesis that the gender gap in web browsing derived from a lockdown-induced gender gap in household time obligations among parents, we find that the significant gender differentials we observe in browsing activity are concentrated among parents. This finding suggests that time constraints can be an important limitation on women's ability to benefit equally from internet access. Interestingly, despite these constraints, we see no significant gender differences in the lockdown effect on human capital investment (online or self-reported).

Although the gender gaps in browsing that we identify suggest that women could have suffered a relative drop in wellbeing, this conclusion is uncertain because the welfare effects of spending more time online are ambiguous, even during a lockdown (Allcott et al. 2020b). We therefore examine gender differences in online job search as an activity linked to more favorable economic outcomes. We saw stark disparity in the lockdown's effects on online job search. Men's time increased by about as much as women's decreased, resulting in a 40 percent relative drop for women, both overall and in a sample of likely job seekers. To address the small number of active job seekers in our sample, we also confirmed the finding of a relative decrease in women's online job search intensity using a different dataset from a widely used Indian job search platform, with tens of millions of active users. Perhaps more than our other gender gaps in browser use, this finding of a relative drop in women's job search indicates potentially significant economic effects. The finding suggests an increase in labor market barriers for women that is especially troubling in the Indian context, where female labor force participation is already depressed and women struggle with job search (Fletcher et al. 2017).

This study contributes to several strands of the Information Systems (IS) literature. First, by showing the impacts of the first Indian lockdown on a wide range of internet browser use outcomes, we contribute to the literature on IT adoption and use by consumers. Outside of the pandemic, researchers have examined outcomes related to internet browsing (Ghose et al. 2012, Chen and Yang 2019; Levy 2021), engagement with social media platforms (Ghose and Han 2011; Han et al. 2015; Bapna et al. 2016; Rishika and Ramaprasad 2019, Ananthakrishnan and Tucker 2021, Guess et al. 2023), and mobile device use (Ramdas and Sungu 2022; Allcott et al. 2022; Aridor 2022). Our specific results for online production and job search also connect with research on IT-related labor market outcomes, such as the returns to IT skills (e.g., Atasoy et al. 2021), the impact of digitization on information workers' time use (Bhansali and Brynjolfsson 2007), and the effects of IT-enabled remote work on productivity (Emanuel and Harrington 2021). Our examination of human capital investments relates to studies of online learning and education (e.g., Leung et al. 2023).

Second, we contribute to the literature on the effects of COVID-19 lockdowns, by examining outcomes related to internet browser use. Our approach to outcome measurement, leveraging digital footprints left by individuals in their ordinary activities, has been used in other studies of the pandemic. However, these studies have typically used aggregate data (from Google Trends in Bacher-Hicks et al. 2021 and Brodeur et al. 2021; from email and meeting meta-data in DeFilippis et al. 2020) or de-contextualized smartphone geolocation data (e.g., Chiou and Tucker 2020; Allcott et al. 2020a; Ananthakrishnan et al. 2020; Chen et al. 2021). By contrast, we study individual-level data that links IT outcomes to demographic characteristics. This approach is closer to that of Emanuel, Harrington, Pallais (2023), who study the impact of the pandemic on IT workers using employee personnel records and online peer feedback.[1] Our specific findings of increased time devoted to online production are also consistent with findings in other settings of increased demand for remote work in the pandemic (Chen et al. 2023; Hou et al. 2021; Brynjolfsson et al. 2020) and with over 40% of our sample starting to work from home during the lockdown. However, we differ from researchers focused on work outcomes by also examining non-production browser uses (leisure, education, job search) – which we are only able to do by virtue of having access to users' entire browser histories on both PCs and mobile devices. Our focus on gender differences in the effects of the pandemic is also the focus of a substantial literature outside of IS that documents gendered effects on a variety of outcomes, using a mix of survey-based measures (e.g., Myers et al. 2020) and non-survey digital measures (e.g., Cui et al. 2021).

Third, our analysis of gender differences in browser activity contributes to the growing literature that is concerned with how the development and diffusion of IT systems affect existing disparities and disadvantaged demographic groups. Our finding of emerging gender gaps in

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[1] Our work also bears similarity with a related study of ours, in which we examine the effects of the Kenyan national COVID-19 curfew on browsing activity. The Kenyan sample differs from the Indian sample in important ways, including smaller sample size and much lower share of women who are married, which together make it impossible to study the childcare and family dimensions of interest in this analysis using the Kenyan data (Citation withheld to preserve anonymity.)

internet use during the lockdown relates directly to research concerned with the "digital divide" or gender gap in adoption and use of information technologies. The fact that our result is present among men and women with established access to computers and internet connections highlights the importance of going beyond extensive margin measures of technological ownership and access to also consider intensive margin measures of frequency and range of uses when assessing gender differences. This need is supported in scholarly and policy work showing gender differences in IT skills and use (Ahuja and Thatcher 2005; United Nations 2014; GMSA 2015). Our finding that the presence of children is a key mediating factor underlying the gender gap in our sample also indicates the importance of non-technological barriers that prevent women from accessing the full benefits of the internet, and result in unequal distributions in gains. The gender difference in online job search intensity that emerged during the lockdown, which our analysis reveals, also adds to the literature concerned with differential impacts of IT in the areas of online job advertisements, search, and hiring (Lambrecht and Tucker 2019; Acquisti and Fong 2020; Chan and Wang 2018; Garg and Telang 2018). Other research on race and gender disparities online studies sharing-economy platforms (Cui et al. 2020; Mejia and Parker 2021), online restaurant reviews for Black-owned business (Mitkina et al. 2022), and online donation requests for antiracist curricular materials (Agarwal and Sen 2022).[2]

Within these literatures, we also contribute by focusing on India, where stark gender disparities are present across a range of economic and social outcomes (Duflo 2012), and where, like other developing countries, research on digital outcomes has been relatively scarce because of data limitations (Walsham et al. 2007).[3] The United Nations SDGs emphasizes providing universal access, pointing towards the extensive margin.[4] Despite rapid expansions in internet connectivity in India, gender gaps in the extensive margin of internet use persist at the population level.[5] This context makes our finding of an emerging gender gap in browser use in India, even

[2] Researchers have also studied the increasing risk of discrimination from personal data digitalization (Leidner and Tona 2021) and gender gaps in promotion rates among IT workers (Langer et al. 2020).

[3] https://www.epw.in/engage/article/where-data-study-internet-india

[4] Available at https://sdgs.un.org/goals/goal9

[5] Recent reports estimate 57% of men and 43% of women in urban India are active online, e.g., https://economictimes.indiatimes.com/tech/technology/india-to-have-900-million-active-internet-users-

among internet-connected men and women, which speaks to the intensive margin of internet use, particularly concerning.

Fourth, we contribute to the interdisciplinary literature on time allocation. Our use of digital trace data resembles Bandiera et al.'s (2020) tracking of CEO time with digital calendar entries, but we differ in our focus on gender differences and home production (Becker 1965; Blau and Kahn 2017; Hamermesh 2016). The browser histories that we observe provide detailed and objective time use data that are not subject to recall or categorization biases and could in principle be used to assess the reliability of self-reported survey data (as in Collopy 1996). However, because childcare takes place primarily offline, only a small share of it is observable in browser records. Naturally, it does not make sense to compare online-only childcare time to responses to our survey questions about own and spousal time devoted to childcare, before and during the pandemic. This is unfortunate because we find a conflict between own reports (where men report significantly larger increases in childcare time than women) and spousal reports (where there is no relative increase among women describing their partners).[6] Although this inconsistency could come from differences across households in the response to the lockdown, it is notable that, despite including individual fixed effects to account for pre-lockdown variation, men reported greater increases in childcare time during the lockdown, while also spending significantly more time online, including in leisure browsing (as shown in the objective browser data).

We investigated but rejected the possibility that some of the additional browsing time observed for men was spent on childcare, e.g., watching children's videos. Using machine learning and textual analysis methods to identify childcare-related browser usage, we find no relative increase for men during the lockdown. We can also empirically reject the explanation that

by-2025-says-report/articleshow/83200683.cms. The gender gap is also reflected in the male dominance in our sample.

[6] Although a relative increase in men's childcare time goes against expectations, it is not dissimilar to the finding in Zhou et al. (2020), a rare pandemic study with longitudinal time-use data, that self-reported housework time increased more for men (3.5 hours) than for women (3 hours) at the onset of the UK lockdown. Most research quantifying the pandemic's effect on time use relies on repeated cross-sections (Teodorovicz et al. 2021) or cross-sectional surveys with retrospective questions to obtain pre-pandemic baselines (Del Boca et al. 2020; Giurge et al. 2021; Adams-Prassl et al. 2020; United Nations 2020b). Time diaries are more reliable (Hamermesh et al. 2005), but more onerous to collect, and infeasible during strict pandemic lockdowns. The American Time Use Study was suspended between March 19 and May 11, 2020.

men increased their childcare and leisure time relative to women because they were more likely to have lost their jobs or started working from home during the lockdown, as neither of these factors explains the effects in our data. Taken together, our results suggest significant caution in using cross-sectional self-reported time use data to measure the gendered impact of the pandemic, as men and women possibly answer questions about childcare time differently, as suggested by prior findings that men overreport household production time (Kan and Pudney 2008) and that fathers devote a higher fraction of their childcare time to secondary care (while engaging in another primary activity) or passive care (Folbre and Yoon 2007).

Finally, beyond its substantive contributions, this paper also advances the literature on digital privacy by implementing an approach to research data collection that is centered on participant control and choice. We worked in partnership with *PY Insights*, a technology platform that emphasizes consensual and minimally invasive digital data sharing, and only gathered browser histories from individuals who affirmatively consented and actively uploaded their data. While this approach is more costly than obtaining records from secondary sources, our study demonstrates that it was feasible to collect data from over 1000 people within a short timeframe during a national initial pandemic lockdown. To the extent that individuals with strong privacy preferences are unwilling to share data with researchers (e.g., Prince and Wallsten 2021; Lin 2022), data collected in this way may not be representative of the full population. This concern is diminished by the fact that we compensate individuals for participation, which can induce even people with high stated privacy preferences to share information (Athey et al. 2017). Our approach to privacy protection in digital trace data may be particularly valuable in countries with weak state institutions and less oversight on how data is used. It can also provide a useful alternative model for consideration as researchers and businesses are driven to increase data privacy standards, because of growing public concern (Tang, Hu and Smith 2007; Schwartz 2019; Goldfarb and Tucker 2019; Acquisti et al. 2016; Al-Natour et al. 2020) and legal restrictions (Johnson 2023) that can undermine the reliability of conventional internet traffic reporting (Goldberg, Johnson, Shriver, 2019).[7]

[7] See, e.g., https://unctad.org/page/data-protection-and-privacy-legislation-worldwide.

2. Data and Predictions

2.1. Primary Data Collection

We collaborated with *PY Insights*, an internet-browser analytics platform, and *Dynata*, a global first-party data platform, in two waves of data collection. Our main analysis focuses on data from a survey we fielded between mid-May and early June of 2020. Individuals drawn from Dynata's marketing pools in India were invited to participate in an online survey that ended with a consensual browser data upload using the *PY Insights* software. *PY Insights'* internet browser extension collects retrospective data stored in each user's browser account history. This is identical to what a participant would observe if they visited the *History* section of their internet browser on their personal computer (see Figure A2 for an illustrative example). The records cover up to 90 days of past activity on the browser account, accumulated across *all* electronic devices (computer, smartphone, tablet). We observe every website visit, including the URL (uniform resource locator, i.e., web address) and timestamp.[8] Although our browser data can include records from multiple types of electronic devices, most smartphone browser apps do not support internet browser extensions or add-ons, so the *PY Insights* technology only accesses participants' data through their personal computers. The accessed data includes browsing records for all devices. No information is collected from private browsing or Incognito mode, and personal identifiers are removed prior to analysis. Participants with valid data were compensated for their participation.

Each URL has an associated title, which conveys meaningful information, such as a Google search phrase, the headline of a newspaper article, or a YouTube video title. Using the URL, title, and timestamp for each website visit, *PY Insights* calculates its duration in seconds and provides a detailed categorization scheme for each website domain.[9] We use these categories to identify websites as being primarily related to leisure (entertainment) or production (non-

[8] The software only captures retrospective data. Once the data transfer is over, it automatically deletes itself and redirects participants to the survey platform.

[9] The categories are based on Google Cloud Platform's natural language processing algorithm. The universe of categories is at https://cloud.google.com/natural-language/docs/categories.

recreational).[10] Because YouTube represents a sizeable portion of usage and is classified as leisure by *PY Insights*, we also conduct robustness checks in which we re-classify YouTube videos as leisure-related or production-related using Google's YouTube API. As discussed in detail later, we are also able to identify child-related browser usage, e.g., by examining the text describing each YouTube video.

We obtained data that met our quality control standards from 1,094 individuals aged 22 to 54 located in 28 states across India, which included mobile browsing data for 1,084 individuals. We prevented individuals using a new browser account or a secondary browser type that is not used regularly from participating by requiring at least 30 days of browser data. We dropped one user who preferred not to state their gender and took two steps to avoid computer bots: we included an attention test question in the survey and manually dropped all users with an average of more than 3,000 URL visits per day.[11]

In total, we collected over 31.5 million webpage visits to 134,123 unique websites. We aggregated these data to the daily level for each participant, using different categories of activity. We also limited our analytical sample to the period between February 22 and May 10, 2020, to avoid dates with few observations, coming from the slightly staggered enrollment timing. Our final dataset includes 81,462 person-day observations of browser usage data with 52,509 observations coming from 701 men and 28,953 observations from 393 women.

Our second wave of data collection, in collaboration with *PY Insights* and *Dynata*, took place in between September and December 2022, with a view to enabling examination of overall mobile device app usage (vs. browser-only mobile device usage). We gathered a sample of survey responses from 10,175 individuals as well as data on all mobile device app activity (2.95 million app clicks, between July 2019 and December 2022, including all browser usage) on a sub-sample

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[10] *Leisure* includes Adults, Arts & Entertainment, Games, Online Communities (including social media), and Shopping. *Production* includes Business & Industrial, Computers & Electronics, Finance, Internet & Telecom (including e-mail and search engines), Jobs & Education, Law & Government, News, Science, and Reference. Other Google Cloud categories combined cover 0.8% of our data. Some websites – such as spam webpages – are also labelled as "other". Median "other" category usage on a day covers 7% of total time use.

[11] The 19 users who failed this requirement show browsing that is unlikely to come from a human, such as spending entire days repeatedly visiting the same handful of business websites, refreshing every 5 seconds.

of 118 individuals. We used Google's Takeout service to collect this backward-looking mobile device usage data.

We separately obtained data from one of the largest job search platforms in India, which hosts tens of millions of resumes. The data we obtained are aggregated daily measures, by gender, for daily job search and average session duration, as well as number of job applications, job searches and job post views, for the period October 2019 – July 2022. We use these data to supplement our analysis of job seeking behavior outside of our main sample.

2.2. Summary Statistics on the Main Sample

Overall, 64% of our participants are male (Table 1). This gap is reflective of the gender gap in digital access in India,[12] because our data collection method requires access to an internet-connected computer. This requirement is also reflected in the high educational attainment in our sample, with over 90% of men and women being college graduates. Most women in our sample (65%) are employed full time, which is lower than men's employment (77%) but much higher than the average for Indian women overall in 2020 (23%).[13] Within our sample, men are about 2.4 years older than women and slightly more likely to have young children at home.

Despite these differences in characteristics, men and women had similar average daily browsing times in the period before the lockdown (Table 2): 4 hours 11 minutes for women and 4 hours 24.5 minutes for men. Almost half of this time is devoted to leisure (51.4% for women, 49.4% for men), which is mainly watching YouTube videos. The daily values of our main browsing time measures are shown in Figure 1, separately by gender.[14] Foreshadowing our main results, the top left panel of the figure shows nearly identical daily browsing time by men and women at the start of the sample period, with higher levels and an emerging gender gap during the lockdown. The other panels of the figure show the trends for different categories, which allows us to observe, for example, the cyclical nature of production browsing, with regular drops on Sundays.

[12] See https://www.oecd.org/going-digital/bridging-the-digital-gender-divide.pdf, and http://rchiips.org/nfhs/factsheet_NFHS-5.shtml
[13] Available at https://data.worldbank.org/indicator/SL.TLF.TOTL.FE.ZS?locations=IN
[14] See Figure A1 for the breakdown on YouTube, Facebook, and Google.

The similarity in initial levels of digital access and use in our sample is not representative of India's population. This means that our findings may not generalize outside of the highly educated, internet-connected, and English-literate people we observe. The results should be interpreted as applying primarily to this relatively advantaged and rapidly growing sub-group of the Indian population.[15] Within the context of the digital divide, this means that our analysis is focused on intensive margin variation, among people who already have digital access and at least some regular internet browser use.

2.3. Predicted Effects of the Lockdown

Our aim in studying how India's COVID-19 lockdown affected browsing activity is to measure how demand for online activities responds to external shocks that reduce the availability of offline activities. Some degree of complementarity exists between online and offline worlds, as some browsing is conducted in combination with in-person business activities (such as meetings) or leisure (streaming a TV show to watch together with friends), sometimes by combining multiple channels (e.g., working on PC and at the same time messaging on smartphone). Nevertheless, we expect that the primary effect of the lockdown will be to increase demand for online activities in general and internet browsing in particular. We first use our browsing data to test this qualitative prediction and to quantify its magnitude.

Our next set of predictions relate to how the pandemic affected the distribution of web browsing across different types of activities. It is not obvious from theory *which* activities would increase at all or more than others. The category with the clearest prediction is online shopping, where we expect a sharp drop during the Indian lockdown, whose severity prevented home deliveries. We confirm this in Figure 1 as a check on our data, but otherwise focus our analysis on more interesting outcomes.[16] Although leisure is likely to increase, it is not obvious which types of content would become more appealing during a lockdown. The effect of the lockdown on productive activities online is more uncertain as it also depends on the extent to which people

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[15] Computer penetration in India is estimated to be about 3 percent and growing at about 15 percent a year (IDC, 2020).

[16] We briefly note that online shopping repeats the common pattern of a relative decline in women's time use during the lockdown, but differs in that women's usage exceeded men's before the lockdown.

are able to work from home. Because about half of our employed sample reported a shift to working at home during the lockdown (Table 1), we see a potential role for increased online production in our sample. However, because a majority of our sample (including many workers and non-workers) will be limited in their capacity to increase production online (due to the nature of their jobs or skillsets), we predict larger effects of the lockdown in leisure categories.

Our main interest in this study is in examining how the lockdown changed the distribution of internet browsing, and specifically how it affected gender gaps in browsing. Because of the widely expected increase in demand for home production that resulted from the lockdown, combined with traditional gender norms in India that assign the bulk of household work and childcare to women, we expect that women will face greater constraints than men that will limit their ability to realize their increased desire for online browsing during the lockdown. As a result, we expect to see larger increases in browsing time for men than for women, whose time online might even decrease.

We also predict interaction effects between gender and family and employment status in how the lockdown affected browser use. First, we expect that women with children will be the group with the greatest increase in time demands for home production during the lockdown (relative to childless women and to men with or without children). We therefore expect larger gender differences among parents. We separately expect that employment status will affect individual responses to the lockdown, particularly in determining the size of the production response, and that these effects may further differ by gender. While working women may be able to devote more time to production-related browsing than non-working women (because they may need to work online to maintain their jobs or reputations), traditional gender norms in India prioritize men's employment over women's. This implies that the impact of the lockdown may differ by gender, even among adults with paid employment. Based on the theory that the lockdown will drive women to spend an increasing amount of their browsing time while multi-tasking and engaged in other activities (e.g., streaming a video while cooking or cleaning), we also separately analyze browsing on mobile devices and the share of browsing that is on those devices. Finally, because the welfare implications of browsing can be ambiguous (Allcott et al. 2020b), we also focus special attention on browsing related to online job search. For this outcome, we again predict that gender norms will lead to a smaller increase for women. However, unlike time spent on online leisure, which may be harmful – for example due to potential digital addition (Allcott et al. 2022), job search is an investment that can improve job matches and employment rates in the future and where gender gaps would be especially concerning.

3. Effects of the Lockdown on Browser Activity

We start by comparing browsing activity during the lockdown (which was announced on March 24, 2020, and started midnight on the next day) and the weeks immediately preceding it. We define the lockdown period based on the date of the first national COVID-19 lockdown in India, which was imposed suddenly and which strictly curtailed activities outside the home.[17] Within our sample period, we treat the lockdown as an exogenous shock to internet browsing that itself resulted from the shock of the pandemic. This is justified in part because neither the spread of the virus, nor the setting of government policy, was affected by our outcomes (various measures of browsing activity) or by other factors that could have plausibly affected internet browsing before the pandemic. Nevertheless, because the first Indian lockdown was preceded by the WHO's declaration of a pandemic, we also report estimates (in Section 3.3) from an analysis that excludes from the pre-lockdown period dates following the WHO declaration. Another identification issue relates to the fact that the lockdown coincided with other contemporaneous policy, economic and social effects of the pandemic. This means that, although we focus on the local temporal variation around the start of the lockdown, we are not able to fully isolate its impact from other pandemic-related factors.[18] We therefore interpret our estimates as capturing a "bundle" of direct and indirect mechanisms through which the pandemic lockdown affected online activity.[19]

Our first finding is a significant increase in internet browsing during the lockdown. This is shown in column 4 of Table 2, which reports changes in browser activity over the full sample of individuals. We find total browser time use was one hour longer per day during the lockdown, which corresponds to 35.7 percent of the pre-lockdown mean. Total daily browser clicks were 48

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[17] The official guidelines are at https://www.mohfw.gov.in/pdf/Annexure_MHA.pdf

[18] These other factors include, e.g., macroeconomic effects from changes in international trade, fear of disease, travel restrictions, or voluntary behavioral changes separate from the lockdown.

[19] This resembles other economic studies of pandemic lockdowns, such as Miller et al. (2020) and Miller et al. (2022) on domestic violence.

percent (or 93 clicks) higher. These findings support our predictions that the lockdown would increase overall browsing. We also show in the remaining rows of column 4 that browsing increased significantly in each of the examined sub-categories, when measured either by time spent or by clicks. Furthermore, we find support for our prediction about the type of browsing in that the increase is larger, both in absolute terms and relative to the pre-lockdown mean, for leisure activities. Having established these overall findings on the full sample, the remainder of the paper focuses on gender differences in the effects of the lockdown.

3.1. Gendered Effects of the Lockdown on Browsing

The raw data in Table 2 indicates that both men (column 5) and women (column 6) significantly increased their browsing time overall, and across a wide range of categories. This suggests that our prediction that the lockdown would increase the value of internet browsing – likely due to decreasing the extent of offline activities – applied to both men and women.

Notwithstanding these consistent increases within gender, the summary statistics in Table 2 also suggest significant gender differences in the effects of the lockdown. While men and women have statistically indistinguishable browsing patterns in the period before the lockdown (overall and across 8 of the 10 variables in column 3 and across all variables in column 7 for the period before the WHO declaration), the increases in browsing activity tend to be much larger for men than for women. Total browsing time increased by 75 minutes (or 40% of the male pre-lockdown mean; column 5) for men but by 50 minutes (30% of the female mean; column 6) for women. This pattern of a relative reduction in women's time online is present for all categories in the table except for online learning time, which shows similar increases by gender.[20]

We examine the observed gender gaps in browsing activity formally in a regression framework by estimating the differential effect of the lockdown by gender in a panel data model with two-way fixed effects for individuals and time. Our unit of analysis is a person-day and our estimation equation takes the form:

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[20] Because it represents a small fraction of browsing time, this category is not a focus of our analysis. Nevertheless, because it relates to human capital and skill development, we also examined it using another measure based on time spent on YouTube videos in the "educational" category (Table A5) and in subjective reports of frequency of "self-investment" activities (Table A2). These alternative measures also show significant increases for men and women that are not statistically distinguishable from one another.

$$Y_{it} = \beta\ Lockdown_t \times\ Female_i +\ \gamma_i + \delta_t +\ \epsilon_{it} \tag{1}$$

Y_{it} is the outcome of interest for individual i on date t. $Lockdown_t$ is a binary variable indicating that date t occurs during the lockdown, $Female_i$ is a binary variable equal to 1 if individual i is female, γ_i is an individual fixed effect and δ_t is a date fixed effect. Standard errors are clustered at the individual level. Our coefficient of interest, β, captures the average differential impact of the lockdown on women relative to men. We apply a natural logarithmic transformation on our outcomes, after adding 1 (second or click) to all daily observations to retain zero values.

Confirming the patterns in the raw data, the regression estimates in Panel A of Table 3 show sizable and significant relative declines in women's time online during the lockdown across a variety of measures. Women's total browser time decreased by 25.3 percent relative to men's – i.e., nearly half an hour less time per day.[21] Women's online time use decreased relative to men's by 27.8 percent for leisure and by 28.6 percent for production websites. We find similar relative declines in our count-based measures of activity in Panel B. Women's daily count of unique URLs visited dropped by 24.4 percent relative to men's, amounting to about 40 fewer URLs per day. We also find significant usage drops for women, relative to men, for video streaming (YouTube, time and clicks), social media (Facebook time) and Google searches.

We next examine internet browsing on mobile devices such as smartphones and tablets, as these provide a crucial medium for internet access in developing countries.[22] Although our sample is limited to individuals who have access to a computer, the browsing histories we collect include participants' mobile internet activity. In this analysis, we classify mobile browsing as visits to URLs that indicate they are intended for mobile users (e.g., m.facebook.com or facebook.com/mobile; see Figure A2 for an illustration). Because this approach will miss mobile visits to webpages that lack separate mobile versions, it is likely to provide a lower bound on the mobile share of browsing in our sample. Despite this limitation, we identify 2.5 million mobile website visits that are generated by 1,084 (of our 1,094) participants. When we repeat the main

[21] Because the outcome is logged, the coefficient of -0.292 implies a change of -25.3% = 100*($e^{-0.292}$-1).

[22] Details at https://www.gsma.com/r/wp-content/uploads/2021/09/The-State-of-Mobile-Internet-Connectivity-Report-2021.pdf

analysis focusing only on mobile browsing, reported in Panels C and D of Table 3, we find a similar gender gap in mobile browsing. Women's total mobile browser time decreased by 33.1 percent relative to men's, at a one percent statistical significance level. The two exceptions are for time spent on YouTube and Facebook. The point estimates remain negative (indicating a relative reduction for women), but are no longer statistically significant.

We also examined within-day variation in internet browsing, overall and on mobile devices, by estimating our regression models separately over a set of twelve 2-hour time intervals. The coefficient estimates for the gendered impact of the lockdown on each of these intervals are shown in Figure 2, with estimates starting at 6 AM on the left. The effects, overall and for mobile browsing, are largest midday and in the late evening. These times coincide with lunch and dinner, which are both typically hot meals in Indian households. Because of gender roles typically assigning South Asian women with responsibility for these tasks (Duflo et al. 2008; Dhar et al. 2018), we expect that women in our sample are more likely than men to be involved in meal preparation, service and clean-up, which could explain the observed gender differences in internet use. The consistent pattern between mobile and overall browsing indicates that women's browsing fell behind even though they may have been able to substitute mobile-based browsing for some of their computer-based browsing, e.g., while cooking.

While an advantage of studying browser data is that we can observe both mobile and computer-based internet activity, it is uncertain *a priori* how mobile browser time use and clicks relate to use of other (non-browser) mobile applications. It is therefore possible that the men's increased mobile browsing during the lockdown was associated with a decline in men's use of other apps. In that case, our estimates from mobile browsing would tend to overstate the overall gender difference in mobile internet use (across all apps).

Because we are not able to assess overall mobile app usage from our primary data collected during the lockdown, we draw on data from a secondary sample of 10,175 individuals, surveyed in late 2022, who were asked to characterize how their dominant mode of internet access changed during the pandemic. We see no relative decline in browser use for men, with around two-thirds of both men and women reporting shifting to *greater* use of their internet browsers (across computers and devices). Only about a quarter of respondents reported shifting to other mobile apps, with a slightly higher rate (1.2 percentage points, statistically significant at the 10% level) among women (Table 4). To examine shifts in browsing in more detail, we next examine data from a sub-sample of 118 individuals, with an average of 303 days of observation per individual, for whom we were able to obtain a full history of mobile app clicks to test whether the correlation between browser use and other app use is typically positive (indicating complementarity) or negative (substitutability). The results (in Table A13) show significant positive correlations, across all models (with or without individual and date fixed effects) and no significant gender differences in the size of the correlation. Taken together, these results suggest that our finding of a gender gap in browsing activity during the lockdown was likely to understate rather than overstate the gap that emerged in all internet activity.

3.2. Trends in Male and Female Browsing Before the Lockdown

This section explores the validity of the empirical approach in equation 1 that treats the lockdown as an exogenous shock that differentially affected men's and women's online activity. We do this by examining trends in men's and women's browsing in our data before the lockdown.

The main complication, noted above, is the WHO pandemic declaration on March 11, 2020, two weeks before the Indian lockdown. For a cleaner pre-pandemic comparison, we therefore focus on the period before March 11. As mentioned above, column 7 of Table 2 shows no gender difference in browser time use or clicks. It is notable that in this highly educated sample, women and men were equally likely to be online prior to the COVID-19 lockdown.

Figure 1 visually depicts the similarity in male and female browsing levels before the pandemic and lockdown. We also conducted formal regression analyses to test for differential levels and trends by gender in the pre-lockdown period for total browsing, leisure, and production duration and count measures. The results, in Table A10, show no significant differences in the linear time trends for women (relative to men) in the pre-lockdown period.[23]

[23] As a further check, we also confirmed our main results on overall time use and counts using the synthetic difference in differences method (Arkhangelsky et al. 2021) that creates a synthetic "control" of women that is designed to match the prior trend for men (Table A11). This approach requires a balanced panel, so we also confirmed that our results hold on that smaller sample.

Finally, to account for the concern that individuals in our sample responded to the WHO announcement before the formal lockdowns was imposed, we repeated our main models from Table 2 excluding data between March 11 to 24. These estimates (in Table A8) confirm the main effects but are consistently larger, which suggests some anticipatory response in advance of the lockdown.

3.3. Robustness Checks

Our main results in Table 3 are robust to various alternative specifications. We first examined alternative definitions of the dependent variables, separating the extensive and intensive margins and using a linear model. We studied the extensive margin using an indicator variable for a person visiting any URL (overall or within a category) in Table A1, Panel A, and the intensive margin separately for daily browser time use and daily count of website visits using the log transform of the outcome variable of interest without adding 1 (which drops zero usage days from the sample) in Table A1 Panels B and C. Finally, we repeated our main estimates from Table 3 without employing the log transformation in Table A1, Panels C and D. Across each of these models, the estimates confirm the main results, except for a few cases where the effects have the same direction but are not statistically significant. Those exceptions are the extensive margin of any browser time in the day, intensive margin on time spent on Facebook and the number of Google searches, and the raw count of production URLs.

We next confirmed the robustness of our results to an alternative clustering structure of standard errors. Table A9 shows the results are unchanged when we use two-way (participant and date) cluster-robust standard errors instead of clustering only on the participant level.

We also considered the possibility that the relative increase in browser time attributed to men is due to their greater sharing of devices with others in the household. Because our survey elicits device sharing, we are able to estimate separate effects for the sub-group that does not share their smartphone, computer, or tablet. Consistently across all regressions in our main analysis in Table 3, we find larger effects for this sub-group (Table A3). Women in this sub-sample decrease their total time online by 40.7 percent relative to men (compared to 25.3 percent in the full sample). This difference suggests that women in the full sample shared their devices more intensively than men, and a greater share of their browser activity was consumed by others. Thus, our full-sample results may underestimate the relative decline in women's time online.

Finally, because YouTube accounts for almost 20 percent of total browser time in our sample, we further parsed the video content of 308,497 unique YouTube URLs using Google Cloud's YouTube Data API. For each URL, the YouTube API provides an array of information about the associated video, such as its title, category, description, and channel name.[24]

We used YouTube video categories to identify videos that are more related to leisure or production. Two-thirds of YouTube time is devoted to leisure in this scheme. The results of our main analysis are unchanged if we revise our category-level usage measures by moving productive YouTube content into the production category (Table A4, Panel A). We confirmed that the pattern of results from the full browsing data is present within YouTube videos as well: women's time devoted to both leisure and production videos drops considerably relative to men's during the lockdown (Tables A4, Panel B).

3.4. Heterogeneous Effects by Family and Employment Status

The relative decline in women's online activity is consistent with the hypothesis that women experienced a greater increase in household obligations after the lockdown that prevented them from spending as much time online. A natural implication is that the gender gap in the impact of the lockdown would be larger for parents, who experienced greater shocks to household production. We investigate this prediction by splitting the sample based on parental status.

Table 5 presents separate estimates for samples of individuals with at least one child and with no children (summary statistics in Table A6). We observe significant drops in total, leisure and production time use for mothers relative to fathers, while among childless adults, we find no significant gender differences in any of these measures. The difference between the two samples is greatest (and statistically significant) for leisure time. Mothers experienced a relative drop in online leisure of 43.3 percent compared to fathers, while childless women experienced an

[24] Details at https://developers.google.com/youtube/v3. This information was not available for videos that had been removed by the time we collected YouTube API data.

insignificant increase relative to childless men. The disproportionate effect of the lockdown on mothers is primarily manifesting in our data as a relative reduction in leisure time.

We next split our sample by employment status, to test whether effects are stronger for women who have less economic power and autonomy. Consistent with this prediction, our estimates for total time use and production time are smaller and less significant in the full-time employed sample (columns 1 and 3 of Table 5, Panel B) than in the sample of individuals not employed full-time (columns 4 and 6). Nevertheless, relative to full-time employed men, full-time employed women had a substantial and significant 38.8 percent decrease in leisure time online. In the sample of part-time and non-employed individuals, we see no significant gender gap in the impact of the lockdown on leisure time online. Instead, that sample shows a significant 48.5 percent drop in women's production time online. This pattern is consistent with full-time employed women having less flexibility than other women to reduce their production time online relative to men's and choosing instead to sacrifice leisure time.[25] It is also consistent with women with weaker ties to employers being less capable than similarly situated men of expanding their productive time online during the lockdown.

4. Gendered Effects of the Lockdown on Online Job Search

4.1. Evidence from Internet Browser Activity

While the analyses in Section 3 provide information about how online behaviors changed, it is ambiguous from browser data alone whether the relative changes we observe correspond to a reduction in overall relative utility for women. For example, although their total time devoted to online activity and to online leisure dropped relative to men's, it is possible that their offline activities provided greater utility. We therefore focus in this section on an activity that is more closely linked to favorable economic outcomes, and that can have lasting effects on labor market outcomes: online job search. Over three-quarters of job applications worldwide are submitted online and India's growing online job market remained active during the lockdown while in-person networking and job applications were strictly disallowed.[26]

[25] Their observed online leisure time is significantly lower than their self-reported ideal allotment.
[26] https://www.statista.com/statistics/881116/recruitment-share-of-job-applications-by-source-worldwide/

We start with our main browser history sample. We created a comprehensive list of job search websites frequented in India and classified website visits as relating to job search if their URL domain is included in this list. Because online job search accounts for a small share of browser time, many observations (i.e., person-days) in our sample have zero time devoted to it. We therefore supplemented our usual log-transformed measure of daily browser time use with a daily indicator for whether the person visited any job-search websites to capture extensive margin responses as well.

The gender differences are striking. The summary statistics show that men's time devoted to online job search increased by about 40 percent during the lockdown, while women's job search time decreased by a similar amount (Table 2). Regression estimates in Table 6 (Panel A) show the significance of the relative drop in women's time spent performing online job search during the lockdown: a 2.2 percentage point drop on the extensive margin (column 1) and a 12.9 percent decrease in duration (column 2).

Because the lockdown is associated with greater job loss for men (4.3 percent) than for women (3.6 percent) in our sample, the relative increase in men's time devoted to job search may come from their greater need for search rather than from women's increased household obligations. We address this concern by identifying individuals who are more likely to be job seekers throughout the 90-day lookback window: those that did not have a full-time job and had no change in employment status over the 90 days preceding their survey date. This sub-sample comprises only about a quarter of our full sample. Nevertheless, we detect statistically significant decreases in both the extensive margin (3.9 percentage points) and in overall duration (24 percent) measures of job search activity for women relative to men on this sub-sample (Table 6 Panel A, columns 3 and 4).

4.2. Evidence from a major Indian online job search portal

Although these findings on job search are significant within our sample, they relate to a relatively small sub-sample of Indian job seekers. We therefore turn to supplementary data from one of the largest online job platforms in India, to measure trends for the overall population of online job seekers. Our unit of observation is gender and day combination, and we observe an intensive margin measure of average values among active platform users on that day. Our sample period is set to match the main sample period for the browser analysis. Table 6 (Panel B) reports estimates from estimating the model Equation 1 above, replacing the individual fixed effects with a *Female* indicator. Our outcome variables are average daily durations (in minutes) of job search (column 1) and platform sessions (column 2) and average daily counts of job applications (column 3), job searches (column 4), and job post views (column 5).

With the exception of job applications, where we see no differential change by gender, the outcomes all show a significant relative decline in women's job search activity in the lockdown period. This pattern echoes the finding in our browser data of a relative drop in online job search. In the platform data, we observe relative drops of 4.2 percent (0.66 minutes a day) and 2.9 percent (0.23 minutes per day) in women's average job search and session durations and drops of 6.2 percent and 4.9 percent for counts of job searches and viewing of job postings. Among active users with resumes, the relative drops in women's time spent on the platform are larger than the initial gender gaps showing that female users tended to spend more time on the platform than male users with resumes, in the pre-lockdown period.[27] By contrast, the relative drops in job searches and views among female active users were smaller than the initial gender gaps in those measures. To the extent that women were also less likely to visit the platform at all during the lockdown (as suggested by the extensive margin results in our browser sample in columns 1 and 3 in Panel A of Table 6), these relative drops among active platform users, are likely to understate the gendered impact of the lockdown on online job search in the population.

Because we lack a measure of offline job search, our results for online job seeking may in part reflect a gendered shift in medium rather than amount, yet they are concerning indicators of worsening gender gaps in Indian labor markets following the lockdown. However, during the strict Indian lockdown it is unlikely that offline job search could have proceeded. Indian women's labor force participation remains low despite the country's economic growth, declining fertility and rising education levels. The absolute decline in women's online job search during the lockdown is particularly troubling in light of prior findings that women have lower access to

[27] The higher average intensity of platform use among female users in the pre-lockdown period was also confirmed in earlier data from the platform and may reflect Indian women's lower efficiency in job search compared to men (Fletcher et al. 2017).

social protections (Cameron 2019), yet often lack information about available jobs and search for jobs less efficiently than men (Fletcher et al. 2017).

5. Gendered Effects of the Lockdown on Childcare

Motivated by the importance of parenthood in producing the gender gap in the response to the COVID-19 lockdown in Section 3.4, this section examines empirical measures of relative changes in childcare time by mothers and fathers in our sample. Because childcare time largely occurs offline, we are not able to use measures of digital activity to create comprehensive measures. We therefore first examine subjective survey responses (from married parents) about average daily time devoted to childcare during and before the lockdown by the respondent and by their spouse or partner. We converted the interval responses (using 2-hour buckets) into a continuous measure by taking the mid-point of each bin and assigning 10 hours to participants who selected 8 or more hours.

The results from self-reports are shown in the left panel of Table 7 panel A. While women report spending significantly more time (0.7 hours/day) than men on childcare before the pandemic, men report a larger (1.5 compared to 0.76 hours) increase, leaving no significant gender difference during the lockdown. This surprising relative increase in men's self-reported time spent with children is not matched in the reports from partners shown in the second panel. Women and men reported nearly identical increases in their partners' time spent on childcare and the gender difference remained highly significant during the lockdown. While it is true that the men and women in the sample are not necessarily married to one another, the inconsistency between the two measures casts doubt on the reliability of the self-reported relative increase in men's time with children (perhaps because men and women define childcare differently, as discussed, e.g., in Kan and Pudney 2008).

Although our browser data are not able to directly resolve this conflict, they can help shed light. In particular, it is notable that fathers' relative increase in self-reported childcare time is happening at same time that they are spending significantly more time online. This suggests that fathers may be reporting an increase in childcare time that comes from "secondary" childcare (supervising or being near their child while engaged in a different activity), which mothers may not report as childcare time (for themselves or their partners). This interpretation is consistent across the three information sources, but we also considered other possibilities that could reconcile the patterns in childcare time across the different sources.

We first examined the possibility that some of men's additional browsing time was in fact devoted to childcare, by consuming child-focused videos and webpages with their children. We identify this content by applying textual analysis and a machine learning algorithm to the website title data and YouTube video descriptions and define three alternative measures of childcare-related browser usage.[28] The first approach applies a manual dictionary of 165 childcare-related keywords used by Indian parents (identified through semi-structured interviews) and codes each visit as childcare-related if a dictionary word appears in the title.[29] Our second approach starts with a small seed of 8 childcare-related words (cartoon, child, infant, kid, nursery, school, toddler, and toy), and then expands the dictionary using a Word2Vec model (Mikolov et al. 2013) trained on our website title and YouTube description data to find the 5 closest (in terms of cosine similarity between word vectors) words for each of the seed words.[30] We use this approach to minimize the dependency on prior human information in creating a dictionary. Our third approach focuses on a set of 26 YouTube channels that exclusively produce child-targeted content.[31]

[28] We resort to dictionary-based methods because we lack labelled data on childcare-related website categories to use as a training dataset and because topic models (e.g., Latent Dirichlet Allocation, as in Blei et al. 2003) are unlikely to endogenously form a childcare-related website category (see Gentzkow et al. 2019).

[29] Although manual dictionary-based methods are common in the literature (e.g., Baker, Bloom, and Davis 2016), a shortcoming of these techniques is that their performance depends heavily on expert knowledge to curate the dictionaries. This makes it difficult for manual dictionaries to comprehensively capture the full range of words that refer to a particular topic.

[30] Word2Vec is a widely adopted word-embedding technique, where each word w is represented by a K-dimensional vector $\vec{w} \in R^K$. We use the skip-gram implementation of Word2Vec. For a given sequence of words $w_1, w_2, .. w_N$, (in a title or video description) the model takes each word as input and aims to predict the surrounding words that come before and after, in a fixed window. Therefore, the objective of the model is to choose word vectors so as to maximize the following likelihood function $\sum_n \sum_{i \in S_n} \log p(w_i|w_n)$, where S_n is the set of words surrounding w_n. Mikolov et al. (2013) show that the resulting word vectors capture semantic and syntactic similarities between words in an efficient way.

[31] As a predictor of child-targeted content usage, YouTube channels would have minimal type 1 error. Therefore, it provides reliable information on a specific type of childcare-related website usage and can serve as a robustness check to validate our textual analysis results.

These approaches produce 3 alternative measures of childcare-related browsing that we study in Table 7 panel B. Although daily browsing time is modest for each of these measures, it is reassuring to see that parents spend more time consuming child-related content than do non-parents (who may still co-reside with children, such as nieces or nephews). Unlike our main estimates of substantial gender differences, we find only small (ranging from < 10 to 50 seconds) and statistically insignificant gender differences in the effect of the lockdown on child-related browser use across the 3 measures.

We also consider the possibility that men's higher rates of job loss, or more shifting to work from home, relaxed their time constraints by more than women's and enabled them to increases both time devoted to childcare and browser time, relative to women. We repeated our main analyses for browser time use and for self-reported childcare time use on a sub-sample that excludes the 44 people who reported losing a job during the pandemic, but the results were unchanged (Table A7, Panel A). Furthermore, we found that significant gender differences persist if we expand our model to control for differential impacts of the lockdown on people experiencing job loss (separately for themselves and their spouses) or starting to work from home (self or spouse) in Table A7, Panel B, or if we account for access to sources of paid or unpaid (family) childcare (see Table A12).

6. Discussion and Conclusions

Around the world, the curtailment of face-to-face activities during the COVID-19 pandemic made the internet a vital avenue for leisure, production, and human capital investment. This paper provides a unique view into how pandemic lockdowns changed digital activity and time use, drawing on novel data from an online survey and continuous clickstream data tracing internet browser histories, collected during the initial Indian lockdown.

This exercise provides a novel demonstration of the value of information that can be extracted by analyzing "digital footprints" left by people going through their normal online activities, even in a setting with strong privacy protections and fully informed consent for all data collection. Collecting data in a consensual manner was more costly than using de-contextualized or anonymized data sources, which limited the scale of the collection, but we managed to obtain data in a short time frame from over a thousand people. The higher cost was more than offset by the availability of supplemental information on demographic, contextual and subjective factors necessary for this analysis. This model can be applied and extended to other settings in which organizations and researchers want to benefit from "big data" but are constrained by legal, ethical, and practical considerations.

Our browser data provide a rich and objective record that enable us to measure changes in online activity and time use around the time of the lockdown. By capturing the substantial increases in browser use among both men and women, across a range of activity domains, our data illustrate the heightened importance of digital access during times of disruption and physical danger. This increased value of digital access during the pandemic lockdown supports greater public and private investment in expanding such access more broadly, and particularly of reducing existing disparities in access between demographic groups.

The benefits of increased internet use that we find on our relatively privileged sample of highly educated Indians with personal computers and internet access were not available to people without such access. This has implications for gender equality because of the digital divide on the extensive margin of internet access by gender, which is in part reflected in the male-dominated composition of our sample. Within our sample, our findings of relative increases in internet activity for men, overall, and across a range of activities, further suggest widening gaps in wellbeing from uneven digital use. Access to a device and an internet connection are not enough to ensure full use when other factors interfere. These results – which highlight the value gained from examining the intensive margin of digital technology usage – have implications for policymakers concerned with IT diffusion and with its uneven distribution.

By combining browser and survey data, we are also able to measure gender differences in the impact of the lockdown for different sub-groups. We find the relative decline for women particularly in the leisure domain, is concentrated among parents. This suggests that a source may be that the lockdown disproportionately exacerbated the caretaking burdens on women. However, this was not detected in our time-use survey on childcare time, where men self-reported relatively larger increases in time spent caring for children than women did. The pattern in self-reports is also not echoed in reports from spouses or in objective data on child-related internet browsing, suggesting that self-reports may be unreliable because of the subjective aspects of responses to simple time use questions about childcare time. With increasing availability of objective digital trace data and development of machine learning methods that enable highly granular measures, similar cross-validation of survey data may become common.

In addition to providing evidence on how the immediate effects of the initial COVID-19 lockdown in India differed by gender, our results also have implications for employers and organizations that seek to attract and retain female talent. Two of our findings suggest additional challenges coming from lower labor force attachment among women without full-time jobs. The first is the relative decline in online production time use for those women compared to similar men. The second is the decrease in women's online job seeking activity, both in absolute terms and relative to men. These outcomes may be directly observable to employers who observe work time and job applications. Our third finding, for full time working women, is less directly visible. These women maintained their productive time online, relative to men, but they experienced significant relative drops in online leisure time. This occurred while in-person leisure activities were largely proscribed and may have long term consequences, such as burnout, that drive some women to leave their jobs. This finding suggests that employers could benefit from investing proactively in inquiring about and supporting the mental health and work-life balance challenges of their workers, in addition to efforts and programs developed in response to the pandemic to expand opportunities for remote and flexible work. That women did not fall behind in human capital development suggests that they continued to aspire towards career advancement despite the setbacks the pandemic caused, a positive outlook that employers and governments could benefit from nurturing.

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FIGURES AND TABLES

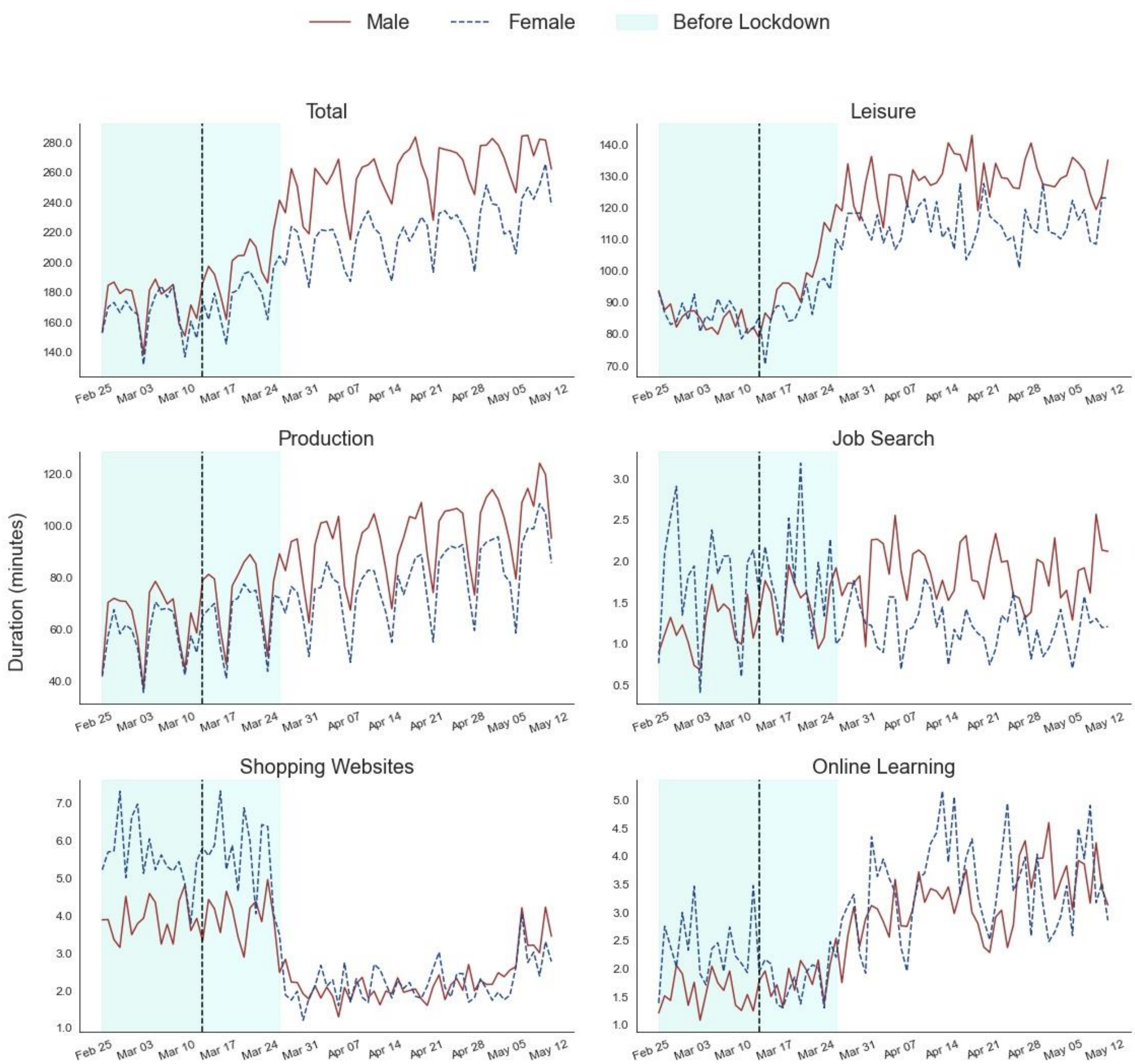
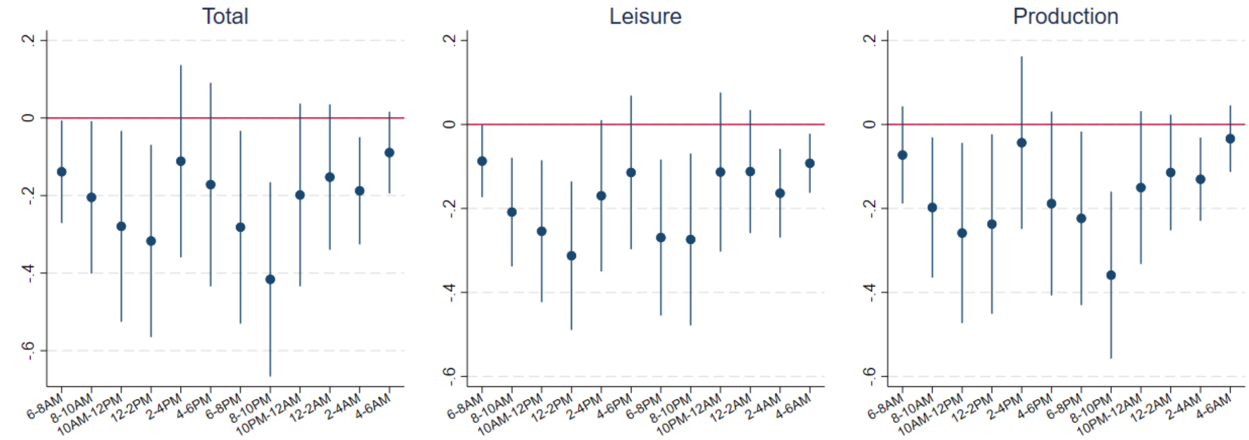


Figure 1 Average Daily Internet Browser Time Use by Gender

Notes. The COVID-19 lockdown in India started on March 25, 2020, and continued through the end of the sample period. The pale blue shaded region represents the pre-lockdown period. The WHO officially declared COVID-19 as a global pandemic on March 11, 2020 (black vertical dashed line).

(A). All Browsing



(B). Mobile Browsing

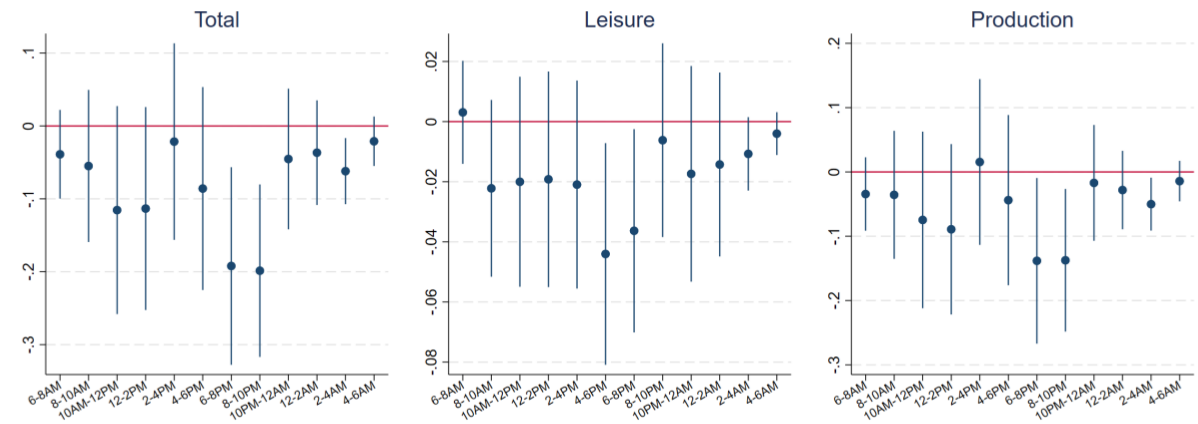


Figure 2 Within-Day Changes in Internet Browser Time Use

Notes. This figure presents separate results for the effects of the lockdown on the gender gap in total daily time use by time of day. The dependent variable is the natural log transformation of the daily browser time plus 1 second. We divided each day into twelve 2-hour intervals and ran a separate regression for each interval, using our model with individual and date fixed effects. The dots depict regression estimates for each of the interaction terms between female and lockdown indicators; bars show 95-percent confidence intervals, with standard errors clustered at the individual level. Panel A presents usage from all browsers linked with the same user account, panel B presents usage on mobile websites.

Table 1 Sample Composition

Variables	Women		Men		Female—Male	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Error
Age	30.71	7.369	33.124	7.864	-2.414	0.485***
Any Children	0.58	0.494	0.612	0.488	-0.032	0.031
Any Children Under 8	0.425	0.495	0.485	0.5	-0.060	0.031*
Married	0.603	0.49	0.642	0.48	-0.039	0.031
College Graduate	0.921	0.27	0.916	0.278	0.005	0.017
Employed Full Time	0.639	0.481	0.772	0.42	-0.133	0.029***
White-Collar Occupation	0.214	0.41	0.27	0.444	-0.058	0.022**
Self-Employed	0.122	0.328	0.18	0.384	-0.057	0.022***
Started Working from Home	0.438	0.497	0.449	0.498	-0.012	0.031
Number of Individuals	393		701		1,094	

Notes. Survey responses from 1,094 individuals in India, between 10 May and 4 June, 2020. Significance at *** p<0.01, ** p<0.05, * p<0.1

Table 2 Daily Browser Use by Gender and Time Period

	Before Lockdown			Increase During Lockdown			Before WHO Announcement
	Male Sample Mean [Std. Dev.]	Female Sample Mean [Std. Dev.]	Gender Difference Mean (Std. Err.)	Full Sample Mean (Std. Err.)	Male Sample Mean (Std. Err.)	Female Sample Mean (Std. Err.)	Gender Difference Mean (Std. Err.)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Total Time	184.5	171.0	-13.55	66.05***	75.48***	49.59***	-7.589
	[216.9]	[207.6]	(10.28)	(4.270)	(5.503)	(6.615)	(10.78)
Total Unique URLs	193.2	177.9	-15.34	93.19***	107.7***	67.65***	-6.422
	[379.8]	[360.0]	(15.72)	(10.43)	(10.40)	(22.33)	(17,22)
Leisure Time	91.08	87.82	-3.269	33.91***	37.98***	26.74***	0.958
	[172.3]	[167.7]	(8.398)	(3.240)	(4.096)	(5.276)	(8.866)
Production Time	68.52	61.01	-7.503*	23.67***	27.03***	17.88***	-6.364
	[94.30]	[83.43]	(4.038)	(1.849)	(2.287)	(3.113)	(4.064)
YouTube Time	62.30	51.78	-10.52	23.64***	27.51***	17.01***	-6.549
	[148.4]	[133.5]	(6.848)	(2.637)	(3.461)	(3.961)	(7.177)
Unique YouTube Videos	5.183	4.061	-1.122*	2.497***	3.230***	1.220***	-0.767
	[14.85]	[11.32]	(0.595)	(0.264)	(0.374)	(0.306)	(0.593)
Unique Google Searches	4.220	4.019	-0.201	1.432***	1.652***	1.046***	-0.0546
	[9.506]	[8.911]	(0.379)	(0.159)	(0.207)	(0.242)	(0.408)
Facebook Time	3.899	4.166	0.267	1.451***	1.973***	0.512	0.347
	[18.78]	[19.65]	(1.077)	(0.336)	(0.479)	(0.359)	(1.238)
Job Search Time	1.323	1.740	0.416	0.147	0.525***	-0.537	0.542
	[8.205]	[15.38]	(0.687)	(0.254)	(0.185)	(0.642)	(0.780)
Online Learning Time	1.695	2.088	0.393	1.472***	1.536***	1.347**	0.770
	[9.867]	[14.29]	(0.560)	(0.310)	(0.346)	(0.610)	(0.746)
Observations	19,675	10,565	30,240	81,462	52,509	28,953	15,906

Notes. Outcomes are at the person-day level and reported here in levels (minutes or counts). Columns (1) and (2) reports the browser use outcome in the pre-lockdown period. Column (3) and (6) reports the estimated gender difference (female – male) for each browser use outcome in the pre-lockdown period and the period prior to the WHO announcement. Columns (4)-(6) report average increases in browser use (lockdown – pre-lockdown) for the full sample (4) and then for male (5) and female (6) sub-samples. Standard errors are clustered at the individual level. Significance at *** p<0.01, ** p<0.05, * p<0.1.

Table 3 Effects of the Lockdown on Gender Gaps in Browser Activity

	Total (1)	Leisure (2)	Production (3)	YouTube (4)	Facebook (5)	Google Search (6)
All Browsing						
Panel A. Daily Browser Time						
Lockdown × Female	-0.292**	-0.326**	-0.337**	-0.344**	-0.295***	
	(0.148)	(0.151)	(0.140)	(0.138)	(0.0720)	
Panel B. Daily Website Visits						
Lockdown × Female	-0.280***	-0.254***	-0.265***	-0.160***		-0.085**
	(0.0897)	(0.0682)	(0.0862)	(0.0421)		(0.0390)
Mobile Browsing						
Panel C. Daily Browser Time						
Lockdown × Female	-0.405***	-0.174**	-0.300***	-0.0632	-0.0274	
	(0.126)	(0.075)	(0.115)	(0.0469)	(0.0245)	
Sample Mean	21.342	5.222	14.529	2.569	0.355	
Panel D. Daily Website Visits						
Lockdown x Female	-0.353***	-0.104***	-0.292***	-0.0420**		-0.0418***
	(0.0919)	(0.0374)	(0.0837)	(0.0180)		(0.0138)
Sample Mean	199.66	8.614	135.02	0.825		0.468
Observations	81,462	81,462	81,462	81,462	81,462	81,462
Number of Individuals	1,094	1,094	1,094	1,094	1,094	1,094
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes. This table presents the main estimates for daily internet browser time use and activity counts. Panel A presents results for browser time use outcomes, and Panel B presents the activity counts, measured as unique URLs generated. Column (1) shows total browser use while subsequent columns are for categories: leisure (2), production (3), YouTube videos (4), Facebook (5) – URLs not examined because extensive activity occurs within the main URL, and Google searches (6) – time on search pages not examined because people typically follow links to results quickly. Standard errors are clustered at the individual level. Dependent variables are the natural log transformation of 1 plus the outcome of interest. Significance at *** p<0.01, ** p<0.05, * p<0.1.

Table 4 Effects of the Lockdown on the Dominant Mode of Internet Access

	Female	Male	*p-value for t-test* Female = Male
More access via internet browser	67.12%	66.80%	0.284
More access via non-browser mobile apps	25.73%	24.50%	0.097
No change	7.15%	8.70%	0.009
Number of Individuals	3,680	6,105	

Notes. Survey responses from 10,175 individuals in India during September – December 2022. Note that we dropped 52 individuals who reported non-binary gender or did not want state their gender, and 281 individuals who did not report an answer. We asked individuals about the change in their dominant mode of internet access during the initial Covid-19 lockdown (i.e., between April-June 2020). More access via internet browser reflects that respondents reported that they started spending more time on internet browser (PC, tablet and smartphone combined) compared to other smartphone apps. More access via non-browser smartphone apps reflects that respondents started spending more time on specific smartphone or tablet apps other than the browser app. P-values report the test for the equality of means with heteroskedasticity-robust standard errors.

Table 5 Heterogeneous Effects by Parental Status and Employment Status

Panel A. Parental Status

	One Child or More			No Children		
	Total	Leisure	Production	Total	Leisure	Production
	(1)	(2)	(3)	(4)	(5)	(6)
Lockdown × Female	-0.395**	-0.567***	-0.370**	-0.153	0.0141	-0.298
	(0.181)	(0.190)	(0.173)	(0.249)	(0.243)	(0.232)
p-value for t-test: Parents = Non-Parents	0.052	0.005	0.185			
Observations	48,879	48,879	48,879	32,583	32,583	32,583
Number of Individuals	657	657	657	437	437	437

Panel B. Employment Status

	Full-time Employed			Not Full-time Employed		
	Total	Leisure	Production	Total	Leisure	Production
	(1)	(2)	(3)	(4)	(5)	(6)
Lockdown × Female	-0.275	-0.491***	-0.244	-0.448	-0.0715	-0.664**
	(0.176)	(0.171)	(0.165)	(0.290)	(0.312)	(0.271)
p-value for t-test: Full Time = Non-FT	0.413	0.021	0.872			
Observations	59,140	59,140	59,140	22,322	22,322	22,322
Number of Individuals	792	792	792	302	302	302

Notes. This table reports the main estimates for the differential effect of the lockdown on women for various samples. All regressions include individual and date fixed effects. Panel A splits the sample by parental status: adults with at least one child are in columns (1)-(3) and those with no children are in columns 4-6. Panel B presents separate estimates for the full-time employed sample in columns (1)-(3) and for others (including students and part-time employed) in columns (4)-(6). The dependent variables in Panels A and B are the natural log transformation plus 1 second of the outcome of interest. Standard errors are clustered at the individual level. Significance at *** p<0.01, ** p<0.05, * p<0.1.

Table 6 Effects of the Lockdown on Job Search

Panel A. Job Search (Browser Data)

	Full Sample		Not FT Employed and No Change	
	Visited a Job Search Page	Job Search Page Time Use	Visited a Job Search Page	Job Search Page Time Use
	(1)	(2)	(3)	(4)
Lockdown × Female	-0.0220**	-0.138**	-0.0404**	-0.275***
	(0.00941)	(0.0580)	(0.0171)	(0.104)
Observations	81,462	81,462	19,824	19,824
Number of Individuals	1,094	1,094	269	269

Panel B. Job Search (major Indian online job search portal)

	Job Search Duration	Session Duration	Number of Job Applications	Number of Job Searches	Number of Job Post Views
	(1)	(2)	(3)	(4)	(5)
Lockdown x Female	-0.658***	-0.231***	0.00341	-0.0726***	-0.152***
	(0.134)	(0.0467)	(0.0185)	(0.0140)	(0.0367)
Female	0.373***	0.203***	0.185***	0.214***	0.523***
	(0.120)	(0.0402)	(0.0171)	(0.0121)	(0.0330)
Sample Mean	15.437	8.059	1.138	1.177	3.078
Observations	158	158	158	158	158
Date FE	Yes	Yes	Yes	Yes	Yes

Notes. This table reports the main estimates for the differential effect of the lockdown on women for daily job search activity on browser and one of the largest Indian job search platforms. Panel A presents the results on the job search websites. In that panel, the outcome in columns (1) and (3) is an indicator variable for whether the person visited a job search website that day, and the outcome in columns (2) and (4) is the time spent on job search websites (with the log transformation to the value plus 1 second). Columns (1) and (2) are from models estimated on the entire sample, while columns (3) and (4) use the subset of participants that were not employed full time at the time of the survey and had no change in employment status over the prior 90 days. Panel B presents the regression estimates for the job search platform's daily job search activity, covering the period between 22 February and 10 May 2020, matching the time window of our browser data. An observation is a gender-date combination. The dependent variables are minutes (columns 1-2) or counts (columns 3-5). All regressions include date fixed effects and those in Panel A also include individual fixed effects. Standard errors in Panel A are clustered at the individual level. Significance at *** p<0.01, ** p<0.05, * p<0.1.

Table 7 Survey-Based Measures of Childcare Time and Childcare-Related Browser Usage

Panel A. Measures of Childcare Time

	Childcare time use	
	Own	Partner's
	Married Sample with Children	*Married Sample with Children*
	(1)	(2)
Female	0.660***	-1.219***
	(0.208)	(0.199)
Lockdown	1.523***	0.735***
	(0.163)	(0.175)
Lockdown × Female	-0.767**	-0.0205
	(0.300)	(0.289)
Constant	2.565***	3.934***
	(0.107)	(0.122)
Observations	1,146	1,146
Number of Individuals	573	573

Panel B. Childcare-related Browser Usage

	Manual Dictionary	Word Embedding	YouTube Kids Channels
	Sample with Children	*Sample with Children*	*Sample with Children*
	(1)	(2)	(3)
Lockdown × Female	-0.729	-0.286	-0.233
	(2.011)	(1.265)	(0.241)
Sample Mean (Parents)	7.059	4.600	0.150
Mean (Non-Parents)	4.947	2.601	0.015
p-value for t-test:			
Parents = Non-Parents	0.043	0.002	0.001
Observations	48,879	48,879	48,879
Number of Individuals	657	657	657
Individual FE	Yes	Yes	Yes
Date FE	Yes	Yes	Yes

Notes. This table presents survey-based measures of childcare time and childcare-related internet usage. Panel A presents the estimates for survey-based time use outcomes related to household production. The unit of observation is a person-period (before or after the lockdown is imposed). Married respondents answered questions about their own and their partners' usual daily time spent on childcare (if they had children). Daily time use was measured as an interval variable using 2-hour buckets up to 8 or more hours. We converted it to a continuous variable using the mid-point of each bin and assigning 10 hours to participants who selected 8 or more hours. The online survey was conducted during the lockdown period, so only the lockdown values are contemporaneous. Robust standard errors are in parentheses Panel B presents the results for childcare-related internet browser usage. Outcome variables are measured in minutes. Standard errors are clustered at the individual level. The subsample means are at the person-day level and reported in levels (minutes). P-values report the test for the equality of means, after clustering the standard errors at the individual level. Significance at *** p<0.01, ** p<0.05, * p<0.1