A Study by

KOAN and OLA MOBILITY INSTITUTE

WOMEN'S ECONOMIC MOBILITY AND ONLINE EXPOSURE

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Koan Advisory Group is a New Delhi-based public policy consultancy. It specialises in policy and regulatory analysis in both traditional and emergent sectors and markets. For more information, please visit: www.koanadvisory.com

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CONTENTS

EXECUTIVE SUMMARY

For every 10 women in the working age-group, only two work in India. In comparison, this ratio stands at 4.4 in China and East Asia, 4.6 in the European Union, North America and Sub-Saharan Africa, 4.7 in Oceania, and 4.1 in Latin America and the Caribbean (World Bank, n.d.). In fact, India ranks 220th in women labour force participation (WLFP), out of 235 countries and regions for which employment data is available. While numerous policies and measures are in place at the Central as well as the state levels to improve WLFP in India, the progress remains slow. The country fared relatively better before 2007-08 when WLFP was in excess of 2.5 out of 10 (World Bank, n.d.).

In this context, we have conducted this study to help improve the economic status of women through their labour force engagement. We examine the instrumental role online exposure plays to improve the time women allot towards employment and related activities. Online exposure imparts necessary digital skills and gives access to work-related information from wide-ranging sources. It also aligns with the government's objective to increase the share of online activities in total value added to 20 percent by 2025, from a paltry 7-8 percent in 2020 (Ministry of Electronics and Information Technology, 2020).

From a primary survey of over 4,000 women across 10 Indian cities and information sources such as the Time Use Survey under the aegis of the National Sample Survey (NSS-TUS), the Periodic Labour Force Survey (PLFS), the National Family Health Survey–5 (NFHS-5), and the World Bank, etc., this report presents a range of empirical tests to examine the impact of online exposure on women's daily time utilisation.
Three major findings emerge, including a first-of-its-kind estimation on the potential contribution of urban women's online exposure to India's Gross Domestic Product (GDP):

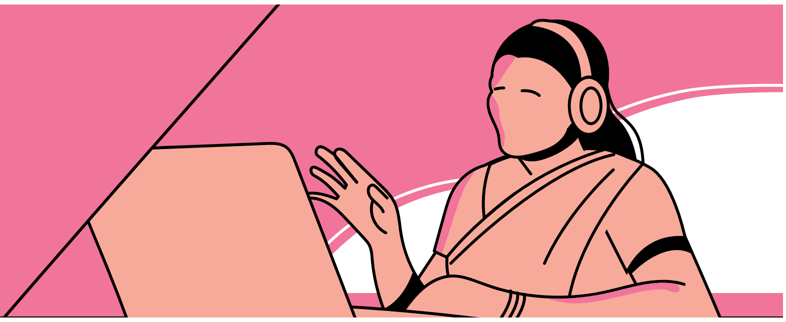
Online exposure has a vital role to play in WLFP. Our findings suggest that online exposure can enable women to play a more active role in their economic mobility, by recalibrating how their time is spent. On average, a woman spends 78 minutes of extra time daily on employment and related activities due to online exposure. However, the time she allots to unpaid household activities does not reduce. This is a novel result vis-à-vis the current pedagogy on WLFP, which focuses on factors where women play a more passive role. It puts forth arguments such as rising household income, declining opportunities for women and gender wage gap, safety concerns and patriarchy, and exigencies of reproduction and care as the root cause of a low and falling WLFP. Therefore, the result of this study fills a palpable void in understanding WLFP in India, by delving into aspects where women can play an active role.

Our findings also suggest that for online exposure to translate into better labour force participation, women require a certain minimum level of skill and resources. These include an intermediate level of education, rising household income, and households with members employed in regular/salaried jobs, self-employment or as employers. This result is useful for policy makers to address low and falling WLFP. They may target reduction in school drop-out rates, creating economic mobility opportunities, greater formalisation of the economy, and stepping up child and elderly care facilities in the country.

Overall, this report, in conjunction with the existing wisdom on WLFP in India, makes two vital points. First, WLFP narrative only portrays a part of the reality where women have a passive role, constrained by socio-cultural norms. It does not take into account dynamic factors such as digitalization that may enable them to have an active stance on their participation in the labour market. Second, with two (or more) groupings, the debate on WLFP should also be in the larger context of gender complementarity for maximising household welfare. Then, the premise for individuals' engagement in work draws from their relative advantages within a household. To some extent, such a paradigm already exists, even though it portrays a dismal picture as per the existing labour accounting standards – which exclude household work from formal labour.

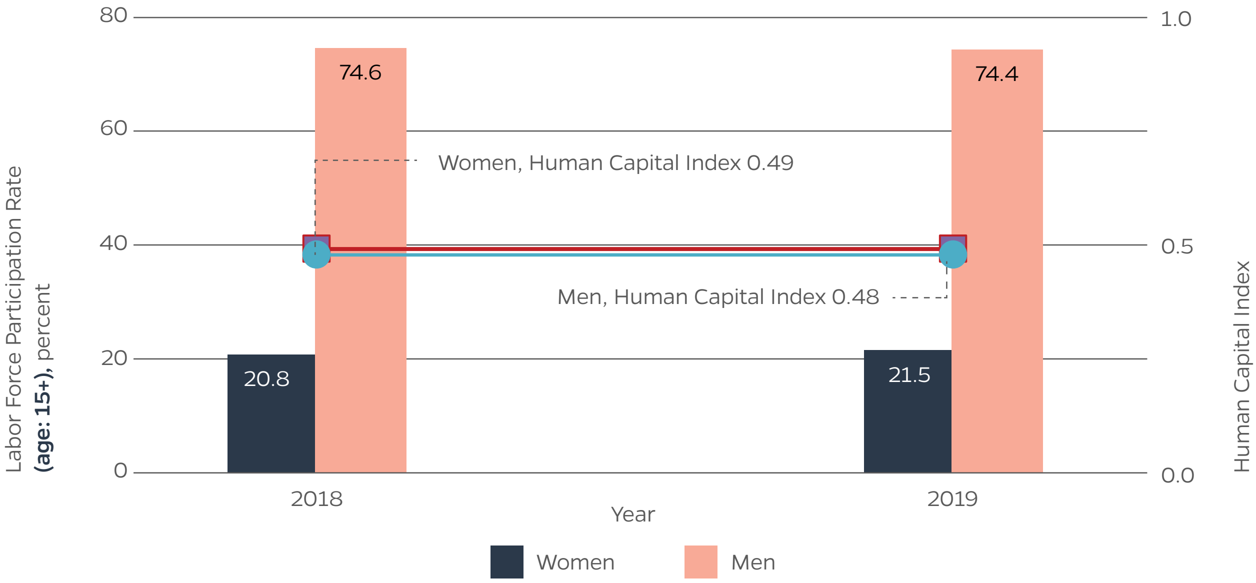
The findings demonstrate the implications of online exposure through WLFP on the aggregate economy. As many as 102 million hours of additional daily time may accrue to paid activities in the economy if women went online. This translates into an additional USD 103 billion of monetary value, amounting to almost 3.9 percent of the Gross Domestic Product (GDP). Nearly 29 percent of this is due to productivity gain on account of online exposure, while the remaining 71 percent is due to additional daily labour. Importantly, these gains are likely to increase as digital services expand their footprint in the country. Overall, this report, in conjunction with the existing wisdom on WLFP in India, makes two vital points. First, WLFP narrative only portrays a part of the reality where women have a passive role, constrained by socio-cultural norms. It does not take into account dynamic factors such as digitalization that may enable them to have an active stance on their participation in the labour market. Second, with two (or more) groupings, the debate on WLFP should also be in the larger context of gender complementarity for maximising household welfare. Then, the premise for individuals' engagement in work draws from their relative advantages within a household. To some extent, such a paradigm already exists, even though it portrays a dismal picture as per the existing labour accounting standards – which exclude household work from formal labour.

INTRODUCTION



Women steer most unpaid activities in India, which include housework and care. While these are essential for the well-being and development of household members' capabilities, there is no explicit monetary compensation to perform these tasks. Besides, such work remains unaccounted in conventional income computation and labour force statistics. Illustratively, the women labour force participation rate in India was less than one-third compared to men, during 2018-19 (Figure 1.1), even though both genders are roughly equal in human capital quality.

Figure 1.1: Gender-wise Labour Force Participation Rate



Source: Ministry of Statistics and Programme Implementation (MOSPI, Government of India), World Bank

A lower economic status of women is a recurrent feature in Indian policy debates, due to four reasons –

- Rising household income
- Declining opportunities for women and gender wage gap
- Safety concerns and patriarchy
- The exigencies of reproduction and care

The Government of India, through its ministries and organisations such as the Ministry of Women and Child Development, Ministry of Human Resource Development, National Skill Development Corporation, and NITI Aayog, has implemented a number of policies aimed at improving the economic status of women. The outcomes of these policies, however, leave a lot to be desired. For example, women's labour force participation is not only low, but also falling in the country (source: MOSPI).

In order to fill this gap, we take a closer look at the instruments, which might improve the economic status of women. Evidence suggests that online exposure can be an important instrument in prompting time allocation towards paid work activities, for three reasons (Freeman, 2002; Atasoy, 2013; Kelly et al., 2017; Jain, 2021).

- First, it improves the ability of users to mine work-related information from wide-ranging sources, including employers, listing platforms and social networks.
- Second, online exposure also imparts necessary digital skills and wider accessibility, which are important in improving employability.
- Third, the share of online activities in total value added of the country, portrays a secular growth.

At 7-8 percent in 2020, the government intends to increase the share of online activities in gross value added (GVA) to 20 percent by 2025 (Ministry of Electronics and Information Technology, 2020). This implies improved employability prospects for those endowed with digital skills.

With online exposure as the plausible instrument, urban India provides a relatively efficient ground to assess women's economic mobility compared to rural India. Notably, nearly half of the women in Indian cities have online exposure, as against only one-third in rural India (source: National Family Health Survey or NFHS-5, implemented during January-December 2019-2021). A similar pattern emerges when we examined the proportion of women who had completed at least 10 years of education – a crucial criteria for employability (source: NFHS-5).

Four-step empirical strategy to examine role of online exposure

Step 01
NFHS-5 and NSS time-use survey analysis

Step 02
An online survey across 10 cities in India

Step 03
Pooling NSS timeuse survey and the online survey, adjusting for the pandemic

Step 04
Using the above results to calculate the effect on the aggregate economy

We adopt **a four-step empirical strategy** to examine the role online exposure plays in influencing women's economic mobility, by analysing information from multiple sources.

01 The NFHS-5 reveals that 50 percent women in urban India have online exposure and the NSS time-use survey (NSS-TUS, implemented during January-December 2019) presents information on women's daily time allocation towards various activities. Since both these sources are sub-nationally representative and have an overlapping implementation period, it is reasonable to assume that the broader finding from the two surveys can be aggregated seamlessly. We surmised that, on average, 50 percent of urban women respondents in the NSS-TUS survey have online exposure.

02 We conducted an online survey across 10 cities in India (implemented during July-August 2021), where, by design, all respondents have online exposure. From the responses, we estimated the responsiveness of an array of socio-economic variables on three key aspects of women's economic mobility – time allocation towards employment and learning, online time and online time allocation towards employment and learning. Three important insights emerged from this exercise.

- Women with at least high school education spend more (online as well as total) time on employment and learning.

- Allocation for total online time as well as online time on employment and learning increases with household income.

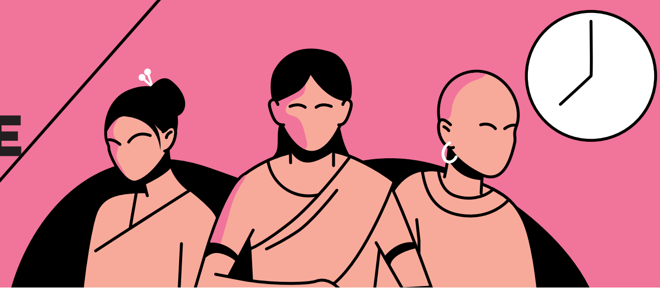
- Total time spent on employment and learning follows a U-shaped relationship with age. In contrast, total online time follows an inverted U-shaped relationship with age, while online time spent on employment and learning follows an inverse relationship with age. These results indicate that with growing educational attainment, a young population and rising income levels in the country, online exposure is one of the most critical fulcrums to advance women's economic mobility.

03 Third, we pool the NSS-TUS and the online survey, after adjusting for the pandemic's effect on women's time-use, using corrective weights from the secondary literature.[2] On the premise that the time allocation pattern for those with online exposure is significantly different from those without it, we employ a treatment-control approach to establish a causal relationship between online exposure and time-use pattern of women. The NSS-TUS respondents, in the same 10 cities as the online survey, represent the control group and the online survey respondents represent the treatment group.

04 Using the results derived from the treatment-control design as well as from other secondary sources, we calculate the effect of online exposure on the aggregate economy. We find that it leads to an additional 102 million hours of daily time spent on paid activities in the economy. Further, online exposure extends women's contribution to the GDP by almost 3.9 percent, which is equivalent to USD 103.45 billion. This increases women's overall contribution to 21.89 percent of the GDP which is equivalent to USD 582.29 billion. Since growing networks like the internet tend to follow a power law in bestowing value (Swann, 2002), these results imply that the impact of online exposure on the aggregate economy will have an accelerated momentum going forward. Therefore, from a policy perspective, it is imperative to ensure an increase in the level of internet adoption among women, from the current 50 percent.

This report makes an important contribution to the literature and debates on women economic mobility, as against the traditional approach to this topic. The traditional approach assumes women to be passive agents. Exogenous factors such as patriarchy, exigencies of reproduction and care, and declining opportunities are primarily used to explain their labour force participation. Andres et al. (2017) look at the role of these as well as several other exogenous socio-economic and demographic characteristics in explaining the women labour force participation decision, which they claim is between 34 to 40 percent. This makes it plausible that some part of the unexplained decision is due to women's active stance for the labour market. The current framework fills this gap, and suggests that online exposure is an important lever for women to participate in formal labour activities. Additionally, this study concludes with a first-of-its-kind estimation on the potential contribution of urban women's online exposure to India's Gross Domestic Product (GDP).

TRENDS IN WOMEN LABOUR FORCE PARTICIPATION



Across the world, women spend more time than men on unpaid care work (ILO, 2019). The global average time spent on unpaid care work by women is 277 minutes, ranging from a maximum of 490 minutes in Cabo Verde to a minimum of 168 minutes in Taiwan, China (ibid).

Indian women spend 299 minutes a day on unpaid domestic services, whereas their male counterparts spend around 97 minutes (NSS-TUS, 2019). In comparison, the time spent on unpaid care work by women is less regressive in other BRICS nations – Brazil (173 minutes), South Africa (229 minutes), China (237 minutes), Russia (259 minutes) (ILO, 2019; World Bank n.d.). Meanwhile, the time spent on unpaid care work by women in developed countries does not vary significantly– 268 minutes in Germany, 264 in the United States and 232 in the United Kingdom (ILO, 2019).

Time spent on unpaid care work in BRICS nations

Brazil
173 MINUTES

South Africa
229 MINUTES

China
237 MINUTES

Russia
259 MINUTES

Time spent on unpaid care work in developed countries

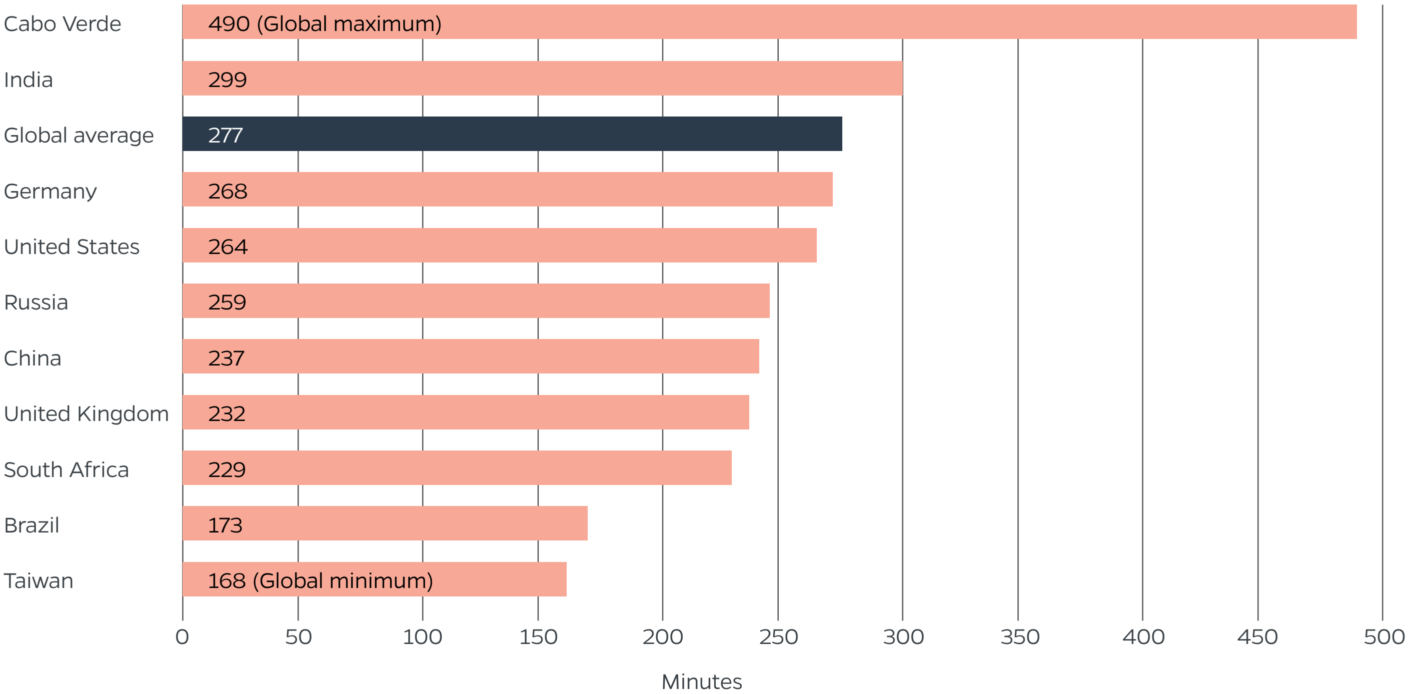
Germany
268 MINUTES

United States
264 MINUTES

United Kingdom
232 MINUTES

[1]Pooling presents some econometric challenges that we address in our empirical setup.

Figure 2.1: Daily Time Spent on Unpaid Care Work, Women



Source: ILO (2019)

Despite India being one of the fastest growing economies in the world, women labour force participation (WLFP) has oscillated between a paltry 16 and 23 percent in the last few years (World Bank, n.d., ILO, n.d.). That only a third of the country's women partake in economic activities shows the expanse of underutilised human resources. At 32.6 percent, India has one of the largest gender gaps in economic participation and opportunities in the world (World Economic Forum, 2021). According to the International Monetary Fund (IMF), reaching gender parity in the economy could boost India's GDP by as much as 27 percent (Lagarde and Solberg, 2018). The World Bank also projects that India's GDP growth rate could breach the nine percent mark, if women had an equitable share of jobs (Dixon, 2018). It also estimates that India's growth could increase by 1.5 percentage points per year if just 50 percent of women could join the workforce.

The declining trend in WLFP has commonly been attributed to several structural insecurities that include (A) increase in household income, (B) employment opportunities and wage differential, (C) safety concerns and patriarchy, and (D) exigencies of reproduction and care. We examine these below.

2.1 Appraisal of the Traditional Arguments on Structural Insecurities and WLFP

Increase in household income and WLFP

Traditionally, there are three arguments correlating increase in household income with low and/or falling WLFP. One, women are not seen as the primary breadwinners of the family, and therefore, a rise in household income precludes them from participating in economic activities to earn (Bhalla and Kaur, 2011). Two, studies show that the popularisation of commercial agriculture has led to a rise in household income (Mehrotra and Sinha, 2017), while child and elderly care support remains extremely limited (Khurana, 2015, 2020). These increased the opportunity cost of domestic activities for women, leading to their withdrawal from the labour force. Three, higher expenditure categories typically have a lower WLFP, especially in rural areas, as per the NSSO data (1970–2018). Here, the withdrawal of women from the paid workforce is perceived as a demonstration of the men's abilities to provide for their families (Nikore, 2019).

"While rising household income is cited as one of the causes of low and falling WLFP, understanding around it is limited. Perhaps, a more relevant approach is to consider the rise in income as a multi-faceted shift, which pushes the quality of living upwards. This implies that within a household and among members who can potentially work, some would cater to quality provisions (which is an allocational problem), while others would ensure that the flow of income keeps growing (or stays intact), or everybody would cater to the both. Advocates of such an argument attribute the fall in WLFP to rising household income and division of work within households (Barnett and Hyde, 2001; Nair et al., 2017). Two additional remarks are also pertinent. One, this line of reasoning gives a relatively active role to women in the household, which unless established otherwise, is a normatively superior position to take. Two, it suggests that the fall in WLFP due to rising household income is transient. That is, WLFP will reverse from a falling trajectory once the quality of life has moved sufficiently upwards. These remarks find sufficient empirical support as well. For example, post-1990, several countries saw a prolonged spell of falling WLFP of over five years or more. These include Bulgaria, Cambodia, China, Czech Republic, Hungary, Iceland, Dem. People's Republic of Korea, Malaysia, Myanmar, Poland, Ukraine and Vietnam (World Bank, n.d.)."

Employment opportunities, wage differential and WLFP

Employment opportunities and wage differential arguments around WLFP build on the pioneering work of Averitt (1968), who suggests that all economies have two distinct parts – a core and the outer periphery. The periphery economy includes lower capital intensity, highly competitive markets, low profit margins, low skilled job requirements, high employee turnover, poor working conditions and low wages. Women form a substantial part of the workforce of the peripheral industry (Bhalla and Kaur, 2011; Duraisamy and Duraisamy, 2016). For example, agro products like cashew, oil meals, and processed food have experienced a fall in demand. This has an impact on the workforce, particularly on informal contract workers, piece-rated wage workers and unpaid family workers, who are largely women (Mehrotra and Sinha, 2017). Moreover, increasing mechanisation of traditionally labour-intensive tasks, even in the services sector, has affected women disproportionately (Nikore, 2019). According to the McKinsey Global Institute's estimates, by 2030, up to 12 million Indian women could lose their jobs to automation in the agriculture, transportation, warehousing, fisheries, and forestry sectors (Madgavkar et al., 2019).

A second argument looks at how wages act as an incentive to work. When women receive substantially lower wages than men, the FLPR is poised to fall. There are predominantly three reasons why women receive lower wages than men – occupational choice (as noted in the above paragraph), social desirability and on-job discrimination. The social desirability argument works through marriage and fertility decisions on the labour market. Jensen (2012), in an experiment conducted in several Indian villages, notes that women's involvement in labour market opportunities lowers their likelihood of getting married or having children. In some cases, several social groups and religions have explicit restrictions on WLFP (such as blanket restrictions on certain occupations, work-related travel and migration), making it perverse (Madheswaran, 2010; Sengupta and Das, 2014; Ara, 2021).

Job discrimination, so far, is backed by a large pool of evidences in the literature (Agrawal, 2014; Deshpande et al. 2018; Poddar and Mukhopadhyay, 2019). It typically refers to the part of the wage differential that is unexplained by socio-economic, demographic or observable labour market characteristics. Of late, several researchers suggest a falling pattern in the gender wage differential in India (Chakroborty and Chakraborty 2009; Duraisamy and Duraisamy 2016).

The arguments around employment opportunities and wage differential, for a low and falling WLFP, raise two important questions, which are not adequately accounted for in literature. One, the reason why women are perceived to be less adaptive to the changing patterns of employment opportunities remains a mystery. Wage differential models, especially those with a focus on gender discrimination, typically use an Oaxaca-Blinder type setup (Oaxaca, 1973; Blinder, 1973). In such cases, the inferences of discrimination are based on the unexplained part of the model, which requires a correct specification for an unbiased inference. Recent employment-unemployment surveys conducted by MOSPI show that societal norms have only marginally evolved to allow women to accept specific tasks and exposure in industries (e.g., managerial/ analyst/clerical job in a services industry).

Safety concerns, patriarchy and WLFP

Safety concerns, especially those related to crime against women, have received considerable interest for their impact on WLFP. Sudarshan and Bhattacharya (2009) find that safety concerns are an important reason behind women's decision to not to work. At a deeper level, Chakraborty et al. (2018) suggests that the implications of safety concerns or crime against women should be seen as a combination of two factors-the probability of being at the receiving end and the corresponding trauma cost. Therefore, an incident or perception that affects either of these two factors will lead to an effect of crime on WLFP. Importantly, it implies that factors such as proximity to home, travel distance, mode of commute, access to toilets, etc., govern women's work opportunities.

A parallel stream in literature suggests that cultural practices and beliefs endorsing patriarchy have a circular relationship with gender gaps in the labour market. Several manifestations of this culture such as dowry practices, decision making within the family, and seclusion of women may have broad implications on gender gaps, including in labour market outcomes. While these patterns of gender relations are difficult to measure, the elements of this patriarchal trend tend to cluster together (Sundaram and Vanneman, 2007). The implications of safety concerns and patriarchy on WLFR must be seen in the context of all other factors that affect the latter. For example, Das and Desai (2003) examine whether job availability or patriarchal attitudes play an important role in shaping the relationship between women's education and labour force participation. They find patriarchy to be less binding than the lack of employment opportunities, even though both factors are important. Additionally, while safety concerns and patriarchy may explain a low WLFP, it remains to be seen if they are as important in explaining a falling WLFP.

Exigencies of reproduction and care

Several authors have argued in favour of exigencies of reproduction and care, as one of the drivers of low WLFP, in addition to the above-mentioned reasons. This argument boils down to two pillars. One, women carry the natural burden of reproduction and early childcare, which pushes them to take a break in their employment, and thus, reduces their employability as well as wages, once re-employed. This is known as the motherhood penalty (Benard and Correll, 2010; Ishizuka, 2021). Two, there is a difference in the glorification of work at the workplace and the household, which reinforces men as the breadwinner and women as the caregiver (Naidu, 2016). Eswaran et al. (2013) refer to the latter as 'status production' à la Papanek (1979), which is to maintain and enhance a family's social standing, and not necessarily that of the woman within a social unit.

Exigencies of reproduction and care vis-à-vis WLFP highlight the inability of our labour statistical systems to capture the 'work' done by women. For example, there is a rise in the share of women engaged in 'domestic duties', mainly from agriculture and other elementary occupations (NSS and PLFS, various rounds), often fetching them a higher wage. However, they remain excluded from the formal labour force. Hirway (2012) echoes a similar concern.

2.2 Studying WLFP Through Time-Use Pattern and Online Exposure Lens

The four arguments, as noted above, point to several socio-economic frictions that preclude women from joining the labour force. However, these often emanate from an external source, which, though valid, remains incomplete. In a step to fill this void, we take an alternate, but complementary, stance on WLFP. That is, we propound women to be active in their labour force participation decisions, as reflected in the recalibration of their time-use pattern with online exposure. Essentially, online exposure offers women 'effective extra time' by economising on several routine and non-routine activities such as office work, learning, socializing and entertainment.
If women allocate this time more towards labour force participation than attending to unpaid household duties, one can infer them being in the driver's seat.

Though women have limited access to mobile phones services than men, their adoption has seen a significant jump – from 19 percent in 2017 to 50 percent in 2020 (GSMA, 2021; NFHS-5). This high growth in mobile internet adoption provides a compelling reason for our assessment. That is, whether online exposure is an effective instrument to address the structural insecurities that women face and/or does it align with their active stance on the need to work, and allow them to allocate more time to economic activities. The subsequent sections elaborate on our analysis.

DATA

This study uses data from an online survey of over 4,000 women, implemented during July-August, 2021. The survey focuses on daily and online time allocation across activities (i.e., paid work, unpaid work and non-work activities), socio-economic attributes (such as education, family size, age-group, marital status, and household type), and exposure to online platforms across categories (such as those for social networking, retail shopping, entertainment and commuting). We also use data from the NSS-Time Use survey (NSS-TUS, implemented during January-December 2019) as a major additional source. It presents information about an individual's daily time allocation towards various activities through a pan-India survey. Several other sources such as the World Bank, and academic and policy reports are also used for the study.

3.1 Survey Design

Selection of Cities

The survey was conducted in 10 cities (Table 1). These include five tier-X cities and five tier-Y cities based on the Seventh Pay Commission's classification, which provides a widely accepted hierarchical structure of Indian cities based on the standard of living. These were chosen because they have the best-developed online infrastructure and the largest online platform adoption rates. Besides, the mix of tier-X and tier-Y cities offer sufficient heterogeneity to the sample, to come up with robust results. For example, the share of women's population ranges between 46 percent (Mumbai) to 50 percent (Mysuru). Alternatively, women's literacy also reveals a considerable range-between 62 percent (Patna) and 86.6 percent (Chennai).

A Survey of Women TIme-Use Pattern

Table 1: Sample Cities

City	State	Tier, Pay Commission Classification	Population, million	Women population, percent	Women literacy, percent
Chennai	Tamil Nadu	X	4.647	49.72	86.60
Bengaluru	Karnataka	X	8.444	48.00	84.01
Delhi	Delhi	X	11.035	46.70	80.80
Mumbai	Maharashtra	X	12.442	46.03	86.50
Kolkata	West Bengal	X	4.496	47.59	74.02
Patna	Bihar	Y	1.684	46.95	61.96
Mysuru	Karnataka	Y	0.893	49.97	67.06
Lucknow	Uttar Pradesh	Y	2.817	48.13	77.30
Jaipur	Rajasthan	Y	3.046	47.37	64.02
Bhopal	Madhya Pradesh	Y	1.798	47.94	74.87

Sample sources: Primary online survey for ~ 4,000 women and comparable data from four samples from the NSS Time-use Survey (NSS-TUS, 2019)
Survey period: July-August, 2021
Key Survey Characteristics: Women, age-group 21-25, are graduates, single, with monthly earnings in the range of Rs 30-50 thousand

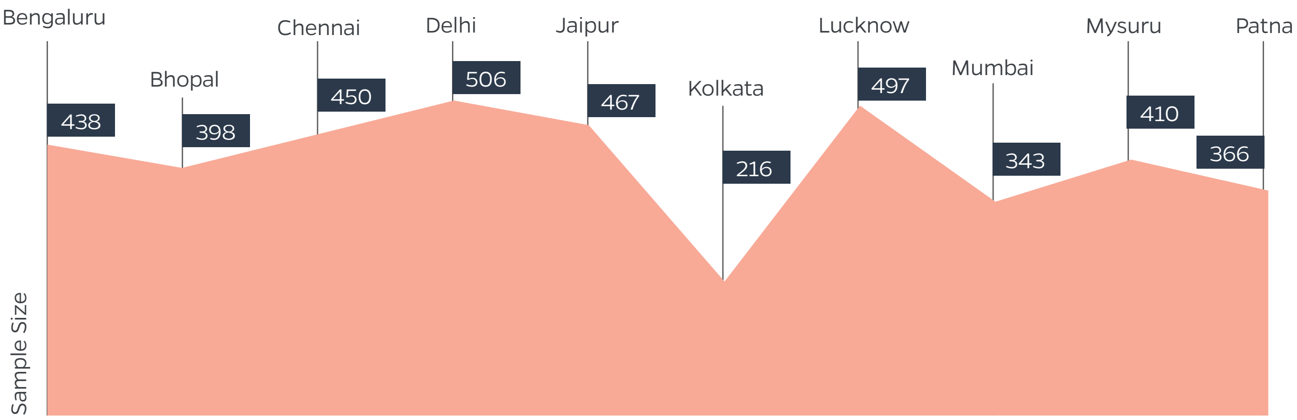
Sample Size Determination

The requirements for a statistically robust sample size determination pertain to specifying a minimum effect size, a level of significance and the power of the design. We assume that the minimum effect size (i.e., the percentage improvement in the time women allot to economic activities due to their exposure to online platforms) to be 20 percent.[3] This threshold is noted to offer robust statistical results (Cohen 1988; Kadam and Bhalerao, 2010). For additional requirements, the usual practice to determine a robust sample size is to peg the level of significance (i.e., the p-value) at five percent, and the power at 80 percent (Kadam and Bhalerao, 2010).[4] Based on these considerations, we determine the minimum sample size for each city to be 199. Figure 3.1 presents the sample size for each of the 10 cities.

3.2 Survey Characteristics

Figure 3.2 presents a basic description of the sample. It reveals considerable heterogeneity across all variables. Most respondents are in the age-group 21-25, are graduates, single, Hindu and belong to the general category. Additionally, they represent households with monthly earnings in the range of Rs 30-50 thousand, to which they contribute a considerable proportion. Additionally, the use of a personal phone is the primary mode to access online services for most respondents. Finally, studies and regular wage/salary work emerge as the principal activities for respondents, while performing domestic duties, being self-employed and job-hunting find modest representation in the sample. Overall, the sample seems representative of the middle and upper class urban Indian households, and is sufficient to assess the impact of online exposure on women's time allocation towards economic activities.

Figure 3.1: City-wise Sample Size

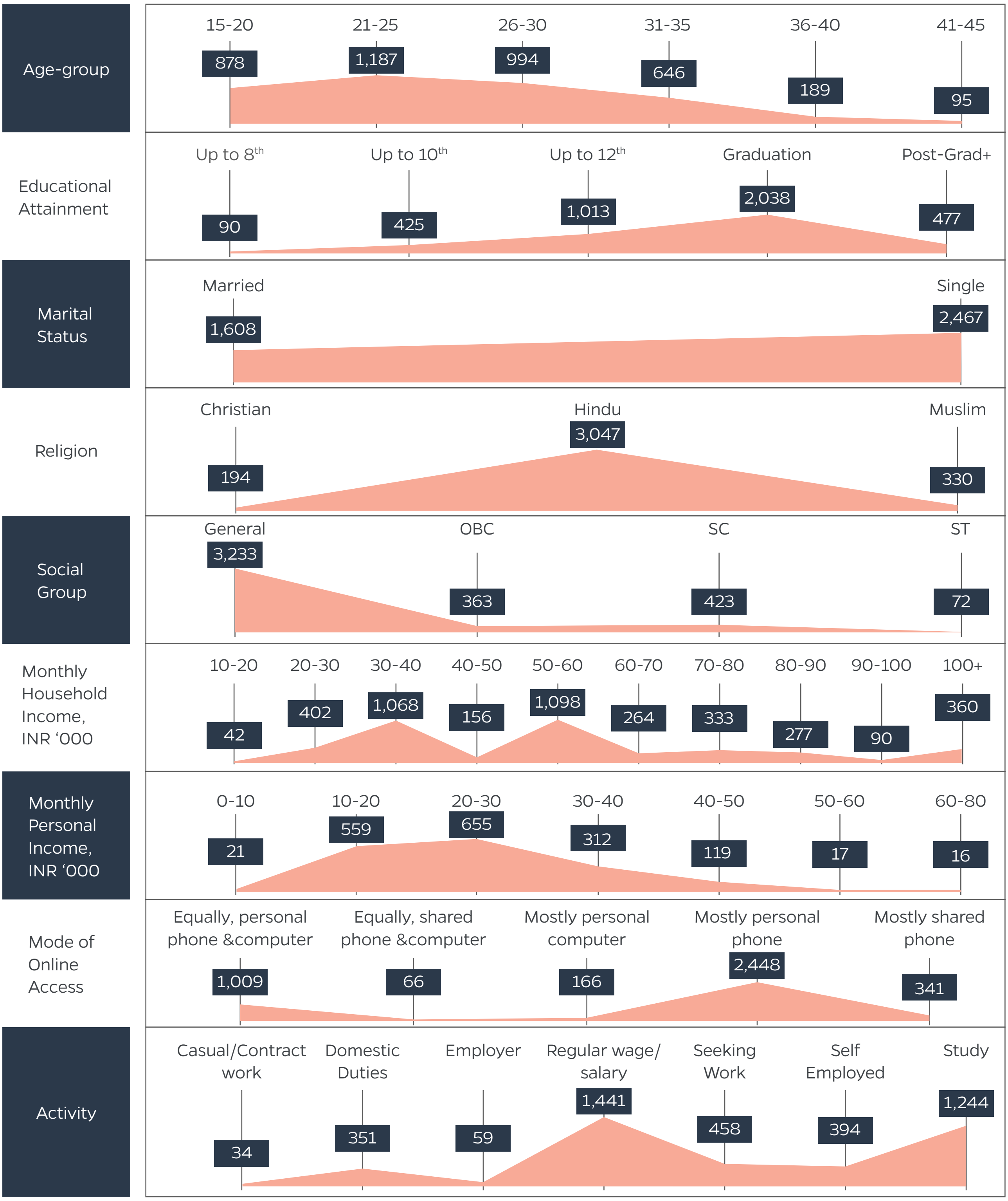


Notes: The online survey was implemented during July-August 2021. Sample size across the 10 cities is 4,091. Source: Primary Survey

[3] Minimum effect size is calculated by taking the difference between the two groups (e.g., the mean of the treatment group minus the mean of the control group), normalised by the standard deviation of one of the groups. Cohen (1988) provides the general guide for sample size calculation. It suggests effect size up to 0.1 can detect even the trivial effect, effect size between 0.1 and 0.3 can detect small effect, effect size between 0.3 and 0.5 can detect moderate effect and, effect size excess of 0.5 can detect only large effect. We choose 0.2 as the minimum effect size, which is noted to provide efficient results (Becker, 2000).

[4] A 5 percent level of significance means that the chance of erroneously reporting a significant effect is 5 percent or less. 80 percent power is the probability of failing to detect a difference in one out of five times, when actually there is a difference.

Figure 3.2: Sample Characteristics

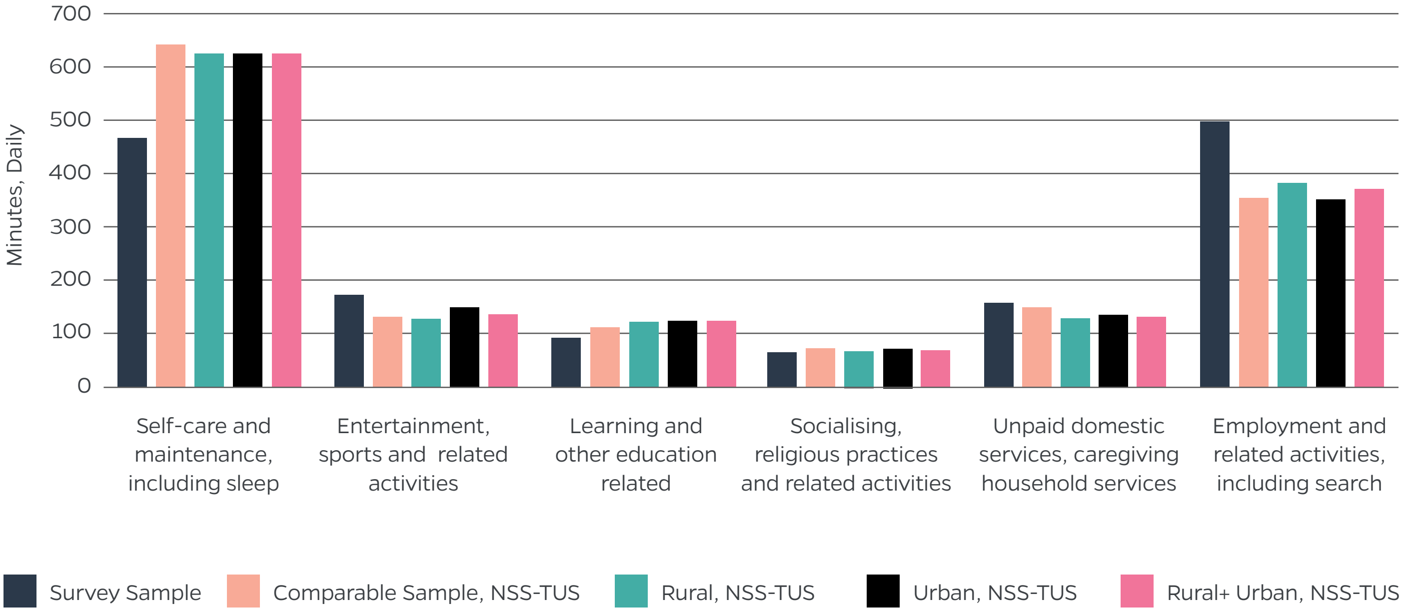


3.3 Time-Use Pattern

Figure 3.3 presents women's average daily time use, in minutes, from the primary online survey and four samples from the NSS Time-use Survey (NSS-TUS, 2019)-comparable, rural, urban sample and rural + urban samples.[5] For the comparable sample, we consider only women respondents in the age-group of 15-45 years, from ten cities of the primary survey. We observe a sizable difference between primary survey respondents and comparable sample respondents in time use for self-care and maintenance, and employment-related activities. Notably, primary survey respondents, relative to their comparable sample counterparts, spend nearly 172 minutes less daily on self-care and maintenance, and nearly 145 minutes more on employment-related activities. They also have an edge over the comparable sample respondents in entertainment-related activities by approximately 40 minutes daily. The other NSS-TUS samples mirror the comparable sample statistics.

To a large extent, these noted differences in time-use across samples seem to be on account of the pandemic. For instance, a natural consequence for the primary sample respondents, (relative to the comparable sample respondent) was to allocate more time to unpaid domestic activities and entertainment-related activities, and less towards learning and socialising-related activities. However, more time allocation towards employment-related activities suggests that the primary sample respondents have, on average, higher levels of education and employability. This is in line with the patterns observed in Figure 3.2. We remain cognizant of these noted differences in our subsequent empirical exercises.

Figure 3.3: Average Time Use



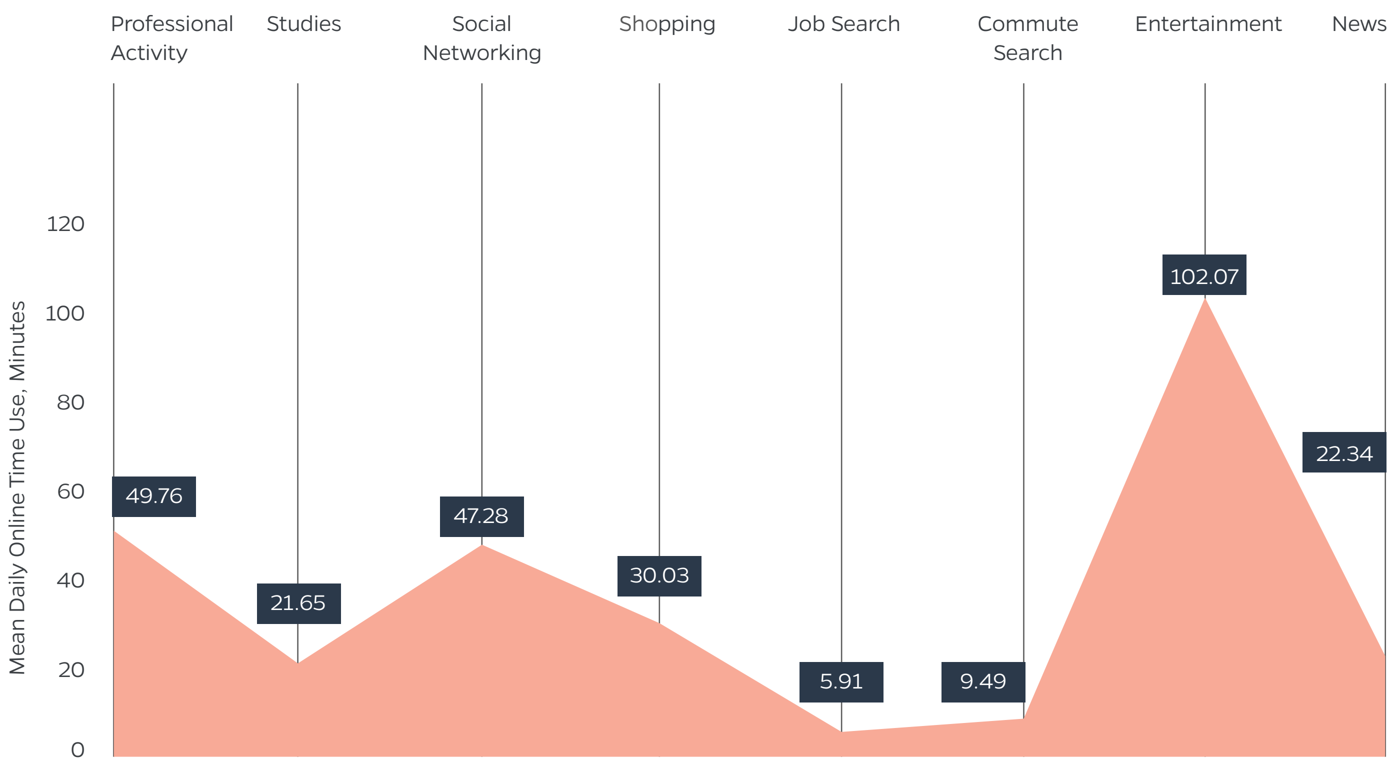
Notes: Comparable sample stats are for age-group 15 to 45 at 10 locations-Chennai, Bengaluru, Delhi, Mumbai, Kolkata, Patna, Mysuru, Lucknow, Jaipur and Bhopal. All-India stats are for age-group 15 and above.
Source: Primary Survey; NSS-TUS.

[5] The NSS-TUS results for men and the aggregate economy are presented in Annexure A

Figure 3.4 presents activity-wise daily average online time use from the primary survey. On average, urban Indian women spend the highest amount of online time (103 minutes) on entertainment-related activities daily. Professional activities and studies together account for about 71 minutes, followed by social networking at about 47 minutes on average. The least amount of time is spent on job hunting and searching for transportation options, which is 6 and 9.5 minutes daily respectively.

hand, those who have finished class 8, are Muslims, share a phone and a computer, and are active as job seekers, spend less time on employment and learning activities, including through online medium. The differences in the time women spend on employment and learning activities do not reveal any systematic pattern based on marital status, social groups, or household or personal incomes.

Figure 3.4: Online Time Use

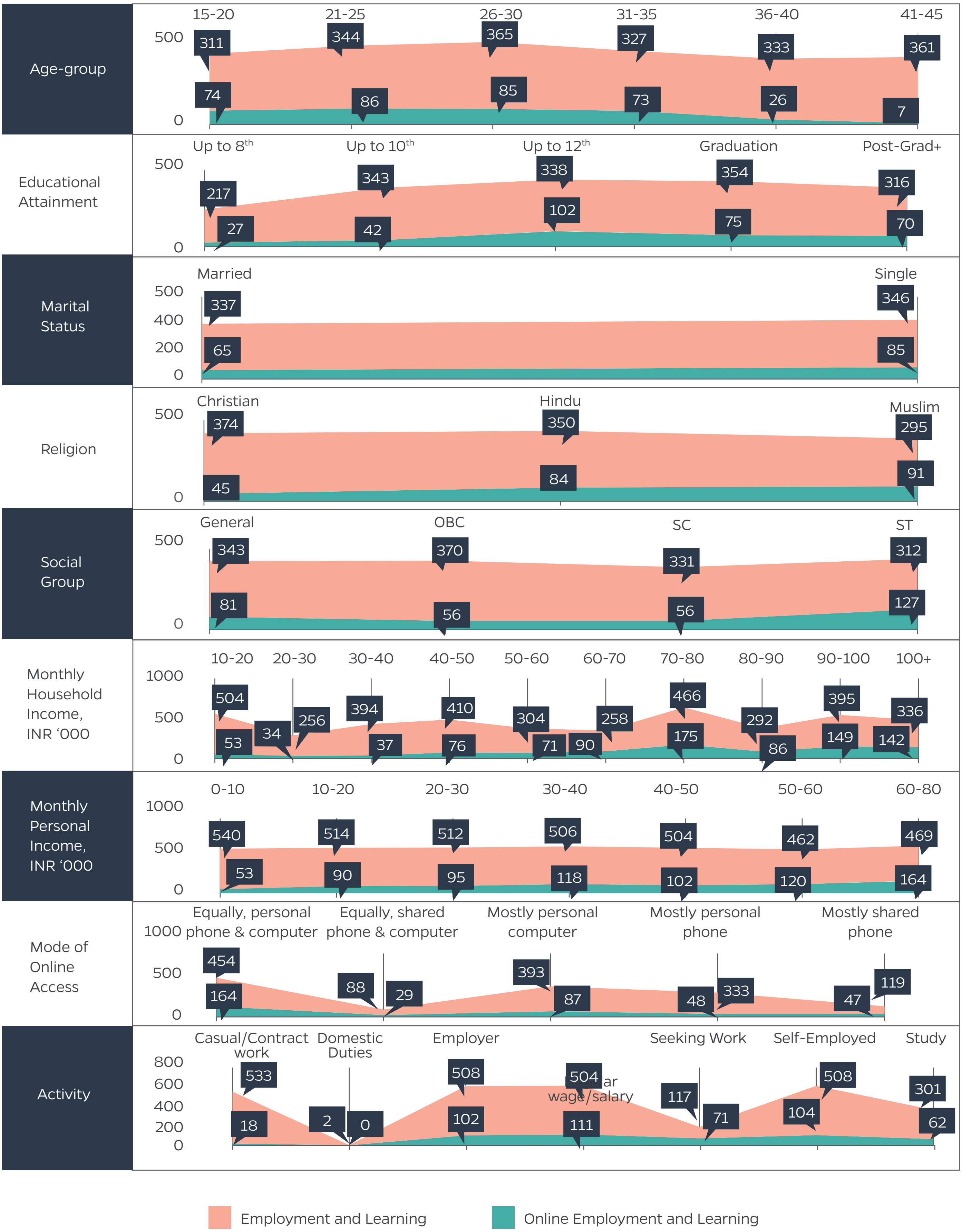


Notes: Total online time allocation across activities is 288.5 minutes.Source: Primary Survey

Figure 3.5 depicts the daily average time allocation of Indian urban women towards employment-related activities based on demographic and socio-economic variables. It suggests that those who are between the ages of 21-30, have at least passed class 10, use a computer and a phone equally, and are active as contract/casual workers, employers, regular wage workers or self-employed, spend a higher amount of time on employment and learning activities, including through online mediums. On the other

The statistics in this section present a descriptive depiction, without accounting for the effect of confounders. In the following section, we discuss the strategy to account for the effect of confounders in establishing a robust inference on the responsiveness of socio-economic covariates with daily online time use, and total and online time spent on employment and learning activities.

Figure 3.5: Average Daily Time Allocation on Employment and Learning Activities, Minutes



Source: Primary Survey

ESTIMATION METHODOLOGY

4.1 Relationship between Socioeconomic Covariates and Time-Use Pattern

We employ the least squares method to estimate the responsiveness of socio-economic covariates to daily online time use, and total and online time spent on employment and learning activities. This regression method offers the projection of the variable of interest (i.e., dependent variable-daily online time use, total/online time spent on employment and learning activities) on a set of explanatory variables (i.e., independent variables-socio-economic covariate) after accounting for the effect of confounders. Additionally, we use robust standard errors to account for heteroscedasticity.[6] The explanatory variables include income level, activity status, age, age-squared, educational attainment, religion, social group, household size and marital status.

4.2 Impact of Online Exposure on Time-Use Pattern

To estimate the impact of online exposure on Indian urban women's time-use, we pool the primary survey data with the NSS Time-use Survey data. In the survey data, all respondents have online exposure by design (as the survey was conducted online), while the NSS-TUS sample is mixed.[7] That is, the NSS-TUS sample does not identify individuals who have online exposure, as against those who do not have online exposure. The pooled sample consists of information on both these groups-those with online exposure and those without online exposure. Under the assumption that the time allocation pattern for those who have online exposure is significantly different from those without, we employ a treatment-control approach on the pooled data, with a maximum likelihood (ML) estimator. The NSS-TUS respondents (in the same 10 cities as in the online survey) represent the control group and the online survey respondents represent the treatment group. A significant advantage with the ML estimator is that it reiterates the initial grouping in a way that the observed data is the most probable fit for the specified statistical model.

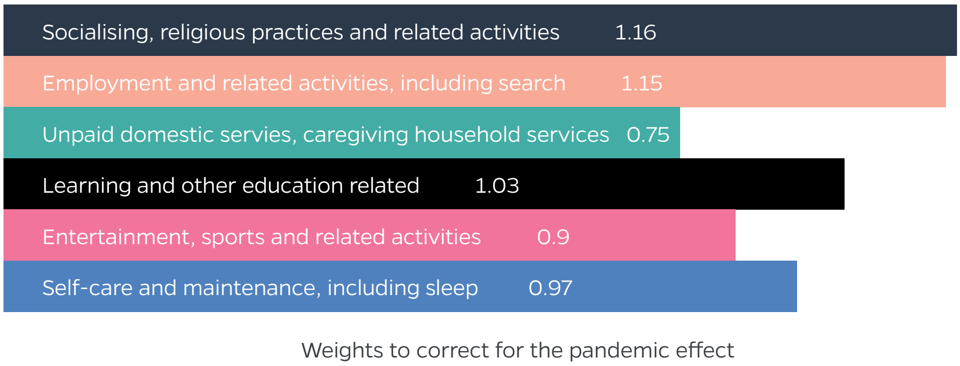
A key issue in estimating the treatment effect of online exposure in the current setting is on account of time-comparability – 2019 is a normal year, while 2021 is a pandemic year. We address this challenge by assigning a pandemic-effect weight, obtained from existing studies.[8] Figure 4.1 presents these weights, which we use as multipliers for the average time-use tendencies in the primary survey.

[6] Heteroscedasticity implies that the variability of random disturbance in a regression is different across elements/groups. Heteroscedasticity is a major concern in regression analysis, as it invalidates statistical tests of significance that assume that the modelling errors all have the same variance

[7] The NSS-TUS does not ask respondents about online exposure. We approximate online exposure statistics for urban Indian women using the National Family Health Survey-5 (NFHS-5). Notably, both these surveys are sub-nationally representative and have overlapping sample period.

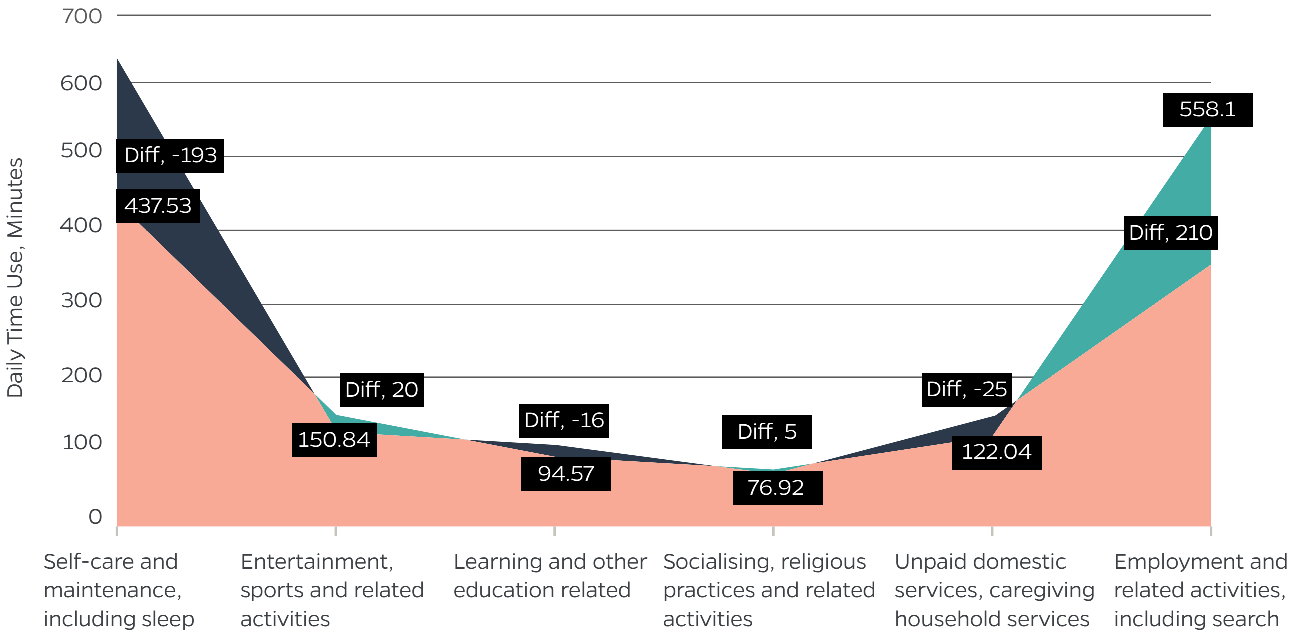
[8] Exact estimates, corresponding to the current sample, are unavailable. We use the closest available estimate.
sample and the comparable NSS-TUS survey in Figure 4.2 stem from an uncontrolled setup and hence are not causal. We discuss the approach to estimating a causal relationship between time-use activities and online exposure below.

Figure 4.1: Estimates for the Pandemic Effect on Time-use



Source: Sinha et al. (2020), US Bureau of Labor Statistics (2021), Stinger and Keys (2021), UN Women (2020), ILO Monitor (2020).

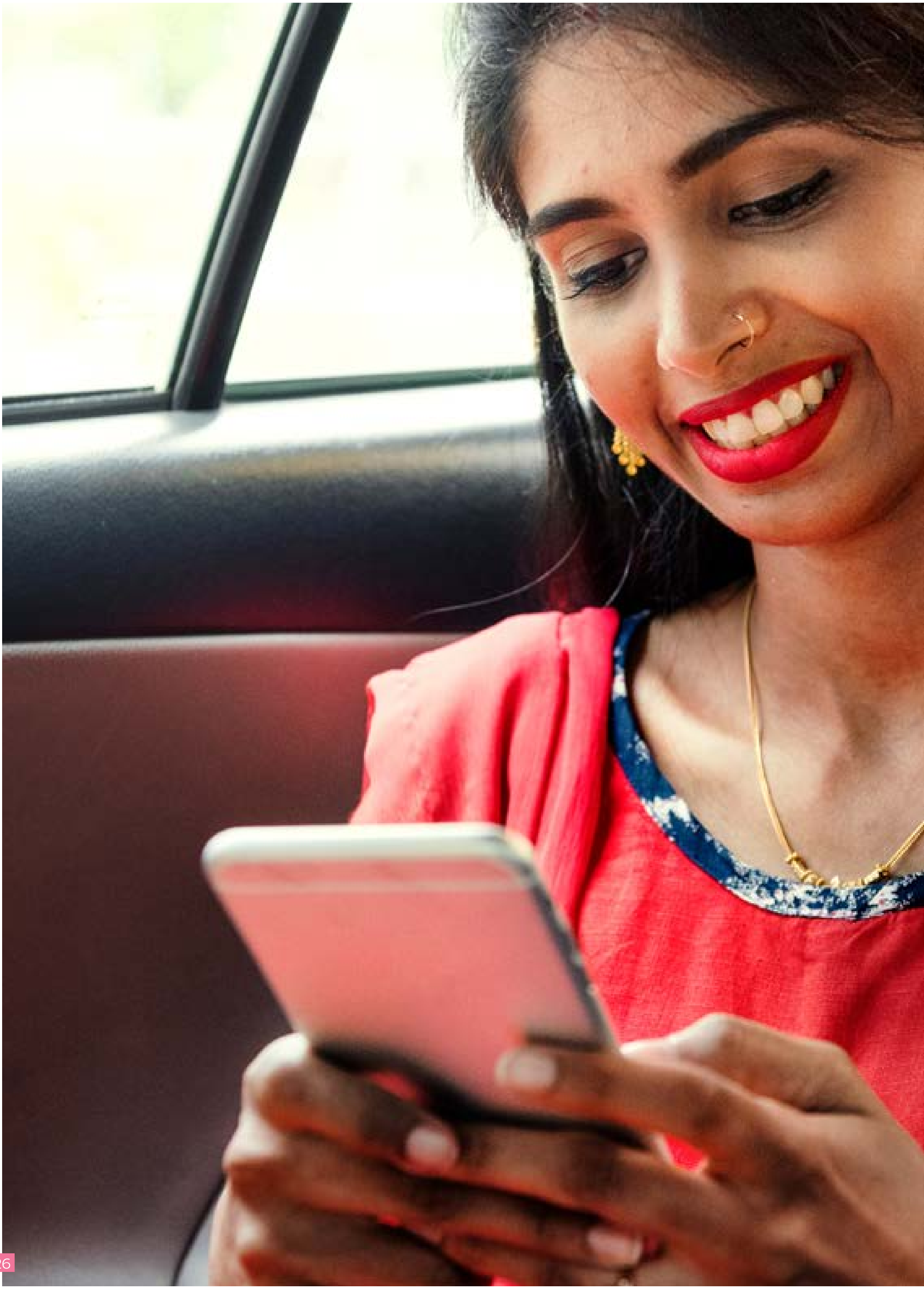
Figure 4.2: Pandemic Effect Corrected Daily Time Use



Notes: Pandemic effect correction weights are in Figure 4.1. Diff represents difference between the pandemic effect corrected time use applied on primary survey data, and the comparable NSS-TUS sample.

For a causal inference, several treatment-control approaches exist, from which we employ the propensity score–inverse probability weighting (PS-IPW) method to estimate the impact of increased online exposure on urban Indian women's time use.[9] This method allows the comparison of the treatment group with the control group using propensity scores (i.e., the probability of belonging to either the treatment or the control group, given the covariates). Then the inverse of these estimated propensity scores (i.e., inverseprobability weights) is used to weigh the outcomes of the treatment and the control groups, while the difference between these weighted outcomes provides an estimate of the treatment effect.[10] We take timeuse across each activity as the set of covariates to estimate the PS-IPW. Annexure B presents a detailed discussion on the PS-IPW method and other estimation issues.

[9] See Rosenbaum and Rubin (1983) for an early account of the propensity score model, and Imbens and Wooldridge (2009) for a detailed discussion on causal models.
scores (i.e., inverse-probability weights) is used to weigh the outcomes of the treatment and the control groups, while the difference between these weighted outcomes provides an estimate of the treatment effect. We take time-use across each activity as the set of covariates to estimate the PS-IPW. Annexure B presents a detailed discussion on the PS-IPW method and other estimation issues.
[10] The weighting scheme corrects for the missing potential outcomes. In fact, PS-IPW is also relatively more efficient in addressing selection bias. See Shiba and Kawahara (2021) for a detailed discussion.



ESTIMATION RESULTS

5.1 Time Spent on Employment and Learning (Total and Online)

We perform three least square regressions on the total time spent on employment and learning, total online time and total time spent on employment and learning to estimate the effect of demographic and socio-economic variables on them. These explanatory variables include location, age and age-squared, educational attainment, religion, social group, household income, household size, marital status and activity type. Figures 5.1-5.4 present the time spent predictions (for the three dependent variables) due to a marginal change in educational attainment, household income, activity type and age, respectively from these regressions.[11]

Marginal effects of educational attainment

Figure 5.1 presents the predicted time spent on employment and learning, total online time and total time spent on employment and learning due to a marginal change in educational attainment. Education up to class 8 forms the base case for the estimation. Three key results emerge.

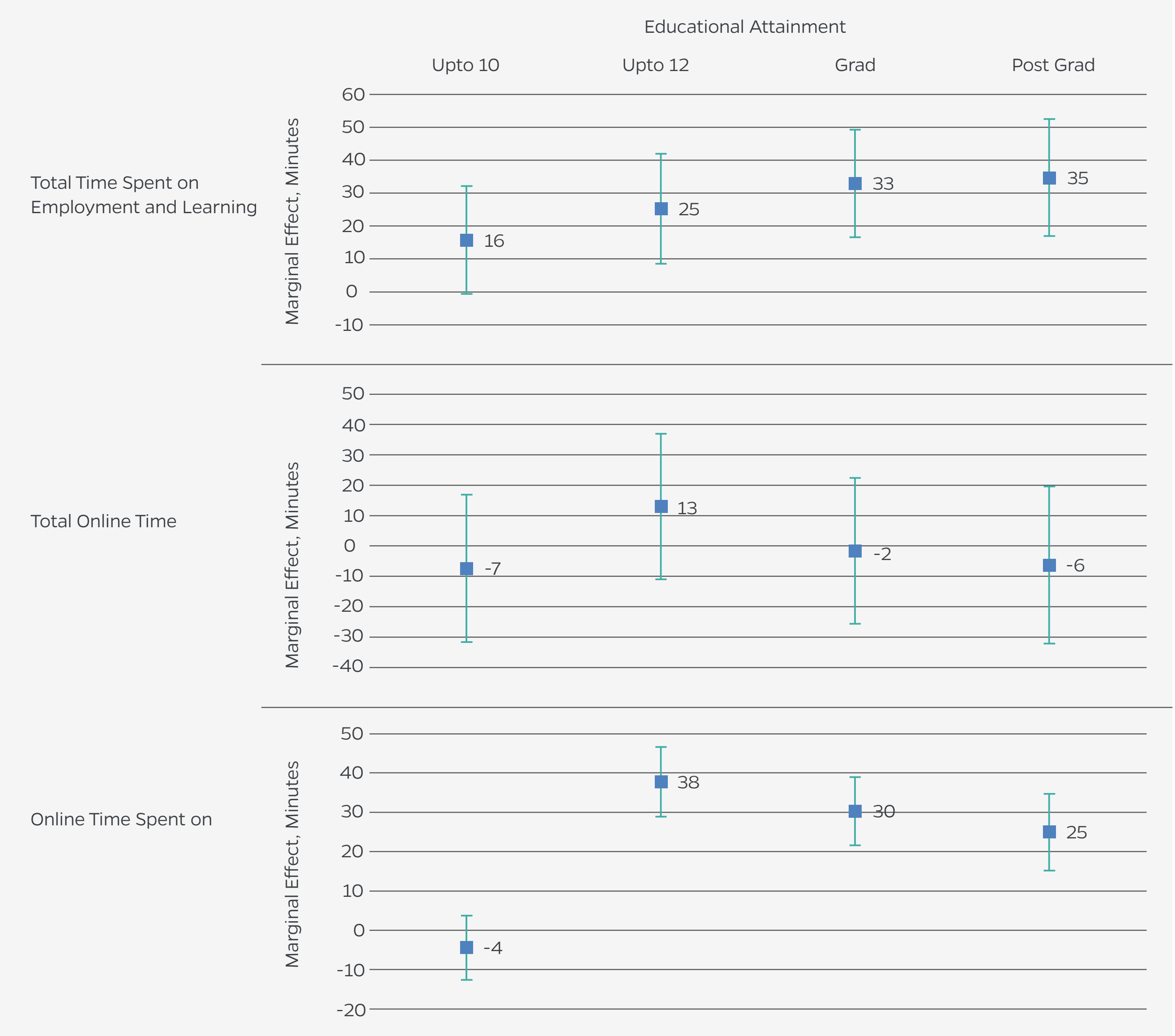
1. Total time spent on employment and learning increases with education. It suggests that those with higher education are also economically more productive, and therefore, are more motivated to develop human capital.

2. Total online time does not depend on education, perhaps because online exposure makes individuals participate in economic and non-economic activities, which seem to neutralise each-other with varied education levels in the current sample.

3. Online time for employment and learning is significantly more for those who have passed class 12 or higher. It suggests a minimum threshold to participate in online economic activities. It is plausible because (A) only those educated till class 12 or higher are more likely to work on or learn technical issues and (B) being online for economically productive purposes requires a minimum level of skill, which students are unlikely to possess before they finish class 12.

[11] For continuous explanatory variables, marginal change refers to an infinitesimal change. For dummy variables (coded as zero and one), marginal change refers to change from zero to one. We present only the main results. Full results can be furnished on request.

Figure 5.1: Marginal Effects of Educational Attainment



Notes: This figure presents marginal effects of educational attainments and the corresponding 95 percent confidence intervals. Educational attainment up to class 8 is the base case for estimating the marginal effects.

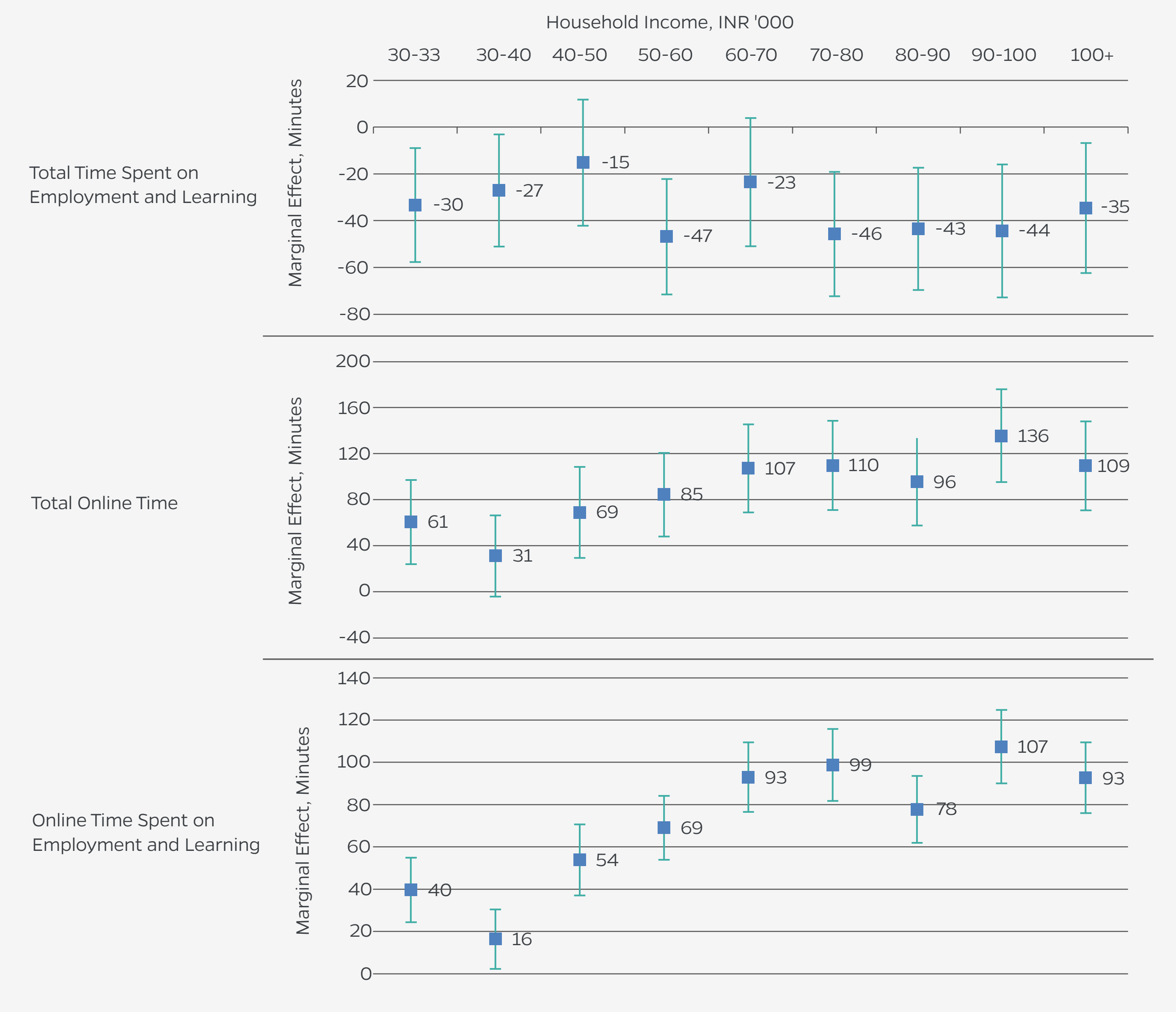
Marginal effects of household income

Figure 5.2 presents the predicted time spent on employment and learning, total online time and total time spent on employment and learning due to a marginal change in monthly household income. Household income between INR 10,000-20,000 per month is the base case for the estimation. The key points from the figure are:

1. As income levels rise, women spend more time online, in aggregate as well as on online employment and learning. This is because higher income increases the opportunity cost of time, while being online offers a convenient way to economise on time.

2. The total time spent on employment and learning does not reveal any systematic pattern amongst different income levels. This is plausibly because the time allotted towards employment and learning is common across all levels, even though differences may exist in the nature and mode of work.

Figure 5.2: Marginal Effects of Household Income



Notes: This figure presents marginal effects of household incomes and the corresponding 95 percent confidence intervals. Household income INR 10-20 thousand is the base case for estimating the marginal effects.

Marginal effects of activity type

Figure 5.3 presents the predicted time spent on employment and learning, total online time and total time spent on employment and learning due to a marginal change in activity types. Regular/salary work is the base case for the estimation. The major takeaways from the figure are:

1. Those who perform domestic duties as their principal activity, spend the least amount of time online, and on total/online employment and learning. This is in line with the existing evidence that women shoulder not only their own activities, but also that of all other household members. While this is a critical support activity for household members, it precludes women from formal employment participation

2. Job-seekers and students follow those who perform domestic duties as their principal activity. This is because women in these activities, relative to regular/salaried workers, spend only a part of their time job-searching and learning, respectively. They allocate the remainder for household care.

3. Employers and self-employed women reveal an almost similar pattern when it comes to spending time online, as regular/salary workers. This suggests that women's time-intensity in these three activities is alike, even though the nature of work (i.e., inherent risk, work flexibility, etc.) may be considerably different.

4. Casual/contract workers also reveal a similar pattern as regular/salaried workers. However, they spend less time online and more offline (and total) time on employment and learning. This is plausible because working conditions for these workers are perverse, which prompts them to use the internet for non-economic activities as a way to achieve work-leisure balance.

Marginal effects of age

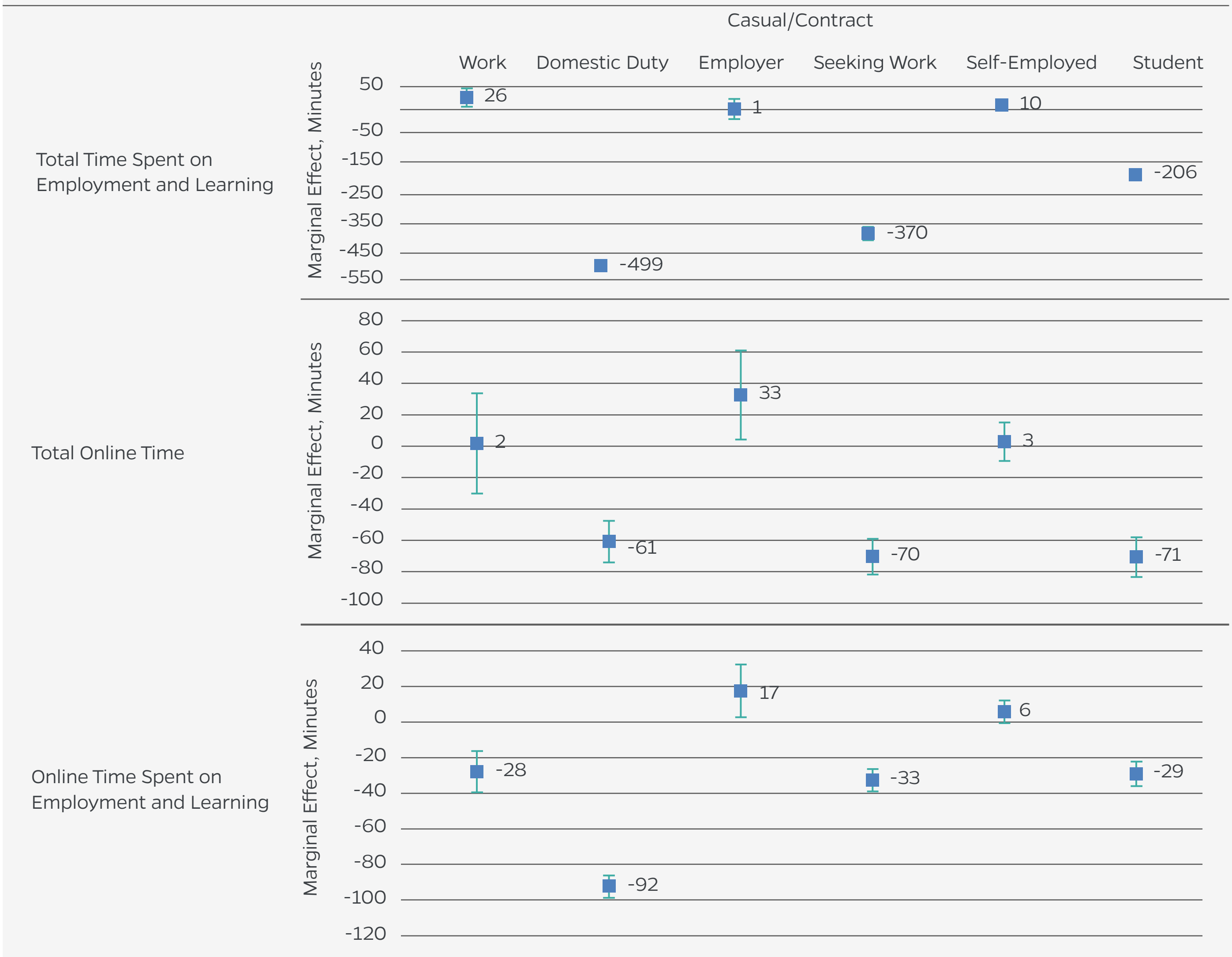
Figure 5.4 depicts the predicted time spent on employment and learning, total online time and total time spent on employment and learning due to a marginal change in age. It highlights the following:

1. The total time spent on employment and learning depicts a U-shaped relationship with age, with the minimum occurring for those aged between 30- 35. This is plausible as the burden of unpaid housework, and subsequently of child care, keeps on increasing till women enter this age group. Then, with child(ren)'s schooling, there is an additional time for women to allocate to employment and learning.

2. In contrast, online time demonstrates an inverted U-shaped relationship with age, with the maximum for those aged between 22-27. This is the time when women give birth to their first child, which implies that they have limited mobility, while they seek information on child care as well as an avenue to balance their daily life. Time spent online fills this gap.

3. Finally, online time spent on employment and learning demonstrates a negative relationship with age. This is plausible as older women are less likely to have necessary digital skills to use them for employment and learning, while they are able to learn and get employed offline.

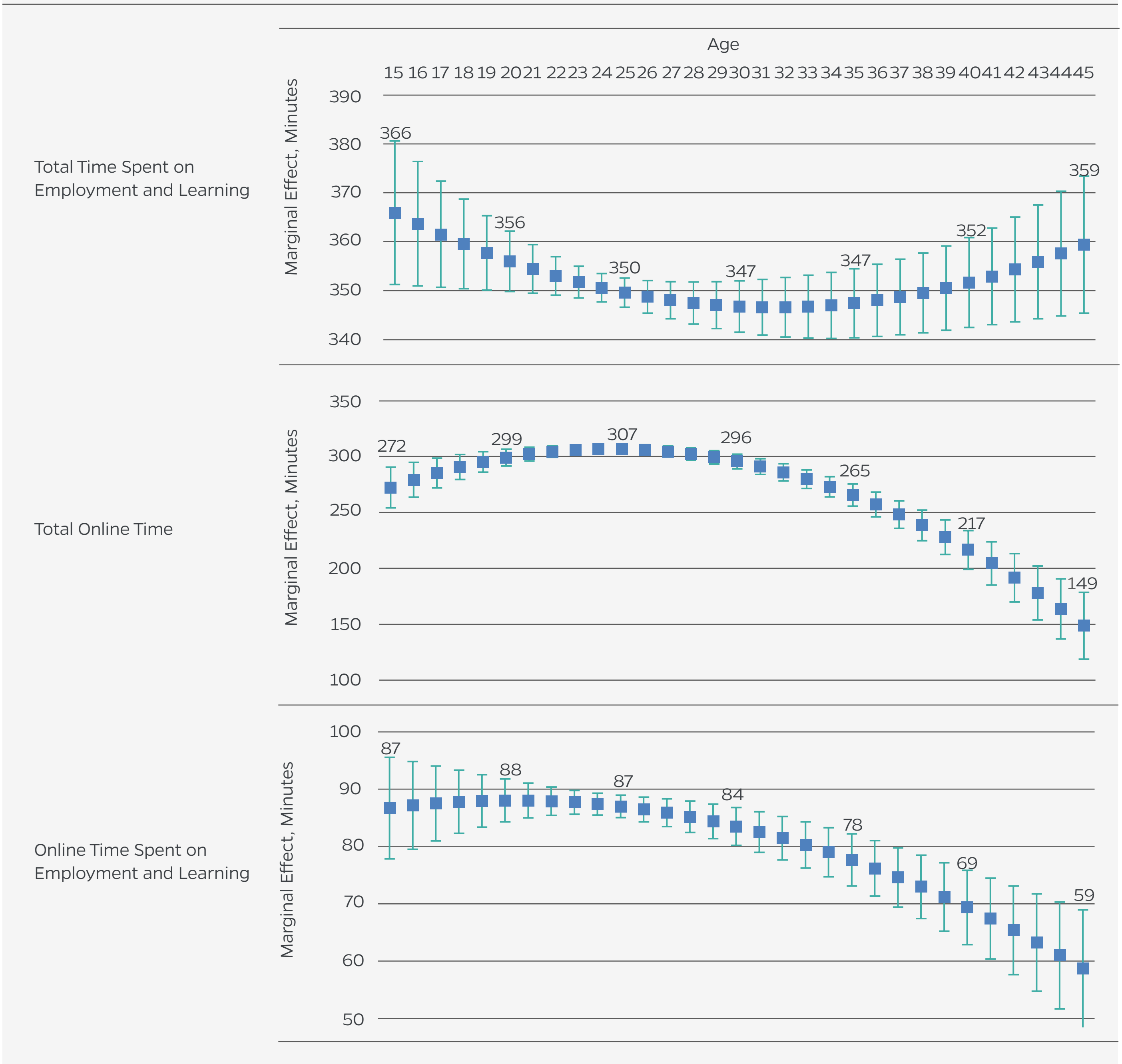
Figure 5.3: Marginal Effects of Activity Type



Notes: This figure presents marginal effects of activity type and the corresponding 95 percent confidence intervals. Regular/salary work is the base case for estimating the marginal effects.

Figure 5.4 depicts the predicted time spent on employment and learning, total online time and total time spent on employment and learning due to a marginal change in age. It highlights the following:

Figure 5.4: Marginal Effects of Age



Notes: This figure presents marginal effects of age, and the corresponding 95 percent confidence intervals. The regression also includes age-squared to capture non-linearity in its correspondence to the dependent variables.

5.2 Causal Relationship between Online Exposure and Urban Women's Daily Time-Use

Figure 5.5 presents the estimates of the average treatment effect (ATE) of online exposure on time use across activities, as well as the 95 percent confidence interval for these estimates. The results suggest the following:

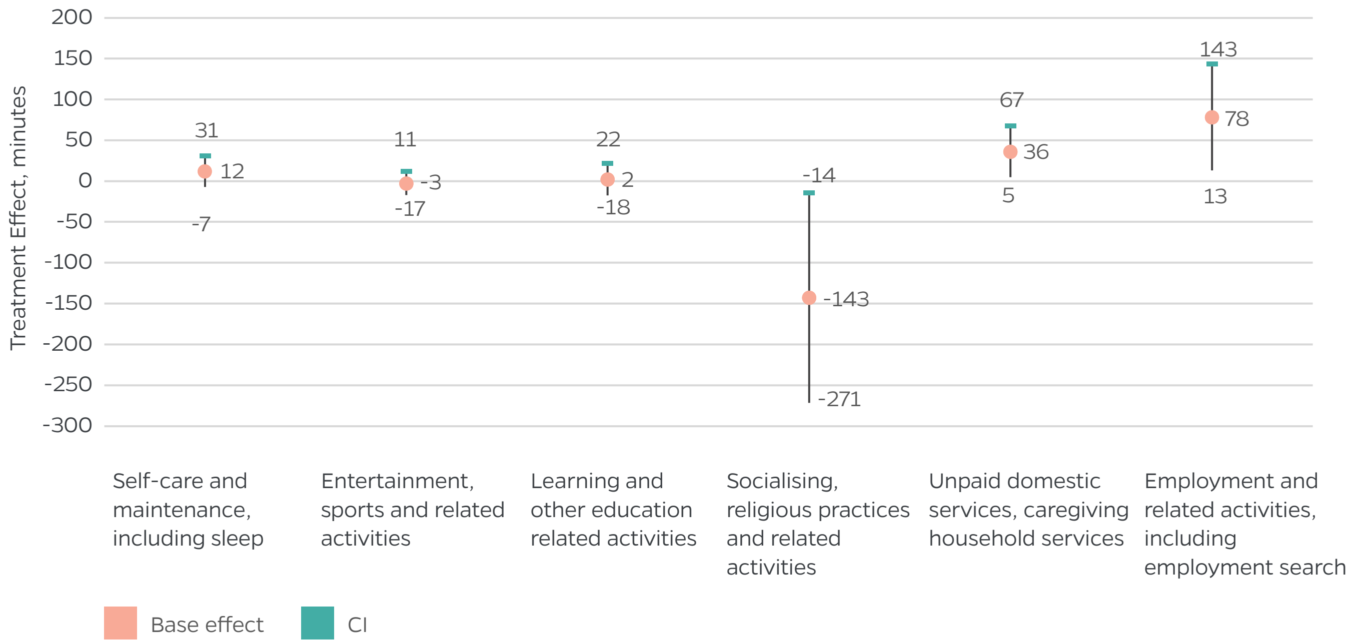
1. Increase in time used for employment and related activities due to increased online exposure is the highest, by nearly 78 minutes. This suggests that the marginal utility from an extra minute spent on employment is the highest.

2. The additional time allocated to education and learning related activities increased negligibly, by just two minutes. This suggests that learning is an inelastic part of women's daily life. That is, irrespective of the mode, the time spent on it remains almost the same.

3. Online exposure leads to an additional 12 minutes spent on selfcare, maintenance related activities, and 36 minutes on unpaid, caregiving activities. This suggests that household work demands considerable time from women, out of the time saved due to online exposure, either through self-selection or as a norm.

4. We observe a negligible fall in time used for entertainment and related activities due to increased online exposure, by three minutes. However, a notable fall accrues to time allotted to socializing and related activities, by 143 minutes, due to online exposure. Here, the time spent on socialising-related activities does not account for online socialising activities. To an extent, the fall in time spent on socialising may be attributed to additional time towards employment. This is in line with the findings of Li et al. (2017) who suggest that increased exposure to social networking sites reduced the desirability to socialise offline.

Figure 5.5: Average Treatment Effect (ATE) of Online Exposure



Note: Average treatment effect (i.e., the effect of online exposure) is in minutes with 95 percent confidence interval (CI).

Overall, with online exposure, urban Indian women spend 80 minutes of additional time on learning and employment related activities (formal economic activities). The corresponding increase in the time allotted to self-care and unpaid services (personal non-economic activities) amounted to 48 minutes, while time accrued to socializing and related activities (social non-economic activities) falls by 143 minutes due to internet exposure.

These patterns occur when 50 percent of the relevant population has online exposure. This conditionality is important as the effect of online exposure may change at a different level of the population's internet exposure. Notably, there is a considerable support for a growing network (such as the internet) to follow the Metcalfe's Law, which suggests that the value of a network is proportional to the square of network size (Swann, 2002). This implies that as online exposure increases amongst a population, its effect on time allocation pattern is likely to be sharper.

5.3 Decomposing the Treatment Effect of Online Exposure

A convenient approach to reconcile the ATEs of online exposure on time use is to consider it as a composite of two effects – an endowment effect and a substitution effect. The endowment effect captures time saved because access to information, and the abilities to transact and network is easy. The substitution effect, on the other hand, leads to a reshuffle in time-use based on the marginal utility derived from incremental time use on each activity.

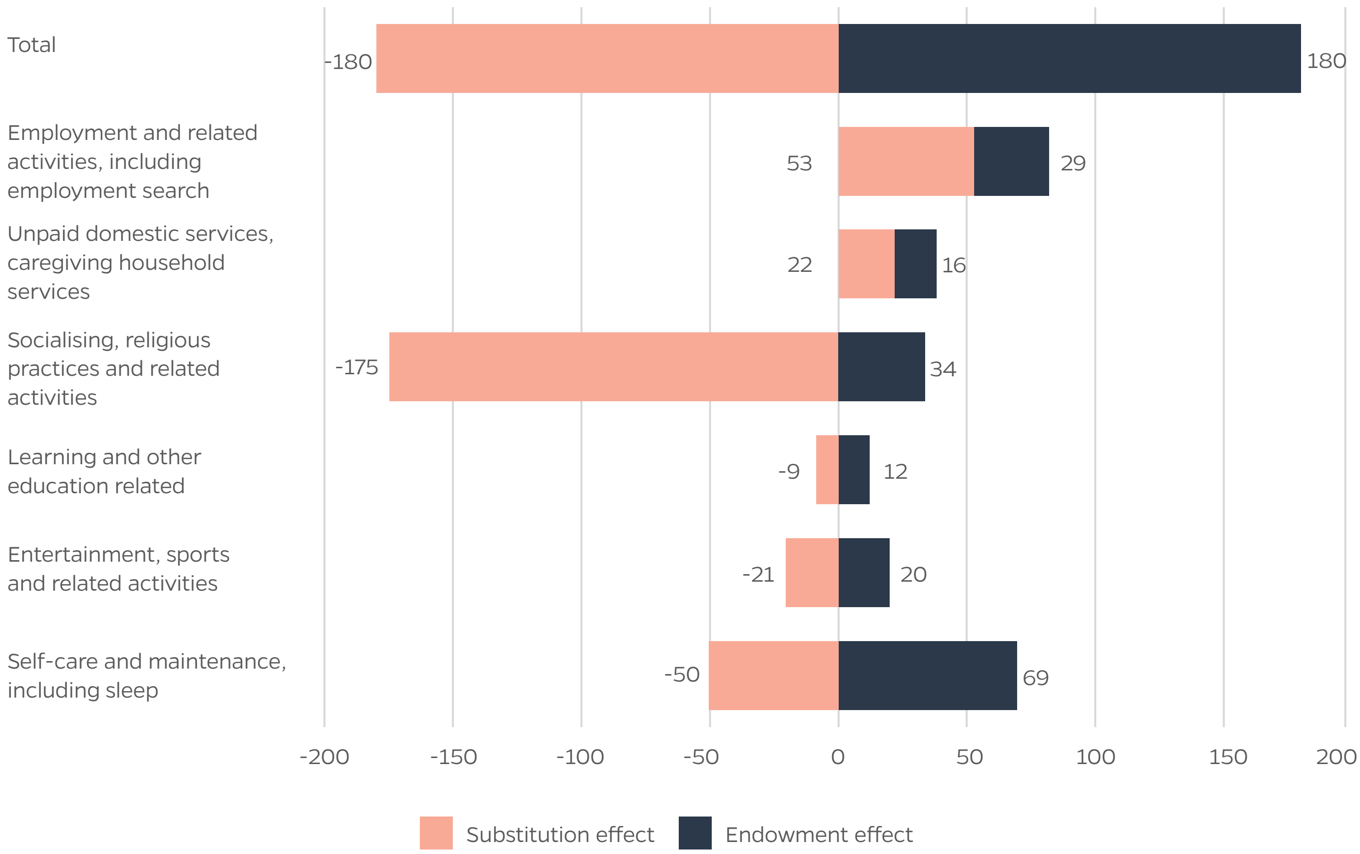
Direct estimates for the endowment effect and the substitution effect of internet adoption on time-use are unavailable. However, we find 'growth in trade due to internet adoption' a close approximation to the endowment effect due to internet adoption on time use. We use this proxy because with activity time use, the effect of online exposure on trade is intricate and entails considerable multi-sided heterogeneity. These include considerations of self-productivity and utility, surroundings and the network, nature of activity, location, and so on. Moreover, the source of efficiency due to online exposure in trade is on account of accessing information, transacting and networking, as with activity time-use.

Osnago and Tan (2016) estimate that a one percent increase in internet adoption leads to a 0.25 percent growth in trade. A linear approximation of this effect, in our case, leads to a 12.5 percent 'effective extra time' (i.e., endowment effect) due to change in online exposure, if such exposure for the relevant population is 50 percent. This implies that individuals in the treatment group have 180 minutes of 'effective extra time' due to online exposure.

Using this estimate of the endowment effect à la Osnago and Tan (2016) and the total effect as ATE estimates, the substitution effect is derived as the total effect net of the endowment effect. Figure 5.6 presents the decomposition of this 'effective extra time' due to online exposure into the endowment effect component and the substitution effect component.

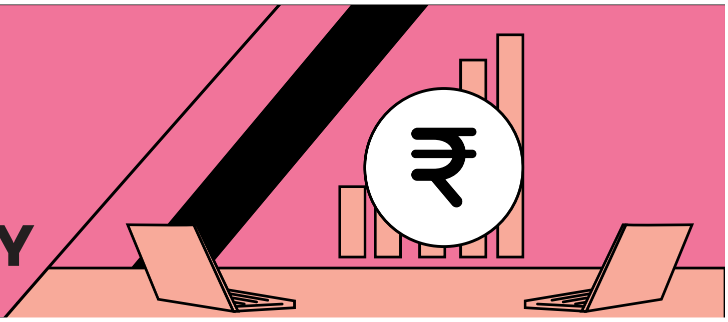
Notably, the marginal utility from an extra minute of time used is the highest in employment and related activities. In contrast, that same measure for socialising, religious practices and related activities is the lowest. Self-care and maintenance also display a considerably low marginal utility per minute of incremental time. For all other activities, marginal utility per minute of incremental time is modest.

Figure 5.6: Endowment and Substitution Effects of Online Exposure



Notes: Approximation for endowment effect is using estimates for growth in trade due to internet adoption, taken from Osnago and Tan (2016). Estimate for the substitution effect is the total effect net of the endowment effect.

EFFECT OF ONLINE EXPOSURE ON THE AGGREGATE ECONOMY



We estimate the effect of women's online exposure on the aggregate economy in two ways as (A) the additional time spent on paid and productive activities and (B) the push to GDP. These parameters reflect the aggregate value addition due to women's online exposure, which is an important policy concern in India. To construct these estimates, we use the results on average treatment effect, and some related statistics from secondary sources.

6.1 Time Allocation to Paid and Productive Activities Due to Online Exposure

We estimate the additional time allocation towards paid and productive activities due to online exposure (Figure 6.1) in the following steps.

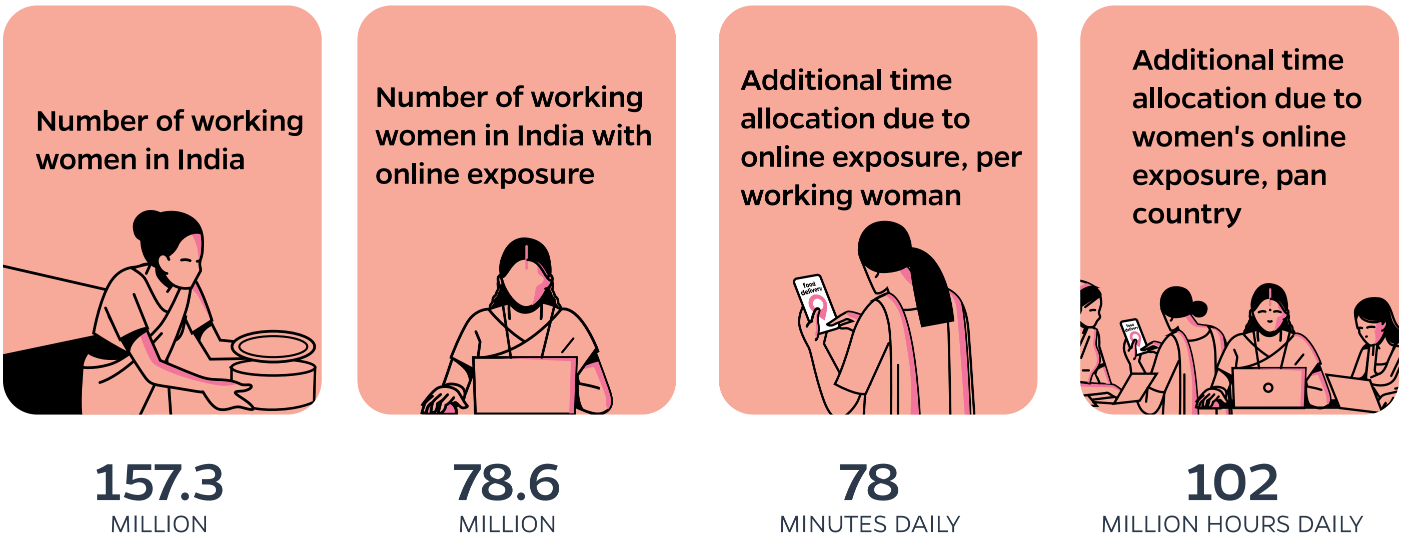
1. We derive the statistic for the size of the women workforce in the country using the worker-population ratio from the Periodic Labour Force Survey 2019-20 (PLFS 2019-20). We find that 157.3 million women in India contribute to the workforce and engage in paid and productive activities.

2. Based on the premise that only 50 percent women in India have internet access, we construe that 78.64 million women have online exposure.

3. We employ the ATE estimates for employment related activities, which is 78 minutes per woman per day, to derive the average additional time spent on paid and productive activities due to online exposure at the aggregate economy level.

4. By multiplying the number of working women who have online exposure with the ATE, we find that online exposure leads to an additional 102 million hours of daily time on paid activities in the economy.

Figure 6.1: Effect of Women's Online Exposure on Additional Time Allocation Towards Paid and Productive Activities



6.2 Women's Contribution to GDP Due to Online Exposure

Figure 6.2 depicts the change in women's contribution to GDP due to online exposure. The estimation involves the following steps.

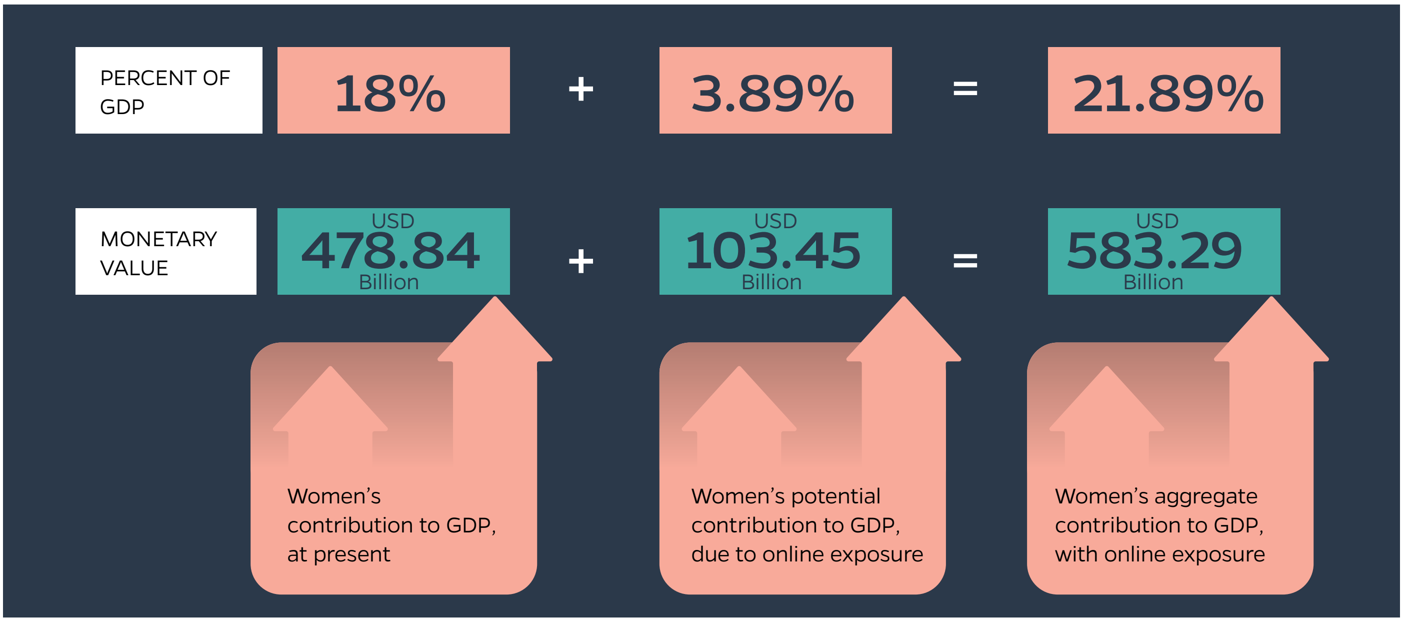
1. We base our estimate on the percentage value of women's contribution to the Indian economy à la Tandon (2018), which is 18 percent of the GDP. We also use the finding by Kathuria et al. (2017), which pegs the internet's contribution to the economy at 16 percent of the GDP in 2020.

2. Using the estimates in step 1 and the time women allot to paid and productive activities through offline and online modes, we estimate their unit time value of the GDP. The latter estimate is a weighted average of time allocation through the offline and online modes, with the internet's contribution to the economy as weight. The unit time value of the GDP quantifies the monetary value of an additional minute spent on employment and related activities.

3. Using the estimate of the unit time value of the GDP and the additional time allocation due to online exposure, we construct the total contribution to GDP purely on account of additional time allocation. It turns out to be USD 73.3 billion, which is approximately 2.75 percent of the GDP.

4. Internet exposure also contributes to the economy through productivity gains, over and above that on account of additional time allocation. This will accrue only to those who transition from offline to the online mode. Using the statistic on the internet's contribution to the economy and unit time value of the GDP, the estimate for women's contribution to GDP through productivity gains turns out to be USD 30.16 billion which is equivalent to 1.13 percent of the GDP.

Figure 6.2: Effect of Women's Online Exposure on GDP



5. Aggregating the two estimates in step 3 and 4, internet exposure increases women's expected contribution to the economy by an additional USD 103 billion, which accounts to almost 3.9 percent of GDP. This will increase women's contribution to the economy from 18 percent to 21.89 percent, amounting to USD 582.3 billion each year.

DISCUSSION AND CONCLUSION

At a time when WLFP in India has been consistently declining for over a decade and policymakers in the country are concerned about the issue, this report makes a contribution to address the problem with different lenses than those traditionally deployed. The traditional mode of understanding low and/or falling WLFP rests on four main pillars– rising household income, declining opportunities for women and gender wage gap, safety concerns and patriarchy, and exigencies of reproduction and care. While there is wide empirical support for these, they don't paint a complete picture of the problem at hand.

One, the four above mentioned pillars construe women as having a passive stance in their labour market outlook, which may only be partially true. In certain circumstances, women may be able to exercise some form of agency when it comes to the decisions on their labour force participation. Two, these arguments create policy dilemmas or impasses to target WLFP. Both, rising household incomes and WLFP, are desirable from a policy standpoint, even though they arguably share an inverse relationship. Alternatively, sectoral transitions are also essential in the developmental trajectory of a country, but they hurt women disproportionately more than men.

The central thesis of this report is to target WLFP issues through digital media. We test and establish this idea using a primary survey of over 4,000 women in 10 different cities of India. Using a treatment-control type causal estimation, we show that online exposure indeed has a vital role to play in WLFP. The finding that a woman spends 78 minutes of extra time daily on employment and related activities due to online exposure, suggests that women's active stance on their labour decisions is as important as those propounded traditionally, if not more. Another advantage of this thesis is that it does not create a policy dilemma or impasse in targeting WLFP, as several traditional explanations do. That is, digital or online penetration is as much a public policy priority as an uptick in WLFP.

Our findings also suggest that online exposure, on its own, does not result in greater labour participation. Rather, it requires a minimum skill and resource threshold, and the quality of time used online for the transmission to work. Education levels, household income, employment type and age turn out to be the most important parameters in this context. These results will also inform policy makers who want to address low and falling WLFR. They may want to target reduction in school drop-out rates, create economic mobility opportunities, ensure greater formalisation of the economy, and incentivise the running of child and elderly care facilities.

Another contribution of this report is to demonstrate the aggregate economy implications of the results. We estimate that women's online exposure leads to an additional 102 million hours of daily time spent on paid activities in the economy. This results in the generation of an additional USD 103 billion of monetary value, or 3.9 percent of the GDP. Almost 29 percent of this gain is due to productivity jump, while the remaining 71 percent is purely due to additional time allocation. Importantly, these gains are likely to increase as digital services expand their footprint in India, because network effects bestow increasing value gains.

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ANNEXURE A: AVERAGE DAILY TIME USE PATTERN IN THE SAMPLE

Table A1 presents women's, men's, and overall average daily time use, in minutes, from the primary survey and four samples from the NSS Time-use Survey (NSS-TUS, 2019) – comparable sample, rural sample, urban sample and rural + urban sample. The comparable sample only considers women respondents in the age-group 15-45 years and belonging to the ten cities as included in the primary survey.

Table A1: Average (Mean) Daily Time Use, Minutes

Use	Survey Sample, 2021	Time Use Survey, 2019			
		Comparable Sample	All India		
			Rural	Urban	Rural+Urban
Women					
Self-care and maintenance, including sleep	458.52	630.46	614.35	613.26	613.91
Entertainment, sports and related activities	170.37	131.01	127.74	149.67	136.67
Learning and other education related	93.33	110.30	123.42	125.66	124.33
Socializing, religious practices and related activities	67.41	72.32	69.37	71.10	70.08
Unpaid domestic services, caregiving household services	157.04	147.53	129.00	133.74	130.93
Employment and related activities, including search	493.33	348.38	376.12	346.56	364.09
Men					
Self-care and maintenance, including sleep	458.52	595.83	624.95	601.28	615.84
Entertainment, sports and related activities	170.37	113.63	116.17	126.40	120.11
Learning and other education related	93.33	123.11	138.66	129.84	135.26
Socializing, religious practices and related activities	67.41	82.74	81.25	82.09	81.57
Unpaid domestic services, caregiving household services	157.04	72.68	76.92	75.27	76.29
Employment and related activities, including search	493.33	452.01	402.05	425.11	410.93
Women + Men					
Self-care and maintenance, including sleep	458.52	601.02	618.30	609.05	614.61
Entertainment, sports and related activities	170.37	132.58	123.42	141.50	130.64
Learning and other education related	93.33	118.54	129.10	127.12	128.31
Socializing, religious practices and related activities	67.41	75.30	73.80	74.98	74.27
Unpaid domestic services, caregiving household services	157.04	115.88	109.59	113.20	111.03
Employment and related activities, including search	493.33	396.68	385.78	374.16	381.15

Notes: Comparable sample stats are for age-group 15 to 45 at 10 locations – Chennai, Bengaluru, Delhi, Mumbai, Kolkata, Patna, Mysuru, Lucknow, Jaipur and Bhopal. All-India stats are for age-group 15 and above.
Source: Primary Survey; Time Use Survey (TUS, 2019) conducted by MOSPI.

ANNEXURE B: ESTIMATION ISSUES

PS-IPW as the preferred estimation method

Two reasons prompt the choice for PS-IPW method. First, it provides a 'balanced' comparison between the treatment and the control group for estimating the treatment effect. That is, individuals in treated and control groups with equal propensity score have the same distributions of the observed covariates. This leads to a greater efficiency than most competing method, as it even includes those observations that have extremely large or small PS and lack corresponding pairs (Littnerova et al., 2013; Shiba and Kawahara, 2021). Second, the PS-IPW offers a parsimonious mechanism to estimate a causal impact. That is, it uses a logistic regression to estimate the propensity score, which is able to aggregate the effect of all covariates in a simple setup (i.e., on a probability scale), including the inherent non-linearities in their association with the treatment and the control groups.

ATE coefficients: Point estimates vs. i nterval estimates

It becomes imperative to reconcile the estimates associated with the ATEs with their intended purpose a la Baker (2016) and Dekkers (2019), given that the coefficients of three activities are insignificant, while for the remaining three they are significant. First, the interval estimates (i.e., estimates' range corresponding to the 95 percent confidence interval) suggest that the insignificant coefficients, given the current framework, are statistically not different from zero in some cases. But they do not suggest that there is no effect. In fact, the interval estimates suggest the extent of plausible values the ATE estimates may take, with the point estimate as the most plausible value. Second, the objective of the current exercise is to 'project' the most plausible extent of change due to online exposure, rather than to expound on the determinants of online exposure. These two considerations prompt us to base our discussion around the point estimates, while remaining cognizant of the interval estimates for the overall validity of the framework.

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