Barriers to Women's Absorption of the Benefits of Growing Telecom Subscriptions

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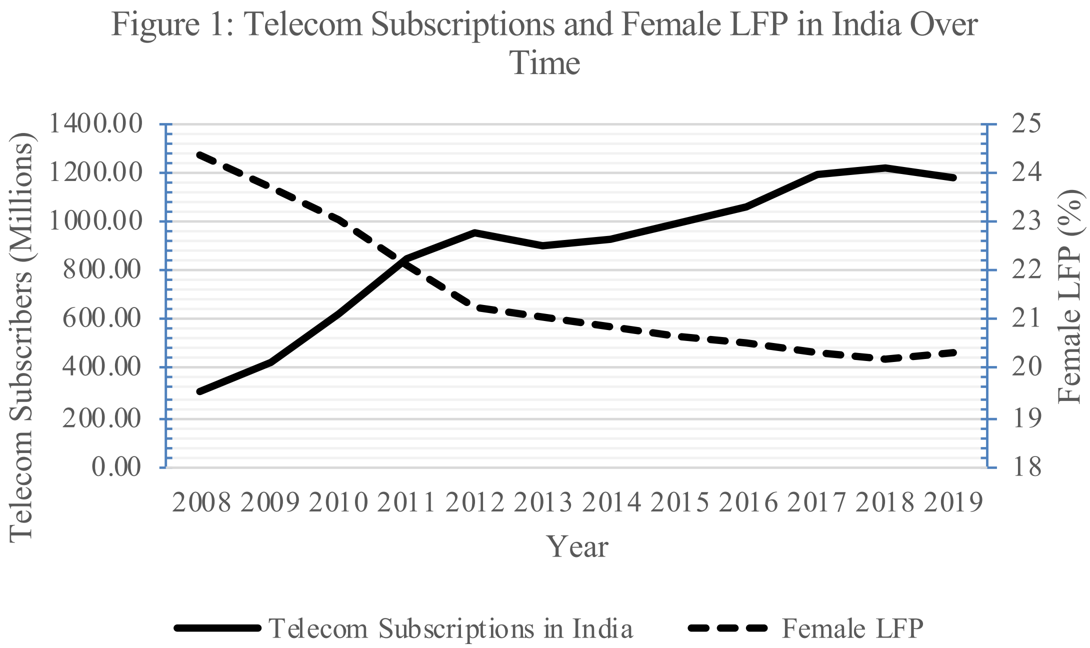
Introduction

Historically, technological inventions have made household labor less time-consuming and enabled women to contribute to the economy in more diverse ways. Tele-density (number of cellphones per 100 persons) in rural India increased from 1.9% to 38% between 2005 and 2012 (Londhe et al. 2014). This was associated with an escape from poverty for many low-income individuals owing to greater connectivity with urban employment opportunities. Nonetheless, a large gender gap persists in labor force participation in India, defined as the proportion of the population that is either employed or seeking employment. According to the World Bank, 56% more Indian men held employment than women in 2020. Given India's struggle with some of the highest domestic violence and assault rates in the world (Wallen 2020), women's access to financial independence and employment is a critical issue in the country. Thus, the exploration of possible technological interventions to increase women's access to jobs is an essential area for research. This leads to the question of how the dissemination of communication technology impacts female employment in India. However, despite the potential of technology to ease domestic duties and open avenues to education and employment, it appears that Indian women are not currently absorbing gains from the dissemination of cellular technology for employment prospects and financial autonomy. Figure 1 on the next page shows that while telecom subscriptions in the country are growing rapidly, female labor force participation (LFP) has actually been moving in the opposite direction and has been on the decline since 2008.



Data on the number of telecom subscribers per year is sourced from the *Telecom Statistics India 2019* report; annual data on female labor force participation in India is sourced from The World Bank's World Development Indicators.

I thus expect that growth in the number of telecom subscribers nationwide is correlated with a decrease in the female labor force participation. This is likely attributable to inhibitors such as limited personal mobile phone ownership among women as well as restricted use of mobile applications among women compared to men (Rotondi et al., 2020), allowing men to benefit more greatly from mobile technologies and get further ahead of women in the economy. Moreover, even though literacy among women is increasing overall in India, partially attributable to greater technology access, it is possible that jobs have not yet been created for the influx of educated women into the economy (Sher Verick, 2014). Alternatively, gender roles may actually be encouraging women to seek out work less as their husbands are able to earn more income by benefiting from technological growth, leading to many women leaving the labor force (Sher Verick, 2014). Finally, it is also possible that more women are actually working as a product of increased connectivity, but that a lot of this work is in the gig economy and goes unmeasured in government statistics on labor force participation.

While previous research has looked at the ways in which mobile technology has helped women stay connected and perform domestic functions more easily in low-income countries and explored the benefits of communication technology for rural workers as a whole, there is little research into the ways access to mobile phones has interacted with financial and economic inclusion for Indian women specifically. Although there has been some research on the ways in which mobile money has increased female income in Africa, there is a lack of such research in India, which has a different financial system wherein the government prefers bank-administered electronic transfers to mobile money managed by telecom providers (Winig & Eaves 2020), as well as a unique cultural and religious mix that defines local gender norms. Most importantly, India currently demonstrates a paradoxical decline in female labor force participation despite increasing telecom subscriptions, which would theoretically increase their access to employment information, connectivity, and financial resources. Specific research into the outcomes of mobile phone access for women in India is therefore required to understand the region-specific gendered patterns in the technology-employment relationship, and why women do not seem to benefit from the dissemination of cellular technologically in terms of employment at present.

India currently sees a rapid expansion of telecom subscriptions, holding the position of the fastest growing mobile application market in the world (ICEA 2020). Given this growth, paired with the exceptionally large gender gap in the labor force participation rate of 56% according to the World Bank (i.e. 56 percentage points more men participate in the labor force than women), it is critical to investigate the relationship between growth in the number of telecom subscribers, reflecting greater female ownership of mobile phones, and the female labor force participation rate — the precise objective of my research. Moreover, given that sociocultural inhibitors in the form of gender roles tend to be more pervasive in rural populations, I will explore the differences in the telecom access and female labor force participation relationship between rural and urban women. I expect that declines in female LFP associated with increasing telecom subscriptions will be larger for rural women, who are more likely to only work out of necessity when their husband's income is insufficient rather than out of aspiration and are also less likely to own personal cellphones.

This research will shed some light into inhibitors of the potential of mobile technology to increase female economic inclusion, serving as a gateway for future investigation and policy design that expands the benefits of mobile phone access to underserved groups of women. This can have powerful social implications for millions of women that suffer from a lack of social and financial autonomy currently as they can be mobilized into becoming independent workers and self-starters with a more equitable place in the Indian economy, as well as in their everyday lives.

Literature Review

Research on the effects of technology dissemination in low-income countries has led to various theories of the ways in which cellular access actually drives gender equity and the inclusion of women into the economy. Nonetheless, other scholars have proposed inhibitors specific to Indian culture that may prevent women from absorbing the gains of cellular technology dissemination relative to men, and put forth theories of how male gains from such technology may actually widen the gender gap in the ability to seek employment.

To elaborate on the former thread of scholarly discussion first, i.e. how technology may drive gender equity, scholars have put forth various theories of the mechanisms through which technology may further women. Doepke et al. (2012) suggests that technology replaces the physical labor traditionally completed by men with intellectual labor that women can carry out efficiently, leading men to relent some patriarchal control as they are motivated by the economic gains that result from greater productivity among women. Some other scholars argue that the gains to women's mobility associated with technology are primarily the result of women having more spare time to invest in the economy when their sociocultural domestic duties are made time-efficient by technology (Olivetti and Petrongolo, 2016). Other scholars attribute mobility gains primarily to increases in learning enabled by technology, in turn driving a demand for human capital acquisition and educational attainment from both genders (Foster and Rosenzweig, 2010; Doepke et al., 2012).

It is important to note here that one growing medium through which mobile phone ownership, in particular smartphone ownership, improves financial inclusion is the introduction of digital payments and online banking. In recent years. India has gravitated away from traditional mobile money services (money transfers through SIM cards for telecom subscribers) and towards the use of their United Payments Interface instead. UPI allows for real time cash transfers via a smartphone app, and the program has been rapidly adopted in the nation's urban regions (Winig & Eaves, 2020). However, poor digital literacy and low rates of bank account ownership in rural regions have kept the rural population relatively insulated from the use of digital payments (Singh and Malik, 2019).

Nonetheless, smartphone penetration is growing exponentially in rural regions. A report by the India Cellular and Electronics Association found that smartphone penetration in rural India grew from 9% in 2015 to 25% in 2018 and continues to grow (ICEA, 2020). Moreover, the Indian Government is leading efforts to expand digital payments to rural regions and move towards a more cashless economy (Singh and Malik, 2019) by enabling national Aadhaar ID-based digital payments that do not require a bank account, and simultaneously encouraging banks to make it easier to open an account (Winig & Eaves, 2020). These trends suggest that the potential for mobile phone ownership, in particular increasing smartphone ownership, to increase women's accessibility to tools that allow them to gain financial autonomy is likely to expand in coming years as the portfolio of digital services accessible in rural regions grows. However, the declining female LFP despite large growth in telecom subscriptions over the last decade suggests that women may not currently be able to absorb the benefits of this expansion. This makes it all the more important to investigate if increasing telecom subscriptions are currently associated with a decline in female LFP as this takes us closer to understanding how we can mobilize women to benefit from mobile and smartphone technology.

Figure 2

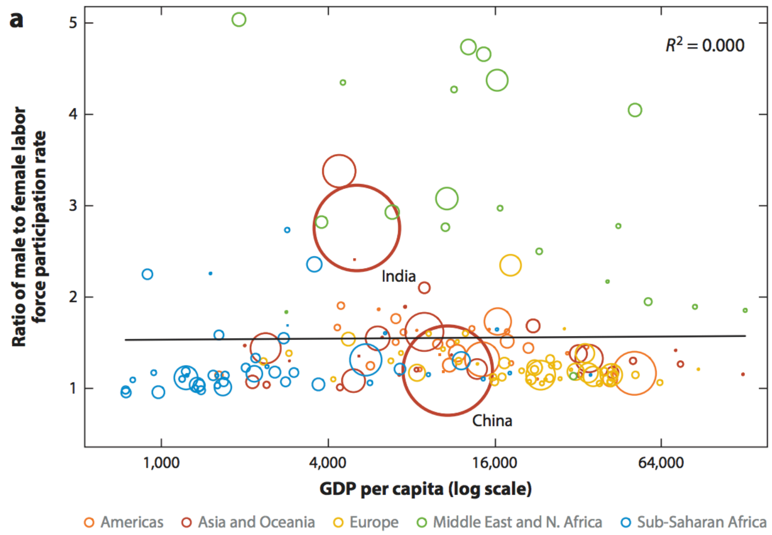


Figure 2; obtained from *The Roots of Gender Inequality in Developing Countries,* authored by Seema Jayachandran (2015). Gender gap in labor force participation. GDP per capita is the purchasing power parity–adjusted value [from World Development Indicators (WDI)] in the year the outcome is measured, expressed in 2011 US dollars. Outcome data are from (a) WDI and (b) the World Values Survey, wave 5.

However, scholars from the aforementioned second thread of literature on inhibitors that may prevent Indian women from absorbing the gains of cellular technology dissemination suggest that large barriers must be overcome before women can fully reap the benefits of the dissemination of mobile technology — these barriers include poverty, patriarchal cultural attitudes, and low education levels (Foster and Rosenzweig, 2010; Jayachandran, 2015). As a meeting ground for all three inhibitors, India emerges as a key incubator within which the relationship between the dissemination of communication technology and female labor force participation can be investigated, especially considering its colossal population, rapid GDP growth, and exceptionally skewed male:female labor force participation ratio of 3:1 (Jayachandran, 2015; see Figure 2 above).

Research on the digital divide suggests that women are actually able to reap a significantly lower proportion of the educational benefits accrued from mobile phone ownership than men. The Mobile Gender Gap Report 2019 released by GSMA shows that women's use of mobile phones is very limited compared to men, as women primarily use phones to make calls and receive texts to perform basic household functions. This is reflected in the gender gap in mobile ownership being 26%, but the gap in mobile internet usage sitting at 56%. Rotondi et al. (2020) suggest that women are less likely to own personal mobile phones and use them less often when they do own them, hindered in large part by poorer ICT skills than men; this creates digital divides that limit returns on technology for women. The researchers suggest that “focusing on ICT skill development, especially among women, can forge an even more promising pathway to leverage mobile phones for attaining sustainable development.” Stark (2020) offers several explanations for the varying usage of the same mobile technology between men and women. She suggests that mobile phones are often actually used in South Asia to surveil women further using technology, inhibiting the development of greater autonomy.

Moreover, phones often reinforce traditional gender roles as women are given family devices or old phones that they are required to use in front of others to simply fulfill household functions and connect with relatives. The role of men here as gatekeepers of women’s access to cellular devices prevents free information acquisition and exploration that would allow women to build more intellectual capital and connectivity whereas men typically own private devices with freer browsing and mobile internet. Such patriarchy often results in financial autonomy not actually translating into empowerment for women, as they feel like they still need a man by their side to achieve social acceptance and validation. It appears then that increasing women’s ability to acquire information and freely explore using devices is what will enable enable them to actually reap the full rewards of growing communication technology. This function can be fulfilled through cheaper devices and internet plans allowing for ownership of personal devices, and greater digital literacy that allows individuals to both seek out such cheaper alternatives and use technology more efficiently.

Sher Verick (2014) suggests that:

> Over the last decade or so, India has made considerable progress in increasing access to education for girls as increasing numbers of women of working age are enrolling in secondary schools. Nonetheless, the nature of economic growth in the country has meant that jobs were not created in large numbers in sectors that could readily absorb women, especially for those in rural areas. Despite inadequate job creation, household incomes did rise, which potentially reduced women's participation, especially in subsidiary activities ("income effect") due to change in preferences. Finally, though most women in India work and contribute to the economy in one form or another, much of their work is not documented or accounted for in official statistics, and thus women's work tends to be under-reported.

This implies that while literacy has actually been increasing among women in India, jobs have not yet been created to accommodate all of these women into the economy. In addition to the availability of roles for women, other important factors are workplace attitudes towards women and safety, given the high rates of violence and assault against women in India. Moreover, it is also possible that as men benefit from technologies and start to earn more, women in those households actually feel that they need to work less due to their larger household income. A 2020 report by the Initiative for What Works to Advance Women and Girls in the Economy reports that half of all female entrepreneurs in India say that they started their business out of necessity rather than an aspiration to take up a business venture. Another important idea raised here is that of measurement error, specifically the exclusion of women working in the gig or informal economy from the reported female labor force participation rate. This is elaborated on in the Discussion section later in this paper.

In summary, literature on the wealth, sociocultural, and literacy barriers to technology utilization suggests that an investigation of the effects of telecom subscriptions on women's labor force participation rate must include sociocultural attitudes, base literacy rates, and regional wealth/economic growth as control variables. More detail on how I measure and incorporate these mediators into my research is provided in the Data and Methodology sections that follow.

Case Studies

My research is intended to add to otherwise limited literature on the potential that the dissemination of mobile technologies has for the livelihoods of women who have otherwise been denied financial inclusion and independence. This is therefore a tale of not only numbers in the form of raw female labor force participation figures, but individual women's lives and stories — rich insight can be derived from their narratives. I therefore narrow in on case studies that shed some light into the ways mobile technology dissemination has changed the everyday lives of women in low-income regions in terms of access and safety.

The examples below actually suggest gains in terms of financial access and safety to women as a result of mobile phone access. This suggests that female labor force participation is only a narrow measure of the gains of technology for Indian women, and that benefits rather than declines may actually manifest in less easily observable/measurable forms. However, the studies below come with the caveat that increased financial access is only seen in the story of a Ugandan rather than Indian woman, who exists in a different social, religious, and economic environment to Indian women. Nonetheless, it sheds light on the potential of technologies to further women's economic wellbeing. Moreover, the case studies on Indian women that are presented below highlight important gains to connectivity and safety, which likely factor into many women's decisions of whether or not participate in the labor force. The examples below summarize my qualitative data collection and are sourced from GSMA's videos on *Connected Women: Life Stories from Uganda* and *India* and *Vodafone Sakhi: Voices of Impact from India*, as well as their report on *Mitigating Women's Safety Concerns with Mobile: Vodafone Idea India Sakhi Service*.

A salient example of how mobile internet has increased financial access comes from Nache, a woman who resides in a small village in Uganda. With the help of mobile-enabled micro-loans, Nache is now an entrepreneur with a small-scale food business. Growing up, she aspired to complete her education, but her parents had limited financial resources. She didn't feel like she could ask them for money so she started to take out micro-loans through mobile money and set up her own business, which has helped her pursue her dreams and pay for her education.

Another benefit accrued to women by mobile phone access is greater connectivity and access to information. Samidha's story captures this effect — Samidha is a woman from Pugaon village in India. She is one of the key caretakers of her 5 year old nephew, who cannot walk or speak. Her mobile phone has allowed her to make and share videos and messages with not only family and friends to stay connected and feel positive, but also to share information with her nephew's doctor and acquire information critical to his development.

A substantial example of the social mobility that mobile phones can grant women by making it safer for them to venture out into the labor force, is Vodafone's Sakhi Service. Vodafone is an international telecom services provider, and one of the five major telecom companies in India, according to Open Signal. In October 2018, Vodafone launched their Sakhi service to meet the safety needs of women in India. The service enables all female subscribers to program 10 emergency contacts who will be immediately notified if the woman sends a broadcast alert when she feels unsafe, even if her credit balance is empty. Given Vodafone's large coverage, this has made immense contributions to women's safety and perceptions of safety in India, allowing them to feel safer when leaving their home, particularly for long hours to pursue work or study. Below are some quotations taken directly from women using the service, reported by GSMA.

> There were men around on bikes and I was the only woman present. I activated the Sakhi emergency alert and thankfully within seconds my brother got in touch with me.
> — a Sakhi user in Peri-Urban-Varanasi (GSMA 2019)

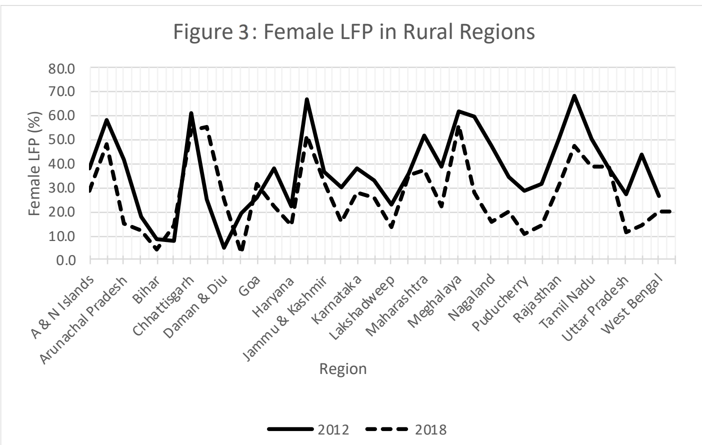
> I think girls who have late tuitions or night jobs will feel less anxious for sure [with Sakhi]. If I get a good night job after my graduation, I could consider it; maybe Sakhi will increase the chances of my parents agreeing to such a job for me.
> — a woman in Uttar Pradesh (GSMA 2019)

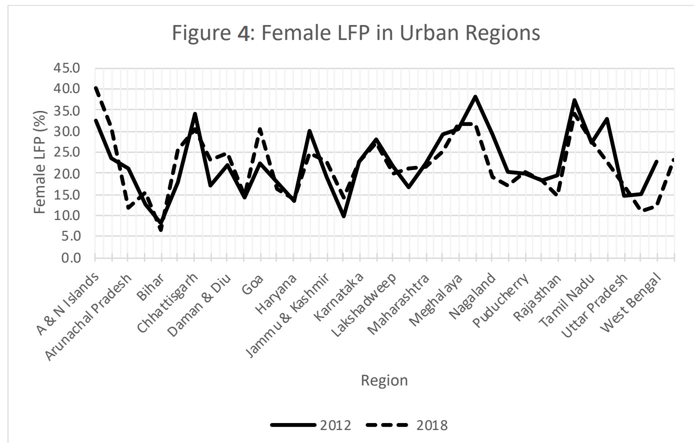
> I feel more safe as Sakhi is like a secret weapon because nobody would know that I have alerted 10 people.
> — a Sakhi user in Lucknow (GSMA 2019)

Data

My data is obtained from the Government of India's publicly available reports on telecommunication services and women's socioeconomic wellbeing. In order to investigate the potential declines to women's labor force participation associated with the dissemination of cellular technology in India, I study the relationship between the female labor force participation rate (LFP) and the number of telecom subscribers in India.

Panel data on female labor force participation (outcome variable) is obtained from the Indian Ministry of Statistics and Program Implementation's periodic *Women and Men in India* reports, which detail state-wise female labor force participation in 2012, 2016, and 2018. These figures are obtained from the "National Sample Survey Office, 68th Round, July 2011 - June 2012", the "Fifth Annual Employment-Unemployment Survey (2015-2016)", and the "Periodic Labour Force Survey (PLFS), NSO, July 2017- June 2018". The panel data is broken down into 35 administrative regions consisting of India's 29 states, major union territories, and cities. The statistics for each state-year are further broken down into: LFP rates in the rural and urban areas of each state, and LFP rates for each gender. The report defines labor force participation rate as the "number of persons in the labor force per 1000 persons [aged 15 and up in the population]," where labor force is defined as the total persons either employed or seeking employment. As engaging in employment allows women to earn independent incomes and is an indication of sufficient skill so as to perform a particular job successfully enough to earn wages, female labor force participation captures women's financial autonomy and ability to participate in the economy and is thus a suitable outcome variable that captures economic mobility. The female labor force participation in different states in the years 2012, the first year in my study, and 2018, the final year in my study, is shown in the figures below. Figures 3 and 4 show that there is a closer overlap between 2012 and 2018 levels of female labor force participation in urban areas rather than rural areas of each state. The 2018 levels of female LFP tend to be below 2012 levels for most states in rural regions, as seen in Figure 3. The most pronounced differences appear to be in Nagaland, Puducherry, Rajasthan, and Tamil Nadu.





The greater decline in female LFP in rural regions may result from both women being left behind as men capitalize on the gains of mobile technology more completely by ownership of personal cellular devices as well as more autonomy, as well as rural women leaving the labor force as they no longer "need" to work as their husbands start to earn more as technology dissemination in the country brings rising incomes. However, it is also possible that this decline at least in some regions is attributable to inaccurate measurement — more women may be taking up small home-business operations or "gigs" and leaving the official labor force to partake in short-term jobs that are enabled by access to mobile technology and greater connectivity. These women may not be documented in the government's labor force statistics, and the possibility of such measurement error is discussed in detail in the Discussion section later in this paper.

My treatment variable is the number of telecom subscriptions, measured in millions of subscribers. Panel data on the number of telecom subscriptions in each of 22 regions, denominated by Indian states and large metropolitan cities, is available for the years 2008-2019. The telecom subscriptions are segmented by rural/urban, wireless/wireline, and private/public subscribers. This data is obtained from the *Telecom Statistics India 2019* report, compiled by the Government of India's Department of Telecommunications. The report is an annual publication that aims to provide consistent time series data on India's telecom sector, drawing from various sources including local Telecom companies, the Telecom Regulatory Authority of India, the General of Commercial Intelligence and Statistics, and various public sector undertakings. For comparability with the outcome variable, female LFP rates, currently available across 35 regions, only regions corresponding to 22 regions into which the telecom subscription panel data is grouped are considered in the analysis. After aligning/truncating the two panels so that the regions in each directly correspond to the other, 19 regions remain. LFP measurements for Arunachal Pradesh, Manipur, Meghalaya, Mizoram, Nagaland, Tripura and Sikkim are averaged to create a North East region measurement that is comparable to the North East measurements available for telecom subscriptions. Tables 1 and 2 shows summary statistics for female labor force participation and the number of telecom subscribers over time in the final panel, after collapsing the panels into 19 regions. The first five columns present statistics for total LFP/ subscriptions across regions, and the last four columns show a breakdown into rural and urban regions.

Consistent with earlier observations in Figures 3 and 4, Table 1 shows that rural regions show consistent large declines in LFP from 2012 to 2018, whereas the overall decline in urban

Table 1: Summary Statistics for Percent Female Labor Force Participation

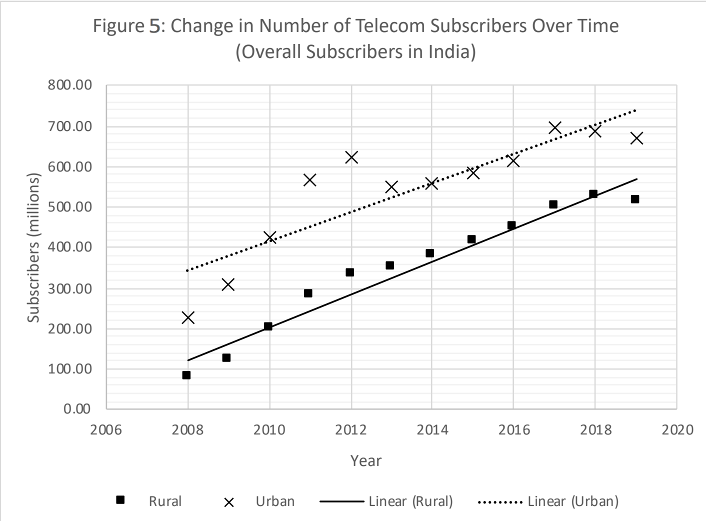
	N	Mean	SD	Min	Max	Rural Mean	Rural SD	Urban Mean	Urban SD
2012	19	23.44	9.95	5.70	49.80	36.66	14.89	20.11	6.14
2016	19	26.00	12.52	10.60	54.80	30.38	15.50	16.83	8.52
2018	19	24.07	11.05	4.10	49.60	25.21	13.59	19.55	6.20

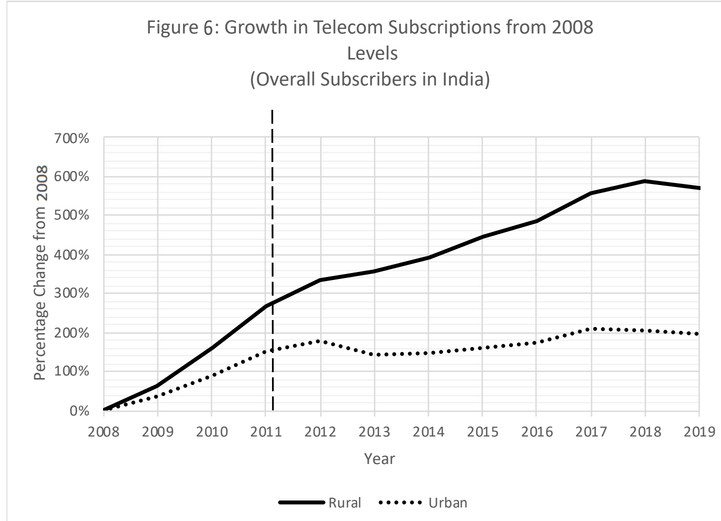
Table 2: Summary Statistics for Number of Telecom Subscribers Across Regions in India (in millions)

	N	Mean	SD	Min	Max	Rural Mean	Rural SD	Urban Mean	Urban SD
2008	19	14.02	8.38	2.46	31.86	3.98	2.64	10.04	6.48
2009	19	20.20	12.22	3.69	49.45	6.44	4.15	13.76	9.11
2010	19	29.54	18.31	5.34	77.50	10.52	7.11	19.01	12.70
2011	19	40.50	25.80	5.97	111.77	14.80	10.54	25.70	17.22
2012	19	46.63	30.53	6.51	130.78	17.36	12.61	29.26	20.29
2013	19	44.33	29.11	7.04	124.04	18.32	13.21	26.01	18.30
2014	19	46.15	29.96	7.37	127.08	19.77	14.28	26.38	18.28
2015	19	49.41	32.14	8.06	136.42	21.78	15.91	27.63	19.31
2016	19	52.56	34.91	9.06	150.77	23.43	17.55	29.13	20.52
2017	19	59.22	39.32	10.58	172.13	26.21	19.42	33.01	23.33
2018	19	60.14	38.63	12.58	168.40	27.41	19.99	32.73	22.40
2019	19	58.71	37.57	10.63	164.34	26.83	21.44	31.88	20.45

regions from 2012 to 2018 is relatively very small if not negligible. It also appears that for urban regions there is a dip in female LFP from 2012 to 2016, which is mostly recovered by 2018. Table 2 shows that the number of telecom subscribers is increasing consistently year to year, with greater growth over the decade in rural regions than urban regions. It appears that the variation in telecom subscription numbers increases with the subscription numbers, suggesting that subscription growth may be concentrated in certain regions, resulting in connectivity gaps widening over time. On the whole, these two tables, alongside Figures 3 and 4 suggest marked differences in female LFP and subscription growth between urban and rural regions over time, emphasizing the need to explore each of these regions in isolation to understand the drivers of an overall observed relationship between LFP and telecom subscriptions.

Figures 5 and 6 on the next page further explore this rural-urban divide in telecom subscription trends. Figures 5 shows that while the number of telecom subscribers over time grows in both rural and urban regions, subscription numbers in rural regions are constantly





below those in urban regions (based on overall subscription numbers across India). This also means that the base level of subscriptions in 2008 was much lower in rural regions, so the marginal effects of each additional million subscriber are likely higher in rural regions as the growth factor would be higher in these regions. Figure 6 thus shows the proportion change in subscribers in each year relative to the number of telecom subscribers in 2008. By 2011, the percentage growth in subscribers per year had started to flatten out in urban regions but continued to grow between 2011 and 2019 in rural regions, meaning the relative growth in subscriptions was much larger in rural regions than urban regions, which were higher in connectivity to begin with. These differences between rural and urban areas suggest that it is important to investigate the differences in the telecom subscription - female LFP relationship between the two regions.

To study the relationship between telecom subscriptions and female labor force participation in better isolation, a handful of control variables are included. As discussed in the literature review, education is associated with both mobile phone access and employment outcomes, and is arguably a driver of the benefits of mobile phones for women's labor force participation. This is because women with higher literacy are able to interact with mobile technology more fully, allowing them to absorb the benefits of the new technology and connectivity more than illiterate women. Educated women should thus be able to use technology to be economically productive and seek out employment more so than uneducated women. Thus, it is important to consider the literacy rates in reach state as they capture the pre-existing ability of individuals to work effectively and interact with mobile phone and internet features successfully. I expect that declines in female LFP are lower in regions with higher female literacy as literate women are able to absorb more of the benefits of mobile technology — that is, I expect the coefficient on literacy rates to be positive. Data on literacy rates, along with controls for sociocultural attitudes (discussed below), are also sourced from the *Women and Men in India* reports released by the Indian Ministry of Statistics and Program Implementation. The reports define literacy rates as the "total percentage of the population of an area at a particular time aged seven years or above who can read and write [in any local language] with understanding." Figures on literacy rates were available only for 2012 and 2018 as state-wide figures, so literacy rates can only be controlled for in one supplementary variant of the model, as explained in the Methodology section that follows. The inability to control for education in the panel is one of the limitations of this study, and future research should seek to collect data the reflects annual literacy rates in each state, segmented into rural and urban regions.

The second control variable, sourced from the same report, is sociocultural attitudes towards women. Research has suggested that social environments/customs and attitudes towards women's independence can acts as major barriers to their ability to work. Therefore, panel data on rates of crime against women, for 35 regions in 2012, 2016, and 2018, is used as a proxy for the level of safety for women and level of misogyny in each state-time. The report defines the rate of crimes against women as the cognizable incidences of rapes, kidnapping of women, dowry deaths, assaults/insults to modesty per 100 lakh women in each state-time. To consider specifically levels of misogyny and inhibition of female empowerment, I take the rate of dowry deaths as a specific control variable for misogynistic sociocultural barriers, allowing the consideration of these social barriers in better isolation from nation-wide threats to safety from crimes such as rape, which can occur regardless of regional female empowerment and education. I expect the coefficient on these sociocultural controls to be negative, meaning declines associated with telecom subscription growth would be higher in regions with high levels of misogyny towards women, as these regions are more likely to push men to get further ahead of women by benefiting from these technologies.

I further include the growth in GDP at each state-time, from a base of 2011-2012 prices, as a macroeconomic control variable intended to capture the relative presence of production and employment/business opportunity in each state-time, as well as the growth in wealth as this impacts people's ability to afford additional telecom services on top of a basic subscription. This controls for any limitations on the benefits of mobile phone access for women resulting from poor economic conditions and periods of austerity that bring about a shortage of jobs. This data is sourced from statistics for 2012-2019 released by the Economic Statistical Organization Punjab, in partnership with the Central Statistical Organization New Delhi. None of the figures obtained from government data for this research contain missing values (for any variable), so imputation of missing values is not be required in data cleaning.

Methodology

Primary Method: State and Time Fixed Effects Models

Given the availability of panel data, I investigate the relationship between the female labor force participation rate and the number of telecom subscribers using a state and time fixed effects regression. This method allows me to efficiently use all available state-time observations while controlling for unobservable cultural factors that vary across states but are constant over time (state-fixed effects), such as local marriage customs and child-rearing practices, as well as those the vary over time but are constant across states (time-fixed effects), such as the sociological effects of national policies or crises. These state-fixed effects are included as a series of constants, modeled as dummy variables for N-1 states — in this case 18 constants — whose coefficients capture the effect of the observation simply belonging to that state. Similarly, time fixed effects are included as T-1 constants — in this case 2 constants. Key assumptions of fixed regressions, as discussed by Stock and Watson (2015) are that (a) there is no heteroskedasticity i.e. the mean of the error term is not conditional upon the regressor terms; (b) for any given state, the draws across time periods ($X_{i1}, X_{i2}, \ldots X_{it}$) are independent and identically distributed draws from the regressor *X*'s distribution; (c) large outliers are unlikely; and (d) there is no perfect multicollinearity, which is why N-1 and T-1 constants are included for states and times, respectively, rather than all N and T constants.

A series of models are considered to investigate the association between telecom subscriptions and female LFP. The first is a naive model, including only the explanatory and outcome variable along with state fixed constants, with no control variables. Model 2 extends this naive model to include time-fixed effects to control for year-specific nation-wide factors that may influence female LFP. For the equation below, as well as all equations that follow, i may take the value of any of the 19 Indian regions included in the panel data, and t = {2012, 2016, 2018}.

$$(\text{fem\_\_LFP})_{i,t} = \beta_0 + \beta_1(telecom_{i,t-1}) + \alpha_i + u_{i,t} \qquad (1)$$

$$(\text{fem\_\_LFP})_{i,t} = \beta_0 + \beta_1(telecom_{i,t-1}) + \alpha_i + \lambda_t + u_{i,t} \qquad (2)$$

If the effects on control variables are not salient, i.e. not significant statistically or in magnitude, then this simple model would suffice to capture the correlation between telecom access and female LFP through the β_1 coefficient. The effect of the increase in telecom subscriptions is included as a lagged effect here, meaning the observation for telecom subscription numbers is that of the year before the female LFP observation. This is because research has suggested that the effects of mobile technology dissemination access are transferred to societies largely through increased education and information. The acquisition of this information is a slow process and it likely takes a year before the effects of increased telecom subscriptions manifest in women's labor force participation (e.g. it might take several months to a year for a woman's husband to find a higher wage job through greater connectivity, which in turn leads her to leave the labor force in the following months as a result of social pressures to be a homemaker).

To incorporate relative levels of economic opportunity into the models, I include the GDP growth rates in Model 3 to account for the current level of economic activity, an indicator of the level of employment opportunities, in each state-time. If the state is in a period of slow growth,

$$(\text{fem\_\_LFP})_{it} = \beta_0 + \beta_1(telecom_{i,t-1}) + \beta_2(GDP\_growth_{i,t}) + \alpha_i + \lambda_t + u_{i,t} \qquad (3)$$

then there may be few jobs available and thus women may be deterred from joining or remaining in the labor force. This may lead to higher declines in female LFP than those associated only with increasing telecom subscriptions.

Research has suggested that sociocultural attitudes and low economic opportunity levels can pose insurmountable barriers to women's abilities to work. It is therefore critical to consider these environmental factors to account for their negative effects on female LFP. If omitted, these variables might make the efficient on telecom subscription changes appear larger. To account for sociocultural barriers, I include the state-time crime rates against women as a regressor in model 4, accounting for both an inhibiting lack of safety due to high sexual assault rates, as well as limiting gender roles, accounted for by higher rates of dowry attacks. Nonetheless, as sexual assault rates are quite high nationwide in India (Wallen, 2020), any woman can be subjected to such attacks due to a lack of safety irrespective of technological skills and levels of social misogyny. Model 5 hence narrows in specifically on misogyny and hostile attitudes towards female autonomy by including only the rates of deaths due to dowry disputes, reflecting a lack of power in the woman's household/marriage, as a sociocultural control.

$$(\text{fem\_\_LFP})_{it} = \beta_0 + \beta_1(telecom_{i,t-1}) + \beta_2(crime\_against\_women_{i,t}) + \beta_3(GDP\_growth_{i,t}) + \alpha_i + \lambda_t + u_{i,t} \qquad (4)$$

$$(\text{fem\_\_LFP})_{it} = \beta_0 + \beta_1(telecom_{i,t-1}) + \beta_2(dowry\_death\_rate_{i,t}) + \beta_3(GDP\_growth_{i,t}) + \alpha_i + \lambda_t + u_{i,t} \qquad (5)$$

Finally, as the growth factor of telecom subscriptions is far higher in rural regions than urban ones (see Figure 6 in Data section), and larger declines in female LFP were observed between 2012 and 2018 in rural regions than urban ones, it important to study the telecom subscription and female LFP relationship in rural and urban areas separately as there may be differences in the effects of telecom subscriptions on female LFP between rural and urban areas. Namely, the declines may be larger for rural areas as initial levels of telecom access in 2008 were far lower therefore a lot of the social and connectivity changes introduced by mobile technology dissemination are completely novel upon introduction. In urban regions, on the other hand, growing subscriptions tend to simply increase the availability of pre-existing services so the effects may be smaller due to diminishing marginal effects (many urban families have already gained access to increased mobile connectivity and many women have already responded to this change by leaving the work force so the effect of incremental telecom subscriptions may be smaller in urban regions). Moreover, rural women tend to face more pervasive gender role pressures that push them to be homemakers if their household income is label enough for them to stay home. Therefore, the regressions in models 1-5 will be repeated separately for rural and urban regions to consider the differences between rural and urban regions, and I expect that the coefficient on telecom subscriptions will be more negative in rural regions.

It is important to note some limitations of using such a state and time fixed effects regression. Firstly, it is often the case that observations for the same state across time periods are autocorrelated, meaning that the value of an observation in one time period is correlated with and predictive of the value in another time period due to the reverberating effects of an outcome over time. This violates the assumption of a fixed effects regression discussed at the start of this section that the draws for any state over time are independently and identically distributed. To account for such autocorrelation, I specify clustered standard errors when running the regression — this calculates standard errors by grouping observations into serially correlated (autocorrelated) clusters by state, while assuming that regression errors are uncorrelated across clusters i.e. states (Stock and Watson 2015). Additionally, using clustered standard errors also allows for any heteroskedasticity to be mitigated when running the regression.

Finally, this study does not involve a randomized treatment, as the increase in telecom subscriptions is not a randomly occurring condition but rather driven by specific economic and cultural contexts that also exert an influence on the rates of female labor force participation. Thus, such cultural and economic extraneous variables are not balanced across conditions and this is simply an observational study rather than an experiment, meaning that causal inferences cannot be made about the effects of telecom access on female LFP. Due to the lack of a randomized treatment, I do not intend to draw causal conclusions. I instead investigate the correlation between the number of telecom subscriptions and the female labor force participation rate.

Secondary Method: Differences-on-Differences Models

An alternative method of investigating the effect of increasing telecom subscriptions on female LFP is using a set of three difference-on-difference models for 2012-2016, 2016-2018, and 2012-2018. This allows us to observe whether the relationship between telecom subscriptions and female LFP is the same across different sub-periods in the panel. Moreover, since female literacy rates are only available as total state figures (i.e. not segmented into rural and urban regions) for 2012 and 2018, the difference-on-difference regression for the 2012-2018 period allows me to control for literacy in the model, which research has suggested plays an important role in whether women can absorb the effects of growing telecom access, but the limited availability of data has prevented me from including as a control in the primary method. In each of these three, I regress the change in female LFP between the two years considered on the change in the number of telecom subscribers between the two years. An important caveat to note is that by segmenting the panel into these three periods here, the number of observations in each regression reduces to 19, a very small sample size. However, these results are only supplementary and serve only as a comparison to the primary method so I will only consider these regression results as indicative rather than conclusive.

For the 2012-2016 and 2016-2018 periods, the specification in model 6 is used, including controls for GDP growth and sociocultural attitudes towards women. For the 2012-2018 period, a control for literacy is added as shown in model 7 given that data on literacy as a statewide figure for these two years. For each of these three periods, the regression is then repeated for rural and urban regions separately using only the model 6 specification (as literacy for 2012-2018 is available only as a statewide total, not by rural and urban regions).

$$\Delta(\text{fem\_\_LFP}) = \beta_0 + \beta_1 \Delta(telecom) + \beta_2 \Delta(crime\_against\_women) + \beta_3 \Delta(GDP\_growth) + \varepsilon \qquad (6)$$

$$\Delta(\text{fem\_\_LFP}) = \beta_0 + \beta_1 \Delta(telecom) + \beta_2 \Delta(literacy) + \beta_3 \Delta(crime\_against\_women) + \beta_4 \Delta(GDP\_growth) + \varepsilon \qquad (7)$$

Similar to how dummy variables for each state in the primary state-fixed effects model control for state-specific cultural factors that are invariant over time, the difference-in-difference model accounts for these state-specific effects as they are canceled out when their difference between the two periods is computed (i.e. their difference is 0 assuming that they act equally/are constant in the two time periods). Robust standard errors are used to control for any possible heteroskedasticity.

Results

Primary Method: State and Time Fixed Effects Models

Table 3 below shows the results of the naive model, where female labor force participation is regressed on the number of telecom subscriptions and only state-fixed effects are included (the coefficients on the 18 dummy variables are hidden in the table below), with no other controls. The coefficients on the number of telecom subscriptions are not statistically significant in the total state or urban-regions only models. However, as expected the coefficient in the rural-regions only model is negative and statistically significant (at the 1% level). The coefficient on the number of telecom subscriptions for the rural model is -0.553, suggesting that for every additional 1 million telecom subscribers in rural areas, rural female labor force participation declines by 0.553 percentage points. This is a substantial decline, given that the female labor force participation rate was only around 21% in 2012 to begin with.

Table 3

VARIABLES	(1) Basic Model Total	(2) Basic Model Rural	(3) Basic Model Urban
tel_total	0.0311		
	(0.0527)		
tel_rural		-0.553***	
		(0.150)	
tel_urban			0.0304
			(0.0539)
Constant	40.15***	71.82***	24.19***
	(3.929)	(4.526)	(2.390)
Observations	57	57	57
R-squared	0.699	0.724	0.751

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4 shows the results of the naive model when time-fixed effects are included alongside state-fixed effects in order to account for any year-specific factors that are constant across states, such as the effects of policy changes, national disasters, or government styles. The coefficients on telecom subscriptions in the total states and urban area models remain non-significant, and now the coefficient in the rural model also becomes statistically insignificant. The coefficient on the 2018 year dummy is large, negative, and statistically significant, suggesting that the seemingly significant result in the previous model may have been driven by the general decrease in female LFP over time rather than the increase in telecom subscriptions, since the significant effect disappears when time-fixed effects are added. Moreover, the R-squared of the model increases, suggesting that year of observation is important in explaining some of the variation in female LFP. Overall, this table suggests that increases in telecom subscription numbers have no effect on female labor force participation.

Table 4

VARIABLES	(1) Time FE Model Total	(2) Time FE Model Rural	(3) TimeFE Model Urban
tel_total	0.0328		
	(0.0960)		
tel_rural		0.153	
		(0.220)	
tel_urban			0.0120
			(0.121)
2016.year	2.271	-7.353	-3.302*
	(3.341)	(4.597)	(1.739)
2018.year	0.0224	-13.21***	-0.651
	(2.275)	(3.073)	(1.696)
Constant	39.26***	57.40***	26.32***
	(6.641)	(5.412)	(5.011)
Observations	57	57	57
R-squared	0.708	0.774	0.792

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5 shows the results of the state and time fixed effects model when GDP growth is included as a control variable to account for general macroeconomic conditions that may affect the availability of jobs in the economy. While I had expected a positive coefficient on GDP growth, expecting more women to partake in the labor force in good economic conditions with positive GDP growth, the coefficient on GDP growth is not statistically significant, suggesting that GDP growth from the previous year has no effect on female LFP. Moreover, the coefficients on telecom subscriptions remain non-significant in all three models, suggesting again that increases in the number of telecom subscribers have no effect on female LFP.

Table 5

VARIABLES	(1) GDP Model Total	(2) GDP Model Rural	(3) GDP Model Urban
tel_total	0.0379		
	(0.0959)		
gdp_growth	-0.507	-0.564	-0.0143
	(0.844)	(0.983)	(0.511)
tel_rural		0.163	
		(0.228)	
tel_urban			0.0121
			(0.123)
Constant	41.80***	60.35***	26.40***
	(8.379)	(7.873)	(5.190)
Observations	57	57	57
R-squared	0.718	0.780	0.792

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Tables 6 and 7 on the next page include additional controls for sociocultural barriers that women might face that would prevent them from participating in the labor force. Table 6 includes the rate of crimes against women (attacks per 100,000 women) as a control for these factors. The coefficient on this control, as well as all other variables, is not statistically significant, suggesting that none of these variables have an effect on female LFP.

Table 6

VARIABLES	(1) Safety Model Total	(2) Safety Model Rural	(3) Safety Model Urban
tel_total	0.0551		
	(0.108)		
gdp_growth	-0.525	-0.613	-0.0261
	(0.823)	(0.892)	(0.492)
crime_rate	0.0388	0.107	0.0279
	(0.0576)	(0.0736)	(0.0278)
tel_rural		0.240	
		(0.283)	
tel_urban			0.0261
			(0.136)
Constant	39.73***	55.92***	25.14***
	(9.507)	(9.668)	(6.256)
Observations	57	57	57
R-squared	0.720	0.790	0.796

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7 simply substitutes crime rates against women, which include crimes such as sexual assault which all women are at risk of regardless of levels of misogyny in their communities, for rates of attacks against women due to dowry disputes as a control for

Table 7

VARIABLES	(1) Social Model Total	(2) Social Model Rural	(3) Social Model Urban
tel_total	0.0367		
	(0.110)		
gdp_growth	-0.506	-0.544	-0.0199
	(0.864)	(0.997)	(0.528)
dowry_deaths	0.166	3.942	-1.302
	(6.839)	(8.140)	(3.121)
tel_rural		0.104	
		(0.257)	
tel_urban			0.0154
			(0.122)
Constant	41.80***	60.09***	26.81***
	(8.571)	(8.931)	(5.342)
Observations	57	57	57
R-squared	0.718	0.782	0.794

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

sociocultural barriers. This specifically captures the status of women in their marriages and communities, and is a more specific proxy for levels of misogyny. However, this does not change the results as Table 7 also does not show statistically significant effects on any of the controls or telecom subscription numbers, suggesting again that none of these variables have any effect on female LFP.

Secondary Method: Differences-on-Differences Model

Table 8 shows the results of the difference-on-difference regression for the 2012-2016 period of the change in female LFP on the change in the number of telecom subscribers and the change in controls. None of these coefficients are statistically significant, but it is important to note that the R-squared in this model is extremely low, likely due to the unreliability of such a small sample size; this makes the results of this regression unreliable. Nonetheless, the finding that the number of telecom subscribers has no effect on female LFP from the primary method's results hold over here.

Table 8

VARIABLES	(1) 2012-2016 Model Total	(2) 2012-2016 Model Rural	(3) 2012-2016 Model Urban
tel_total	-0.662		
	(0.746)		
gdp_growth	0.00221	-0.0187	0.253
	(0.712)	(0.794)	(0.359)
crime_rate	0.0490	0.114	0.0233
	(0.0871)	(0.103)	(0.0397)
tel_rural		0.378	
		(0.750)	
tel_urban			-0.299
			(0.202)
Constant	0.506	-13.09	-3.364
	(6.292)	(10.78)	(3.695)
Observations	19	19	19
R-squared	0.023	0.063	0.139

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9 shows the results of repeating the analysis for the 2016 to 2018 period. The only statically significant coefficient here is on GDP growth from the previous year, suggesting that a 1 percentage point increase in GDP growth is correlated with a decrease of 1.93 percentage points in female labor force participation. However, the R-squared here is also quite low and the sample size is, again, limited so this finding cannot be taken as an indicator of GDP growth having an effect on female LFP, especially as all other models have suggested a non-significant effect on this coefficient. The finding that the coefficients on other controls and the number of telecom subscribers are not significant holds over here.

Table 9

VARIABLES	(1) 2016-2018 Model Total	(2) 2016-2018 Model Rural	(3) 2016-2018 Model Urban
tel_total	0.469		
	(0.758)		
gdp_growth	-1.933**	-1.720	-0.987
	(0.862)	(1.245)	(0.582)
crime_rate	0.00858	0.306	-0.0847
	(0.367)	(0.460)	(0.169)
tel_rural		-0.577	
		(1.262)	
tel_urban			0.301
			(0.328)
Constant	-6.892	-4.626	-1.588
	(5.939)	(10.14)	(4.082)
Observations	19	19	19
R-squared	0.242	0.269	0.220

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10 shows the results of repeating the analysis for the 2012-2018 period (omitting observations from 2016). The total state model includes an additional control for female literacy rates as this data was available only as state-wide for 2012 and 2018. The coefficient on literacy is not statistically significant, suggesting that literacy has no effect on female LFP. However, the

R-squared here is also too low to make reliable deductions. Nonetheless, as suggested by previous models in both the primary and secondary method, none of the coefficients on the control variables or telecom subscriber numbers are statistically significant, suggesting these variables have no effect on female LFP.

Table 10

VARIABLES	(1) 2012-2018 Model Total	(2) 2012-2018 Model Rural	(3) 2012-2018 Model Urban
tel_total	0.161		
	(0.240)		
total_lit	-0.0116		
	(0.411)		
gdp_growth	-0.171	-0.230	0.201
	(0.616)	(0.481)	(0.461)
crime_rate	0.0108	0.0349	0.0272
	(0.0261)	(0.0460)	(0.0173)
tel_rural		0.224	
		(0.209)	
tel_urban			0.0337
			(0.109)
Constant	0.0738	-14.52***	-2.391
	(2.517)	(3.351)	(2.189)
Observations	19	19	19
R-squared	0.048	0.108	0.082

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Overall, considering the results of both methodologies (but emphasizing mainly on the primary method), it appears that telecom subscriptions have no effect on female labor force participation. While this agrees with my expectation that women are not absorbing the potential gains from mobile technology dissemination, it disagrees with my expectation of a negative relationship between an increase in telecom subscribers and female LFP. This suggests that larger gains to men due to increasing telecom subscribers may not be causing women to leave the labor force, but that women are still not benefitting from cellular technology in the capacity possible.

Discussion

It appears that while female labor force participation is on the decline while telecom subscription numbers in India are on the rise, the latter is not contributing to the decline of female LFP. While men benefit more from the dissemination of mobile technologies in India, the non-significant coefficient results seen in the previous section suggest that this is not directly pushing women out of the labor force by benefitting men more strongly or increasing their husband's income enough that they no longer "need" to work when gender roles already discourage them from working. Instead, telecom subscription numbers seem to have no effect on female LFP. This still suggests however that while women are not directly dropping out of the labor force in association with telecom subscription increases, they are not absorbing the economic benefits of increased connectivity from greater telecom subscriptions.

However, perhaps the biggest barrier to this research is the possibility of inaccurate measurement in government reports of female labor force participation in India. All of the surveys referenced by the Indian Ministry of Statistics and Program Implementation use a combination of face-to-face interviews and paper questionnaires in their fieldwork. This means that the survey method largely relies on self-reports of individuals' claims to working or not. Self-report methods are typically subject to inaccuracy due to lying or omission by participants, and it is possible that many women may omit reporting their economic activity in order to avoid taxation or due to familial pressures to report men in the household as the primary breadwinners.

Moreover, the Indian Ministry of Labor and Employment reports that their estimated of labor force participation are based on the Usual Principal and Subsidiary Status (UPSS) Approach, under which any person who has "worked even for 30 days or more in any economic activity during the reference period of last twelve months is considered as employed under this approach". While this method is actually friendly to women's employment patterns given that many women may take up short-term jobs or work on-and-off, it also suggests that many female workers may actually work for only small period of time in the year, which are easy to underreport or neglect in reporting, leading to deflated estimates of female labor force participation. Table 11 below is taken from the Indian Ministry of Labor and Employment's *Report on Fifth Annual Employment - Unemployment Survey* and shows the differences in labor force participation estimates between the UPS approach, which only counts individuals to be employed over the last year if they worked at least 183 days, and the UPSS approach, which considers individuals to be employed as long as they worked at least 30 days.

Table 11

Labour Force Participation Rate (LFPR)

Table 3.1: LFPR based on UPS & UPSS approach for persons aged 15 years & above **All India (in %)**

Approach	Rural				Urban				Rural+ Urban			
	M	F	T	P	M	F	T	P	M	F	T	P
UPS	77.3	26.7	51.1	53	69.1	16.2	41.2	43.5	75	23.7	48	50.3
UPSS	78	31.7	52.2	55.8	69.1	16.6	41.2	43.7	75.5	27.4	48.8	52.4

The columns labeled "F" show female LFP and likewise the columns labeled "M" show male LFP. The table shows that women's labor force participation is consistently underestimated by the UPS approach, than the UPSS approach, which is inclusive of workers who work for short periods during the year. This underestimation is much larger in rural regions in particular. The estimated LFP for men, however, is quite similar using both approaches. This suggests that women work more inconsistently (i.e. for fewer months or more intermittently) than men, which also makes their work easier to underreport even though the more inclusive UPSS approach is used in government reports of LFP.

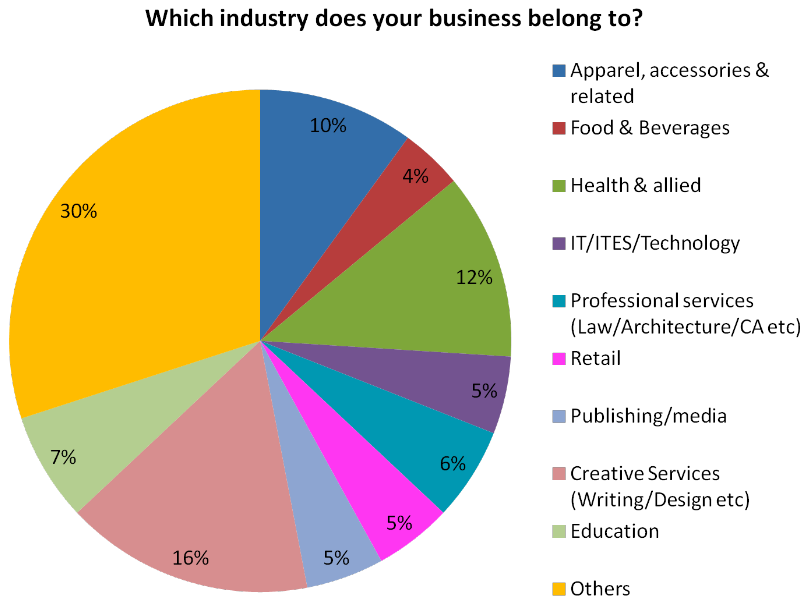
Another measurement error stems from the poor measurement of activity in the sectors that women are concentrated in. The *Women and Men in India Report 2018* states:

> Participation of women in economic activities in formal sectors of industries, services and agricultural sector is measurable, but activities of women in informal sectors such as house works, training and education of children, activities in agricultural sectors and household services are still not measured. (2019)

Many Indian women work in unorganized sectors, help with family businesses, offer domestic and childcare services for a charge, or are otherwise involved in the gig economy. Hence, the omission of these categories of women can lead to very deflated figures of female LFP. A *Women's Web* survey of female business owners suggests that women-owned businesses are segmented as outlined in Figure 7 on the next page. Many of these businesses are classified as "other" or are in the creative sector, both of which are likely considered informal sector activity in many cases. While it could be the case that while many women have left the labor force over the last decade, many may also have just migrated over to the informal sector by benefiting from greater mobile connectivity, meaning what may appear to be a negative or null relationship between telecom access and female LFP may actually be a disguised positive relationship.

Furthermore, in addition to working in informal sectors, many women, particularly in rural regions are self-employed. The *Women and Men in India Report 2018* also states that "as per NSS 68th Round, in rural areas most of the females and male workers are self employed at 59.3 and 54.5% respectively." Such a large proportion of self-employment activity is both easy

Figure 7



for individuals to omit in their self-reports and for formal sector-oriented government surveys to fail to measure. A 2019 report by Bain & Company and Google suggests that the proportion of enterprises that are women-owned has actually increased from 14% to 20% over the past decade despite falling female labor force participation, with further growth projected for the next decade. This suggests that measurement error in the self-employed sector may be driving large errors in estimates of the female LFP in India.

Therefore, if panel data could be obtained on the number of women-owned startups, which is currently only available as a cross-sectional survey in 2014, or the number of home-operated businesses, those metrics may better capture female economic mobility gains from increased connectivity from telecom subscriptions. Alternatively, these variables could be used as instruments for female LFP in an instrumental variable regression methodology. Nonetheless, an important consideration is that financial barriers to entrepreneurship may supersede any benefits from mobile connectivity for women in India as an article by IndiaSpend on the barriers to female entrepreneurship states that Indian female entrepreneurs report difficulties in securing institutional financing for their business:

> The problems related mostly to social attitudes and bias, difficulty in securing collateral-based loans (most women do not own property), and poor awareness or knowledge of financial schemes including those that provide collateral-free financing. (2021)

This suggests that a more important alternative study of how women can can mobilized into labor force participation is one of financial barriers rather than connectivity.

Conclusion

While the results of this study are significant, it still raises an important concern. The lack of a significant relationship between telecom subscription numbers and Indian female labor force participation suggests that Indian women are at present not absorbing the potential gains that increased connectivity and access to digital resources that telecom subscriptions bring with them. Past research has shown that with access to mobile phones and subscriptions, women are able to access financial resources and literacy that tend to improve their ability to work and increase their financial autonomy. However, the consistent decline of female LFP in India over the last decade raises concerns regarding why these mobile technology benefits are not transferred to Indian women in the capacity that research suggests there is potential for.

The most likely explanation for this is inhibitors such as gender roles, a lack of safety, and inappropriate or unavailable workplace environments for women in South Asia. These factors likely continue to benefit men while preventing increases in telecom subscription numbers to produce economic gains for women. Thus, while the non-significant results suggest that there isn't a negative relationship between telecom subscriptions and female LFP, meaning that growing subscriptions are not pushing women out of labor force by benefiting men (particularly men in the same household) more, they also suggest that women are not seeing any effects at all of growing telecom penetration in terms of their labor force participation.

Nonetheless, as discussed in the previous section, these seemingly null effects may largely be the effect of measurement error as government surveys do not currently accurately capture the intermittent and short-term work many women partake in, nor do they accurately measure activity in sectors that women are concentrated in. If we looked specifically at under-reported home-operated business activity or female entrepreneurship, we may find that growing telecom subscriptions actually increase female economic activity. Thus, if more granular data on female entrepreneurship activity becomes available, we will see scope for essential new research into how the role of women in the economy interacts with the dissemination of new communication technologies.

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Appendix 1: Overall Telecom Subscriptions in India

Service Area wise Subscribers : Overall							
Telecom Subscribers (Millions)							
At the end of March	**Total**	**Wireline**	**Wireless**	**Rural**	**Urban**	**Public**	**Private**
2008	300.49	39.41	261.08	76.50	223.99	79.55	220.94
2009	429.73	37.96	391.76	123.51	306.21	89.55	340.18
2010	621.28	36.96	584.32	200.77	420.51	105.87	515.41
2011	846.33	34.73	811.60	282.29	564.04	126.00	720.33
2012	951.35	32.17	919.17	330.83	620.52	130.27	821.08
2013	898.02	30.21	867.81	349.21	548.80	130.11	767.91
2014	933.02	28.50	904.52	377.78	555.23	120.05	812.96
2015	996.13	26.59	969.54	416.08	580.05	100.34	895.79
2016	1059.33	25.22	1034.11	447.77	611.56	108.65	950.68
2017	1194.99	24.40	1170.59	501.81	693.18	122.18	1072.81
2018	1211.80	22.81	1188.99	525.87	685.93	131.66	1080.14
2019	1183.41	21.70	1161.71	514.27	669.14	133.51	1049.90
Teledensity (per 100 Inhabitants)							
At the end of March	**Total**	**Wireline**	**Wireless**	**Rural**	**Urban**	**Public**	**Private**
2008	26.22	3.44	22.78	9.46	66.39	6.94	19.28
2009	36.98	3.27	33.71	15.11	88.84	7.71	29.27
2010	52.74	3.14	49.60	24.31	119.45	8.99	43.75
2011	70.89	2.91	67.98	33.83	156.93	10.55	60.34
2012	78.66	2.66	76.00	39.26	169.17	10.77	67.89
2013	73.32	2.47	70.85	41.05	146.64	10.62	62.69
2014	75.23	2.30	72.94	44.01	145.46	9.68	65.55
2015	79.36	2.12	77.24	48.04	149.04	7.99	71.36
2016	83.40	1.99	81.41	51.26	154.18	8.55	74.85
2017	93.01	1.90	91.11	56.98	171.52	9.51	83.50
2018	93.27	1.76	91.51	59.25	166.64	10.13	83.14
2019	90.10	1.65	88.45	57.50	159.66	10.16	79.94

Source - DOT compiled Data

Appendix 2: Statewise Telecom Subscriptions (Millions) - Lagged Years Included in Panel

Region	Year	Total	Wireline	Wireless	Rural	Urban
Andhra Pradesh	2011	63.05	2.37	60.68	20.66	42.39
Assam	2011	11.93	0.26	11.67	6.23	5.70
Bihar	2011	54.74	1.20	53.54	24.41	30.32
Gujarat	2011	48.90	1.95	46.96	16.63	32.28
Haryana	2011	21.04	0.65	20.39	8.67	12.37
Himachal Pradesh	2011	7.55	0.34	7.22	4.25	3.31
Jammu & Kashmir	2011	5.97	0.22	5.75	2.58	3.40
Karnataka	2011	52.19	2.74	49.45	13.11	39.09
Kerala	2011	34.66	3.30	31.36	13.74	20.92
Madhya Pradesh	2011	47.21	1.38	45.83	16.26	30.95
Maharashtra	2011	64.57	2.85	61.72	28.25	36.32
North-East	2011	7.45	0.27	7.18	3.24	4.21
Odisha	2011	22.99	0.57	22.42	9.64	13.34
Punjab	2011	30.34	1.58	28.76	9.81	20.53
Rajasthan	2011	44.39	1.29	43.10	20.05	24.34
Tamil Nadu	2011	58.71	1.98	56.73	15.11	43.59
Uttar Pradesh	2011	111.77	2.32	109.45	43.59	68.18
West Bengal	2011	40.42	0.76	39.66	23.93	16.49
Kolkata	2011	24.61	1.40	23.21	0.92	23.70
Chennai	2011	14.38	1.48	12.90	0.11	14.27
Delhi	2011	41.66	2.84	38.82	1.10	40.56
Mumbai	2011	37.79	2.99	34.80	0.00	37.79
Andhra Pradesh	2015	73.82	1.87	71.95	31.02	42.80
Assam	2015	17.32	0.17	17.15	10.58	6.74
Bihar	2015	69.67	0.36	69.31	38.91	30.77
Gujarat	2015	60.12	1.55	58.56	22.72	37.40
Haryana	2015	22.41	0.41	22.01	10.40	12.01
Himachal Pradesh	2015	8.06	0.21	7.86	5.28	2.78
Jammu & Kashmir	2015	9.46	0.15	9.31	4.97	4.49
Karnataka	2015	60.32	2.28	58.05	18.64	41.68
Kerala	2015	33.94	2.59	31.35	17.81	16.13
Madhya Pradesh	2015	61.71	1.11	60.60	27.43	34.28
Maharashtra	2015	79.06	2.12	76.94	37.78	41.28
North-East	2015	10.63	0.13	10.50	5.29	5.34
Odisha	2015	28.19	0.32	27.87	15.46	12.73
Punjab	2015	31.75	1.12	30.63	12.47	19.28
Rajasthan	2015	56.03	0.82	55.21	29.28	26.75
Tamil Nadu	2015	83.08	2.76	80.32	24.05	59.02
Uttar Pradesh	2015	136.42	1.00	135.42	67.71	68.71
West Bengal	2015	47.52	0.44	47.07	31.79	15.73
Kolkata	2015	23.56	1.00	22.56	1.59	21.97
Chennai	2015	Included in Tamil Nadu	Included in Tamil Nadu	Included in Tamil Nadu	Included in Tamil Nadu	Included in Tamil Nadu
Delhi	2015	49.33	3.14	46.19	2.22	47.11
Mumbai	2015	33.73	3.06	30.67	0.68	33.06
Andhra Pradesh	2017	86.58	1.64	84.94	38.73	47.85
Assam	2017	21.99	0.16	21.84	13.81	8.19
Bihar	2017	84.93	0.31	84.61	48.91	36.02
Gujarat	2017	73.20	1.36	71.84	28.10	45.10
Haryana	2017	25.39	0.35	25.05	11.45	13.94
Himachal Pradesh	2017	10.58	0.15	10.43	7.10	3.48

Jammu & Kashmir	2017	12.04	0.13	11.91	5.89	6.15
Karnataka	2017	71.39	2.24	69.14	22.51	48.88
Kerala	2017	41.28	2.11	39.16	18.69	22.59
Madhya Pradesh	2017	70.60	1.02	69.58	33.17	37.43
Maharashtra	2017	95.78	1.88	93.90	43.14	52.64
North-East	2017	12.69	0.12	12.57	6.37	6.32
Odisha	2017	34.58	0.29	34.29	20.45	14.13
Punjab	2017	36.97	1.01	35.97	13.99	22.99
Rajasthan	2017	68.10	0.74	67.36	34.62	33.48
Tamil Nadu	2017	91.80	2.55	89.26	26.28	65.53
Uttar Pradesh	2017	172.13	0.89	171.24	82.44	89.69
West Bengal	2017	58.58	0.33	58.25	39.86	18.72
Kolkata	2017	30.18	0.86	29.32	2.38	27.80
Chennai	2017	Included in Tamil Nadu	Included in Tamil Nadu	Included in Tamil Nadu	Included in Tamil Nadu	Included in Tamil Nadu
Delhi	2017	56.57	3.22	53.35	2.54	54.03
Mumbai	2017	39.62	3.04	36.58	1.40	38.23

Appendix 3: Female LFP 2012

	[2012] 4.8 : State-wise Labour Force Participation Rate(%) for persons aged 15 years & above							
Name of States/UTs	Rural			Urban			Total		
	Female	Male	Total	Female	Male	Total	Female	Male	Total
A & N Islands	37.9	80.8	59.4	32.4	81.9	56.8	28.1	61.4	44.9
Andhra Pradesh	58.1	82.2	69.7	23.7	77.0	50.4	36.1	60.0	47.9
Arunachal Pradesh	41.5	73.9	57.9	21.2	69.6	47.5	25.6	48.8	37.6
Assam	17.9	83.1	51.5	12.5	77.0	46.0	12.6	56.5	35.8
Bihar	8.7	78.3	45.3	8.0	66.6	40.2	5.7	48.2	28.3
Chandigarh	7.6	91.0	55.9	17.9	80.2	51.4	12.9	57.8	37.6
Chhattisgarh	61.3	83.8	72.6	34.3	75.7	55.5	38.2	55.3	46.9
Dadra & Nagar Haveli	24.8	73.2	49.4	16.9	86.7	54.5	14.2	52.9	34.4
Daman & Diu	5.2	92.4	59.5	22.0	80.5	50.2	7.8	66.8	40.4
Delhi	19.6	80.5	52.6	14.4	75.7	47.2	11.1	54.8	35.0
Goa	26.1	71.7	49.0	22.4	69.4	46.0	19.3	55.6	37.6
Gujarat	38.4	84.9	62.6	18.0	80.2	51.5	22.2	60.4	42.4
Haryana	22.1	75.8	50.6	13.6	72.9	44.7	14.5	53.3	35.4
Himachal Pradesh	67.2	76.3	71.5	30.1	77.6	55.1	49.8	55.5	52.6
Jammu & Kashmir	36.6	76.9	57.5	19.0	73.5	47.5	23.6	56.0	40.3
Jharkhand	30.2	85.3	57.9	9.7	73.5	42.4	17.6	53.3	36.0
Karnataka	38.2	82.4	60.2	22.9	77.8	51.3	24.6	61.0	43.0
Kerala	33.4	77.3	53.6	28.0	75.1	49.8	24.8	57.9	40.3
Lakshadweep	22.7	81.8	50.6	21.4	76.3	49.5	17.8	59.0	38.8
Madhya Pradesh	35.8	83.3	60.5	16.5	75.1	46.7	20.8	55.6	38.8
Maharashtra	51.6	79.4	66.0	22.4	75.3	49.5	29.0	57.2	43.7
Manipur	38.5	76.8	58.0	29.1	75.1	51.7	25.2	51.2	38.6
Meghalaya	62.1	81.1	71.7	30.3	67.7	48.4	35.3	52.7	43.8
Mizoram	59.9	87.5	74.2	38.2	74.8	56.0	33.6	55.5	44.6
Nagaland	47.3	81.1	64.0	29.3	69.5	50.3	32.1	56.1	44.5
Odisha	34.7	85.4	59.6	20.2	81.3	52.0	23.8	60.5	42.2
Puducherry	29.1	73.1	49.3	19.9	74.5	47.2	18.0	54.8	36.2
Punjab	31.7	79.5	56.1	18.2	77.8	49.8	20.3	58.1	40.1
Rajasthan	50.4	77.9	64.1	19.6	71.5	46.6	30.1	50.1	40.5
Sikkim	68.1	80.0	74.1	37.5	83.6	62.6	45.4	59.4	52.5
Tamil Nadu	50.4	81.5	65.5	27.2	78.0	52.3	30.8	60.4	45.4
Tripura	38.3	85.3	62.0	32.8	76.8	54.5	28.2	59.8	44.5
Uttar Pradesh	27.5	81.5	54.5	14.7	77.5	47.3	16.3	50.4	33.9
Uttarakhand	43.8	71.1	56.9	15.0	73.8	45.3	26.3	47.9	37.3
West Bengal	26.4	85.0	55.8	22.9	77.9	51.5	19.2	61.0	40.5
India	**35.8**	**81.3**	**58.7**	**20.5**	**76.4**	**49.3**	**22.5**	**55.6**	**39.5**

Source: National Sample Survey Office, 68 th Round, July 2011 – June 2012.

Appendix 4: Female LFP 2016

[2016 LFP]									
States/UTs	Rural			Urban			Total		
	Female	Male	Person	Female	Male	Person	Female	Male	Person
A & N Islands	39	86.7	63.2	29.9	82	57.9	36.2	85.2	61.5
Andhra Pradesh	59	82.4	70.9	22.2	67.9	44.9	48.8	78.5	63.8
Arunachal Pradesh	58.5	77.4	68.2	20.1	63.6	42.2	53.2	75.5	64.6
Assam	27.5	75.3	53.1	22.1	75.6	50.1	26.7	75.3	52.7
Bihar	19.6	78.6	51.4	8.3	73.6	43.5	18.5	78.1	50.7
Chandigarh	6.9	76.3	45.9	8.3	62.8	38.2	8.2	63.2	38.4
Chhattisgarh	62.6	83.1	73	22.2	72.1	48.5	54.8	80.9	68.2
Dadra & Nagar Haveli	21.6	74.9	50.2	12	66.5	42.4	17.4	71	46.7
Daman & Diu	16.4	74.7	47.6	15.3	83.2	51	15.5	81.2	50.2
Delhi	21.8	76	51.2	12.3	66.7	41.8	12.6	67	42.1
Goa	24.6	80.8	51.9	25.3	71.3	47.4	25	75	49.1
Gujarat	25.4	79.1	53.3	10.3	71.5	42.1	20	76.4	49.3
Haryana	22.9	71.7	48.3	12.6	68.2	41.5	19.7	70.6	46.2
Himachal Pradesh	18.2	72.9	45.7	16.9	69.4	44.1	18	72.5	45.5
Jammu & Kashmir	10.1	65.7	39.2	12.2	65.2	39.7	10.6	65.6	39.3
Jharkhand	59.2	84.4	72.7	14.9	73.2	45.6	49	82	66.6
Karnataka	38.1	79.3	59.3	26.5	74.3	50.8	33.9	77.5	56.2
Kerala	31.9	72.6	51.2	30.9	70.5	49.6	31.4	71.7	50.5
Lakshadweep	24.5	34	29	15.8	62.3	37.3	16.9	58.3	36.2
Madhya Pradesh	21.5	73	48.6	9	66.1	39	18.3	71.2	46.2
Maharashtra	46.9	76.5	61.9	12.9	64.4	39.8	33.4	71.5	53
Manipur	58.2	74.7	66.6	31.1	79.8	54.2	47.7	76.5	62
Meghalaya	54.8	78.2	66.8	49.1	71.8	60.2	53.6	77	65.5
Mizoram	70.6	79.3	75	50.2	74.2	61.3	60.4	77	68.4
Nagaland	64.8	75.7	70.6	45.5	69.6	57.9	59.6	74.1	67.2
Odisha	27.4	80	54.7	14.2	72.9	44.7	25.4	78.9	53.2
Puducherry	36.4	82.4	57.6	27.9	74.3	50.9	31.3	77.3	53.4
Punjab	11.5	72.6	43	11.8	69.2	41.9	11.6	71.5	42.7
Rajasthan	39.2	77.6	59.3	9.9	67.6	40	32.8	75.4	55.1
Sikkim	59.5	78.6	69.5	40.3	76.4	59.9	55.6	78.1	67.4
Tamil Nadu	55.2	81.2	68.2	25	69.1	46.8	41.5	75.8	58.5
Telangana	53.7	72.3	63	26.7	70.2	49.1	44.5	71.5	58.1
Tripura	59.1	82.9	71	36.2	84.7	59.4	54.4	83.3	68.7
Uttar Pradesh	15.6	77.5	48.5	7.8	65.1	38.1	14	75	46.4
Uttarakhand	26	72.6	49.9	11.6	65.5	40.5	22.5	70.7	47.5
West Bengal	24.4	83.7	55.1	16.2	75.2	46.3	22	81.3	52.5
India	**31.7**	**78**	**55.8**	**16.6**	**69.1**	**43.7**	**27.4**	**75.5**	**52.4**
Source: 5th Annual									

Appendix 5: Female LFP 2018

[2018] Table 4.10 : State-wise Labour Force Participation Rate for persons aged 15 years & above									
Name of States/UTs	Rural			Urban			Total		
	Female	Male	Person	Female	Male	Person	Female	Male	Person
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
A & N Islands	29.1	81.8	56.3	40.2	79.0	60.3	33.5	80.7	57.9
Andhra Pradesh	48.4	79.5	63.3	30.7	78.3	52.8	42.5	79.1	59.9
Arunachal Pradesh	15.3	70.2	45.7	11.7	67.1	41.1	14.7	69.8	45.0
Assam	12.3	80.9	47.7	15.4	75.3	45.7	12.7	80.3	47.5
Bihar	3.9	68.8	38.2	6.4	66.5	38.2	4.1	68.6	38.2
Chandigarh	14.6	76.5	48.8	25.6	78.1	51.6	25.2	78.0	51.5
Chhattisgarh	54.0	79.6	67.1	30.5	77.6	54.0	49.3	79.2	64.5
D & N Haveli	55.7	86.3	71.5	23.0	88.0	62.4	39.7	87.3	66.6
Daman & Diu	25.5	78.4	51.8	24.8	89.9	67.9	24.9	88.4	65.2
Delhi	3.1	81.2	45.5	14.6	74.8	47.1	14.3	75.0	47.1
Goa	31.7	77.3	53.6	30.4	65.0	47.2	30.9	70.0	49.8
Gujarat	22.5	78.7	51.7	16.2	76.6	47.1	19.9	77.8	49.8
Haryana	14.7	73.9	45.5	13.7	74.8	45.5	14.3	74.3	45.5
Himachal Pradesh	52.0	75.9	63.5	24.7	75.3	52.9	49.6	75.8	62.4
Jammu & Kashmir	32.3	76.7	55.5	22.9	73.2	48.4	30.2	75.9	53.9
Jharkhand	15.7	75.7	46.3	14.3	66.9	40.2	15.4	73.9	45.1
Karnataka	28.2	80.5	54.0	22.8	73.8	48.0	26.0	77.8	51.6
Kerala	25.9	71.1	46.6	27.3	68.9	46.4	26.5	70.1	46.5
Lakshadweep	13.8	82.0	48.5	20.1	71.3	41.7	18.4	74.9	43.7
Madhya Pradesh	35.3	81.5	59.3	21.0	75.4	49.0	31.7	80.0	56.7
Maharashtra	37.7	75.4	56.8	21.6	74.2	48.2	30.8	74.9	53.1
Manipur	22.6	72.4	48.7	25.4	68.5	46.6	23.5	71.3	48.1
Meghalaya	56.0	78.5	66.7	31.8	68.2	49.5	51.2	76.4	63.2
Mizoram	28.2	77.7	53.7	31.7	68.9	49.3	30.0	73.6	51.6
Nagaland	15.7	65.6	42.0	19.0	62.9	41.1	16.7	64.8	41.8
Odisha	20.0	79.4	49.0	16.9	74.6	44.8	19.5	78.6	48.3
Puducherry	10.6	67.2	37.6	20.4	70.6	44.5	17.1	69.4	42.2
Punjab	14.0	72.9	44.5	18.2	78.2	49.6	15.5	74.9	46.5
Rajasthan	30.8	73.9	52.6	14.5	72.2	44.8	27.0	73.5	50.7
Sikkim	47.6	75.7	62.3	34.0	76.8	57.3	43.9	76.0	60.9
Tamil Nadu	39.0	78.5	58.3	27.6	76.7	51.4	33.7	77.7	55.1
Telangana	39.2	73.7	56.6	22.9	76.7	49.9	32.6	74.9	53.9
Tripura	11.2	75.7	45.3	17.1	72.3	44.1	12.5	75.0	45.1
Uttar Pradesh	14.2	75.6	44.9	11.1	73.4	43.4	13.5	75.1	44.6
Uttarakhand	20.3	69.1	44.5	12.3	71.3	42.5	18.1	69.8	43.9
West Bengal	19.8	81.3	50.4	23.0	75.1	49.2	20.8	79.3	50.1
India	**24.6**	**76.4**	**50.7**	**20.4**	**74.5**	**47.6**	**23.3**	**75.8**	**49.8**

Source: Periodic Labour Force Survey (PLFS), NSO, July 2017- June 2018.
Notes: 1. Figures are based on usual status approach and includes principal status and subsidiary status persons of all ages.
2. The figures represent size of labour force as percentage of population