Does Digital Infrastructure Spur Female Labour Force Participation: Evidence from Urban India

Cledwyn Fernandez[1] Havishaye Puri[2]

Abstract

This paper analyses the casual effect of mobile phones and broadband access on female labour force participation (FLPR) in urban India. Using the 78th round of the National Sample Survey of India, we find that an increase in mobile phone access (shared & exclusive) and broadband access has a positive impact on FLPR. We employ an instrumental variable approach, with state-wise urban tele-density as our instrument to test for causality. Our results our robust to alternative measures of state-level income, and household characteristics. At a sub-sample level, we find that the impact is the largest for women within the age cohort of 30-64, those that belong to households that are above the median level of income, and those that have one child or less. We find that women that have achieved basic digital literacy, are much more likely to utilise exclusive use of mobile phone and broadband access to participate in the labour force. The overall results indicate that the labour effect of digital infrastructure dominates the leisure effect for women thereby having an overall positive impact on FLPR.

Keywords: broadband, female labour force participation, mobile phones, urban

JEL Classification: J21, O11, O13, L86

[1] Cledwyn Fernandez is a Fellow at The Indian Council for Research on International Economic Relations
[2] Havishaye Puri is a Research Assistant at The Indian Council for Research on International Economic Relations

1. Introduction

During the last decade (2012-21), India has achieved some significant socio-economic milestones. Its Gross Domestic Product (GDP) per capita has grown with a Compounded Annual Growth Rate (CAGR) of 3.9%[3], the share of population with access to electricity has increased from 79.9% to 99.6%[4] and the tertiary education enrolment within the country has increased from 24% to 31%[5] . As a result of this economic development, the share of multidimensionally poor in the country have reduced from 24.85% in 2015-16 to 14.96% in 2019-21[6]. Despite these remarkable achievements, India's female labour force participation rate (FLPR) in 2022 stood at 24 percent, much lower than China (61%), Vietnam (69.1%), Bangladesh (38%), and other neighbouring and emerging economies[7]. Why has FLPR remained so low, in spite of positive growth in other socio-economic indicators. What explains this paradox?

The reasons for the low FLPR in India could be broadly classified into two factors: demand side factors and supply side factors. Demand side factors include structural changes in employment patterns, technological innovations, lack of gender inclusive policies, and gender wage gaps. There has been extensive research on the negative impact of gender segregation of jobs (Anker, 1998; Swaminathan and Majumdar, 2006; Rustagi, 2010). On the supply side, marital status (Goldin, 2006; Kleven et al., 2019) and fertility rate (Bhalotra and Fernandez, 2021) are leading causes for the declining FLPR. Cultural factors too play a very significant role in determining female labour participation. Using the 1970 Census data of the United States, it was seen that cultural proxies play a significant role in explaining the FLPR (Fernández and Fogli 2009). The effect of culture on female labour participation is more pronounced in the South Asia region. It is widely believed that the role of the female is that of caregiving within the household; thereby restricting them from participating in the labour force (Das and Desai, 2003; Desai and Jain, 1994; Goksel, 2012; Jaeger, 2010). Pieters and Klasen

[3] World Bank (2022)
[4] World Bank (2022)
[5] World Bank (2021)
[6] UNDP (2023)
[7] World Bank (2022)

(2011) show the effect of the economic boom on India's FLPR. Furthermore, Klasen and Pieters (2015) ascribed the role of social status to the declining labour force participation rate and showed that higher social status has a negative impact on women's labour force participation in India.

The FLPR is an important socio-economic indicator across the globe. Reducing the gender gap in employment has massive economic and social benefits. Pennings (2022) shows that narrowing the gender employment gap index in the Pacific Islands can increase GDP per capita by almost 20 percent. Hossain and Tisdell (2005) provides evidence that improving female labour participation rate reduces gender earning differences and fosters self-esteem and equality within the household. Furthermore, including women into the workforce will have an increased benefit as men and women complement each other in the workplace in terms of different skills and perspectives, including different attitudes toward risk and collaboration. (Ostry et al., 2018)

Governments play a significant role in boosting the overall FLPR in an economy. There are multiple ways in which government policy can bring about a more inclusive workforce. First, infrastructure investment can lead to higher FLPR. Evidence from South Africa shows that electrification improved the FLPR by 9 percent **(**Dinkelman, 2011; Rati & Vermaak, 2018**).** Furthermore, safer public transportation can increase the likelihood of women joining the workforce (Lei et al., 2019). Second, access to finance is critical in supporting female entrepreneurship. The ownership of bank accounts, and the access to financial services play a critical role in the FLPR (Field et al., 2016). Lastly, promoting equal rights, improves the chances of women entering the labour force. For instance, countries such as Peru and Malawi have brought about significant changes in their legal frameworks that has significantly increase female labour participation **(**Gonzales et al., 2015**).**

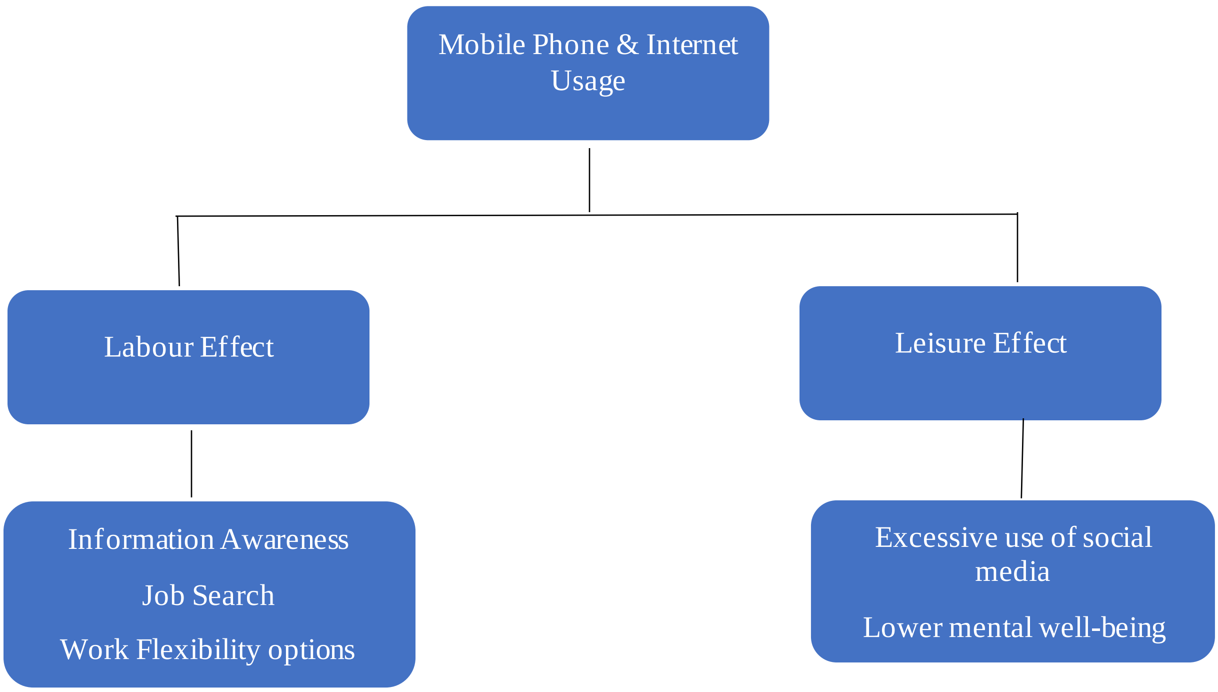
A recent significant enabler of FLPR is digital infrastructure. The impact of digitalization on gender equality, income, and employment has attracted considerable research interest (Alozie & Akpan-Obong, 2017; Dettling, 2017; Hilbert, 2011; Ma, Grafton, et al., 2020; Viollaz & Winkler, 2022; Amber & Chichaibelu, 2023). Digital infrastructure broadly includes internet and mobile phone access. Mobile phones have a positive association with various aspects of development. Extant research has provided evidence on the positive aspects of mobile phone usage on off-farm employment (Rajkhowa & Qaim, 2022), status and well-being (Lee & Jayachandra, 2009).

Despite a high penetration of digital infrastructure, there still exists a higher gender inequality with regard to access to digital infrastructure. The Mobile Gender Gap Report 2023 reports that women are 19 percent less likely than men to use mobile internet. In total, 900 million women who are still not using it, almost two-thirds live in South Asia and Sub-Saharan Africa, where mobile gender gaps are widest.[8] Digital Inclusion implies that the women in the household have access to these digital infrastructures. Thus, while digital infrastructure is an enabler, digital inclusion reduces the inequality in infrastructure access within a household and improves women decision making empowerment.

Against this background, this paper studies the impact of digital infrastructure and digital inclusion on the FLPR in India. We choose India as our context due to two specific reasons. First, there has been a massive increase in mobile phone adoption over the years. Smartphone penetration has increased from 2.75 percent in 2010 to 66.2 percent in 2022.[9] Second, close to almost 50 percent of the population uses internet in India, which is close to 600 million individuals.[10] The power of both, the internet and mobile, has multiple advantages for labour market participation. It increases information awareness about jobs (Nga and Ma, 2008); it provides a medium for digital transaction of wages (Aker and Mbiti, 2010); and allows for communication while at the workplace (Ureta, 2008); and allows for work flexibility, by mothers who wish to spend time raising their children to still work, at least part-time (Berniellie et al., 2021). It is equally important to emphasize that access to the internet and mobile could also have a negative effect on labour market participation through the *leisure* effect (Figure 1). Higher use of digital infrastructure could lead to consumption of leisure, which would reduce the incentive and motivation to participate in employment (Hahn, 2008). Leisure effects could include high consumption of social media (Salehan & Negahban, 2013), online gaming, and other addictive activities which could possibly lead to lowering of mental well-being (Golin, 2022). Therefore, the effect of digital infrastructure on female labour force participation is ambiguous, and it is critical to examine which effect dominates more in this context.

[8] GSMA | Gender Gap - Mobile for Development
[9] India: smartphone penetration rate 2040 | Statista, accessed on July 27, 2023
[10] Individuals using the Internet (% of population) - India | Data (worldbank.org), accessed on July 27, 2023

Figure 1: Possible effects of the use of mobile phones and broadband access



We test the causal impact of the use of mobile phones and broadband access on female labour force participation in India. Using the 78th round of the National Sample Survey (NSS) of India, that was undertaken in 2020-21, we examine whether access to mobile phones and broadband increase female labour force participation in India. We focus on the urban counterpart for two reasons. First, given that the services sector contributes the highest employment opportunities in the urban sector, mobile phones could be leveraged to improve labour participation.[11] Second, the higher rollout of 4G connectivity in urban India provides a greater scope for exploiting the use of digital infrastructure for employment opportunities.[12]

[11] Service sector emerges as highest employment generator this year: Survey - The Economic Times (indiatimes.com), accessed on August 08, 2023
[12] India's 4G coverage expected to cross 90% availability mark in 2 years: Cisco's Sanjay Kaul, ET Telecom (indiatimes.com), accessed on August 08, 2023

The results of the study point to the fact that access to digital infrastructure (shared and exclusive) increases the probability of a woman entering the labour force in urban India. In addition, the impact of digital inclusion (which is measured by the exclusive use of a mobile phone by the female in the household) also increases the probability of a women entering the labour force, albeit lower than the average increase from access to digital infrastructure. We perform a host of sensitivity and robustness analysis and find that our results hold true under all circumstances. Finally, we run a sub-sample analysis on the sample to determine how the effect of mobile phones and broadband access on female labour phone participation varies across different sub-samples. We find that mobile phone access (both shared and exclusive), along with broadband access has a greater impact on FLPR for females in richer households (above median income level). In addition, the impact of an exclusive mobile phone access on FLPR is the highest for females in the age cohort 30-64. Lastly, mobile phone access has a positive and significant impact for women with no children, and those belonging to the general category of caste.

Our paper contributes to the existing literature on female labour force participation as well as digital infrastructure. First, to the best of our knowledge there is no previous literature on the effect of digital infrastructure on FLPR within Urban cohort of India. Our work comes closest to (Rajkhowa and Qaim, 2022) that investigate the impact of a women using a mobile phone on mobility for the rural non-farm sector.-We complement the work that has been done on the impact of technology (white goods) on female labour force participation (Bose et al., 2021), as well as the studies on the effect of internet technology on job search (Kroft and Pope 2014; Kuhn and Mansour 2014). Second, we also contribute to the literature on gender inclusiveness as we estimate the impact of exclusive mobile usage on FLPR. Research on the barriers to the adoption to mobile phone usage by women has been well examined (Barboni et al., 2018). We extend this line of research by examining how narrowing the gender divide for digital infrastructure can have positive labour market outcomes.

The remaining part of the paper is divided in the following way. Section 2 discusses the data and methodology. It provides a background of the different sources from where the data was collected and the rationale behind the estimation strategies that were employed. Section 3 discusses the main results, along with robustness tests, and sub-sample analysis. It begins by outlining the basic results of the main explanatory variables on FLPR. This is followed by an analysis done at the sub-sample level to examine how this effect varies across different cohorts of the sample. Section 4 concludes with policy implications and limitations of this study.

2. Data & Methodology

2.1 Data Sources

The paper primarily uses the unit level household and individual level data of the NSS 78th round: Multiple Indicator Survey (MIS), which was held between January 2020 and August 2021. The survey covers 276,409 households across all states and union territories of India, with it covering 111,880 households in the urban areas of the country. The survey also collects data at an individual level for the people within these households, recording responses for a total of 449,915 individuals within urban areas of India. We further refine the dataset by including households that were in the original sample frame (not substituted due to non-response) and the informant within these households were co-operative and capable. Thus, our final dataset of analysis contains a total 128,817 females distributed across urban India. The paper also used datasets exogenous to the MIS survey, which include data on certain State level variables used in our model. All of these variables were obtained from the Reserve Bank of India's (RBI) Handbook of Statistics on Indian States 2020-21 and the Telecom Regulatory Authority of India's (TRAI) key performance indicators in 2020 and 2021.

2.2 Methodology

Our primary objective is to quantify the impact of access to mobile phone and broadband access on the decision of a women to participate in the labour force. The MIS survey collects data on the labour force participation status[13] of each individual surveyed within a particular household. Hence for our dependent variable, we categorise the labour force participation status of each individual (above the age of 15) that is surveyed as a binary response. Thus, the dependent variable Y_{ihs} takes the value 1 if the surveyed female 'i' in household 'h' within state 's' is part of the labour force and Y_{ihs} takes the value 0 if the surveyed female is not part of the labour force. Our explanatory variable of interest is an individual's access to mobile phone and broadband access. The MIS survey collects data on whether an individual has used a mobile

[13] The labour force status is recorded according to the usual principal activity status methodology. The usual principal activity status is determined by considering the activity in which an individual in the labor force spends a significant amount of time (major time criterion) during the 365-day reference period before the survey date (National Statistics Office, 2019).

phone with an active sim card in the past three months. This use of mobile phone can either be exclusive, shared with a household member or share with someone outside the household. Any individual that hasn't used a mobile phone in any of the three methods mentioned above can give a negative response. Using this information, we create a binary variable which takes the value "1" if an individual has used a mobile phone (whether it be exclusively, having shared with a household or non-household member) and "0" if the individual has given a negative response on mobile phone use.

Our choice problem is described by the individual level latent variable model:

(1) $$Y_{ihs}^{*} = X_{ihs}\alpha + W_{hs}\beta + V_s\gamma + M_{ihs}\theta + \varepsilon_{ihs}$$

where Y_{ihs}^{*} is the net benefit a female 'i' in household 'h' in state 's' receives from entering the labour force, X_{ihs} is a vector of individual characteristics like age, marital status, highest level of education and number of children aged zero to five. W_{hs} is a vector of household characteristics like land possessed, gender of the household head and highest education level of the household head. V_s is a vector of state level characteristics to account for socio-economic effects within a region (Klasen,2019; Klasen et al.,2021; Sarkar et al.,2019; Schaner &Das,2016). M_{ihs} is a dummy variable indicating access to an active mobile phone and ε_{ihs} is a normally distributed random error with zero mean and unit variance. Females will only participate in the labour force if the expected net benefits of participation are positive, and thus the probability that a female participates in the labour force is

(2) $$\text{Prob}\ [Y_{ihs} = 1\ ] = \text{Prob}\ [X_{ihs}\alpha + W_{hs}\beta + V_s\gamma + M_{ihs}\theta + \varepsilon_{ihs} > 0] = \phi[X_{ihs}\alpha + W_{hs}\beta + V_s\gamma + M_{ihs}\theta]$$

where $\phi[]$ is the evaluation of the standard normal cumulative distribution function.

The equation in (1) can be estimated using a standard univariate probit model. To measure the quantitative importance of our independent variable of interest, we report the marginal effect $\delta\ \text{prob}(Y_{ihs} = 1\ )/\delta\ M_{ihs}$ for a reference woman[14].

Using (1) we also estimate a Linear Probability model (LPM) through Ordinary Least Squares (OLS). The OLS estimates of the LPM are considered reliable when the predicted probabilities are close to 0.5 (Woolridge, 2002). This reliability arises because the underlying Conditional

[14] For our analysis, the reference woman has an age of 39.17 years, having approximately 4.88 individuals including her in the household and a monthly household consumption expenditure of INR 14,382.

Expectation Function (CEF) is roughly linear in the middle. A major advantage of using a LPM model is that the coefficients of the independent variables are easily interpreted, indicating the probability by which the independent variables impact the outcome. However, a major shortcoming of LPM estimates is that they are not bounded to the unit interval. As Horrace and Oaxaca (2006) demonstrate, the potential bias associated to the LPM is proportional to the share of LPM predicted probabilities that fall outside the unit interval. Hence, the LPM estimates at best serve as a robustness check for the marginal effects of our univariate probit model.

A limitation of our primary explanatory variable is that it doesn't give us ample information whether the mobile phone is being used exclusively by a woman. To rectify this issue and see the impact of exclusive mobile phone use, we create another binary variable which takes the value "1" if a woman exclusively uses the mobile phone and "0" if she doesn't have exclusive use i.e., she shares the mobile phone with a household/ non-household member or she doesn't use a mobile phone. Another limitation of our primary explanatory variable is that our data doesn't allow us to observe whether a woman who has access to an active mobile also uses internet or other digital features of the device. Within the MIS dataset there is another variable which relays information on whether a household has access to broadband services within the premises. Thus, we can substitute our explanatory variable of interest by a binary variable which takes the value "1" if a woman has access to her mobile phone exclusively and her household has access to broadband within their premise and "0" if the women doesn't use her mobile phone exclusively i.e., she has shared use with a household/ non-household member or she don't use a mobile phone irrespective of the broadband availability in the household. The assumption behind this variable is that if a woman in a particular household has an exclusive mobile and the household she resides within reports broadband availability, then that woman may be using the internet or other digital features in her mobile phone.

However, all of the explanatory variables of interest mentioned above can suffer from endogeneity. The access/use of a mobile phone is potentially endogenous because a woman's decision to use a mobile phone is based on both observed and unobserved characteristics. Some of these unobserved characteristics could be correlated to the women's decision to participate in the labour force. For instance, it is possible that women that have access to or use mobile phone are from households that positively encourage them to participate in the labour force. Furthermore, mobile phone use or access and participation in the labour force can also be jointly determined by specific factors that are not observed. For instance, a woman could obtain a mobile phone just because it's a necessary requirement for her employment.

As Chiburis et al. (2012) points out, researchers can use two common approaches to measure the causal impact in a model with binary endogenous regressors and binary outcome variables. The first approach is to estimate a standard Linear Probability Model (LPM) with Instrumental Variables (IV) using the Two Stage Least Squares(2SLS) approach. This technique quantifies causality by ignoring the binary nature of the outcome and the endogenous variable. The second approach is based on the Maximum Likelihood Estimation (MLE) of a Bivariate Probit Model as conceptualised in Heckman (1978). The 2SLS approach is advocated by Angrist & Pischke (2009: p 198-204) and supported by much real-world experience comparing partial effects from more plausibly correct models to the partial effects from a linear probability model with an IV (Wooldridge 2008, Katz et al. 2000 p.28 fn.34). This method also has the advantage of easily interpreted coefficients measuring effects in the probability metric. However, the biggest fallacy within this approach is that having a non-linear first stage combined with a non-linear second stage leads to the infamous "Forbidden Regression" by Jerry Hausman, which fails to produce consistent estimates (Woolridge, 2002 p 477-478; Angrist & Pischke , 2008 p 142-144).The bivariate probit model can also be used to estimate causal impact in case of binary endogenous and outcome variables(Evans & Schwab, 1995). The estimates obtained from this approach don't suffer from consistency issues as with the case of 2SLS (Woolridge, 2002 p 478; Angrist & Pischke , 2009 p 201). Some drawbacks of the bivariate model include the difficulty in estimation and problems in presence of heteroskedasticity (Chiburis et al.,2012). On testing both the techniques, Bhattacharya et al (2006) argues in favour of using the bivariate probit rather than the two-step or linear probability model estimators, especially when the average probability of the dependent variable is close to 0 or 1, or when the data generating process is not normal. Given the average probability of our dependent variable i.e. FLPR is 18.9%, we use the Bivariate Probit Model, with Huber-White sandwiched estimators to control for heteroscedasticity.

Following the latent variable model in equation (1), suppose that the net benefits of using a mobile phone is given by M^{*}_{ihs} , which can be written as:

$$M^{*}_{ihs} = X_{ihs}\pi_1 + W_{hs}\pi_2 + V_s\pi_3 + Z_s\pi_4 + \mu_{ihs} \qquad (3)$$

where X_{ihs}, W_{hs} , V_s and Z_s are a vector of observables and μ_{ihs} is a random error.

A woman will use a mobile phone if the net benefits of using are positive; i.e., if $M^*_{ihs} > 0$. To allow for the possibility that the unobserved determinants of woman's decision to use a mobile phone and the unobserved determinants of a woman's decision to participate in the labour force are correlated, we assume that ε_{ihs} and μ_{ihs} are distributed bivariate normal, with E [ε_{ihs}] = E [μ_{ihs}] = 0, var [ε_{ihs}] = var [μ_{ihs}] = 1 and cov [$\varepsilon_{ihs}, \mu_{ihs}$] = ρ. As both decisions we model are dichotomous, there are four possible states of the world i.e., Y_{ihs} = 0 or 1 and M_{ihs} = 0 or 1. Thus, the likelihood function corresponding to this set of events is a bivariate probit as in Heckman (1978). If the error terms ε_{ihs} and μ_{ihs} are correlated, then the outcomes are endogenously determined; a significance test on the correlation parameter ρ is a test of exogeneity between mobile phone use and labour force participation (Fabbri et al., 2004). This system is identified if at least one variable in (3) is not contained in (1).

For our instrument Z_s , we use the State Wise Total Tele Density in Urban India. This instrument is defined as the Number of telephone connections (fixed lines and mobile phone subscribers) per 100 inhabitants within urban areas of each state in India[15].

2.3 Validity of Instrument

If State Wise Urban Total Tele Density is a valid instrument, then (i) it must be a determinant of the decision of a woman to use/access a mobile phone i.e., it must be sufficiently correlated with the endogenous variable but (ii) it must not be a determinant of the decision of a woman to participate in the labour force i.e., it must not be correlated with the error term ε_{ihs}.

The first part is relatively easy to prove, Staiger & Stock (1997) suggest a rule of thumb that, in case of a single endogenous regressor, instruments are deemed weak if the first-stage F statistic (of a 2SLS[16] technique) is less than 10. This suggestion was based on the relative bias of 2SLS. This thumb rule by Staiger & Stock (1997) is approximately a 5% significance test that the worst-case relative bias is approximately 10% or less. Stock & Yogo (2005) suggest another first-stage F statistic value which controls for size distortion. In this case, the F statistic value to have an expected maximal size of not more than 10 percent with a statistical

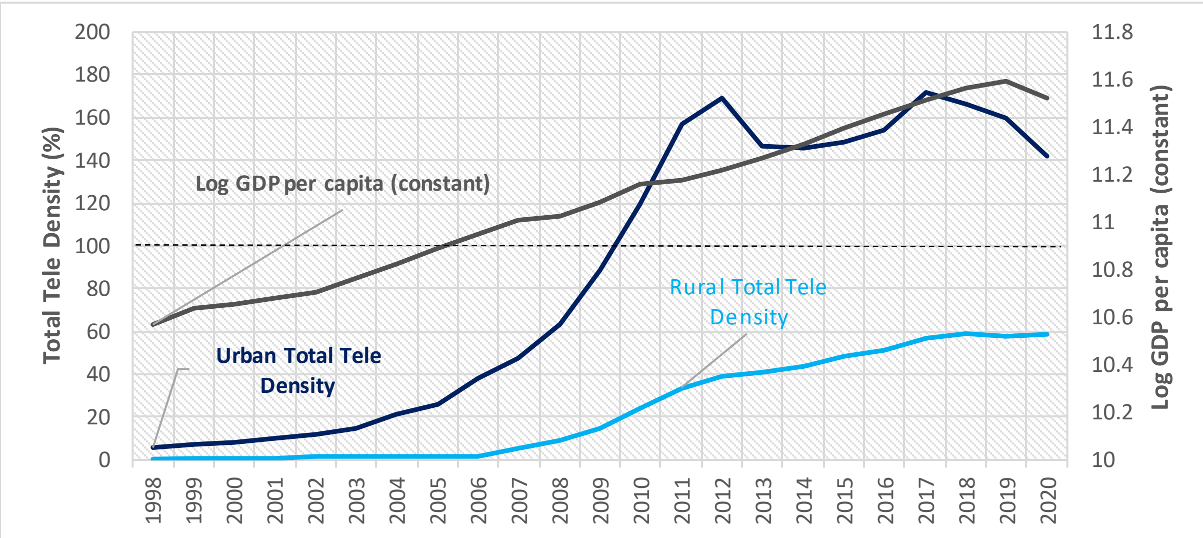
[15] TRAI Information Note to the Press (Press Release No. 04/2020), Page 2

[16] In our model, the non-linear first stage can be modelled through a standard probit equation with the non-linear second stage being the cause for the "Forbidden Regression" (Angrist & Pischke , 2008 p 143) .

significance of 5 percent is at least 16. In our model, the instrument State Wise Urban Total Tele density has a corresponding F statistic value of 23.54, 80.40 and 101.64 for the endogenous variables Access to Mobile, Exclusive Access to Mobile and Exclusive Access to Mobile & broadband in Household respectively.

The second part is trickier to prove through statistical tests, leading us to primarily rely on economic theory for the proof. A possible concern with the validity of this instrument is that Urban Total Tele density can be a function of economic development of a region, which can also impact the decision of a woman to participate in the labour force. However, this concern can be disparaged by looking at the evolution of urban total tele density in India since the turn of the century.

Figure 2: Evolution of Total Tele Density in India



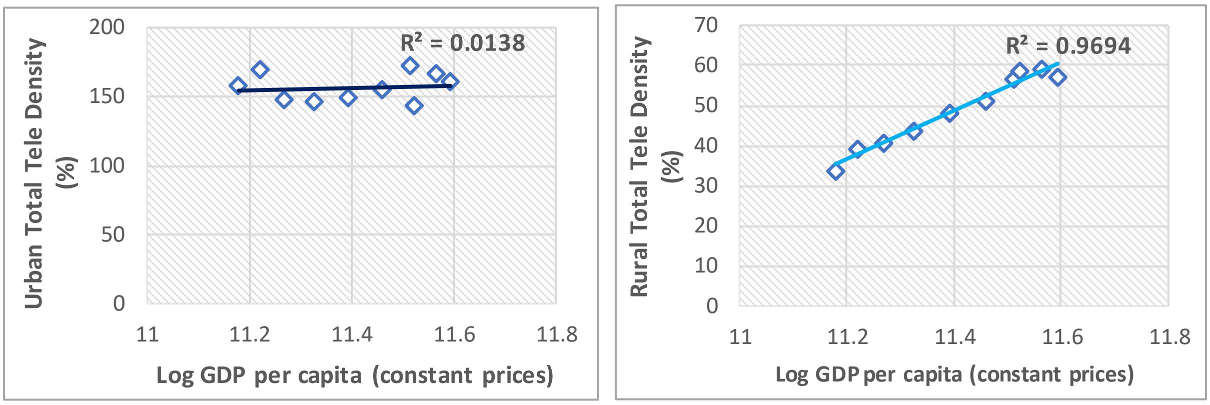
Source: TRAI and National Accounts of India

As Figure 2 illustrates, India's urban total tele density crossed the 100%[17] mark in 2009, after which it peaked in 2011 and has been slowly saturating ever since. This saturation can be observed by the fact that over the last decade, India's per capita income grew at a CAGR of 3.5%, its rural tele density grew at a CAGR of 5.7% but its urban tele density actually declined by CAGR of 1%. With total tele density saturating within urban India, it is plausible that this metric has been delinked from economic development in the country. This notion can be easily proved by plotting India's GDP per capita with its urban total density over the past decade. As

[17] A 100% total tele density refers to the fact that there are now fixed and mobile connections in urban India which equal its total population. However, this metric doesn't reflect that each individual in urban India has a fixed line or mobile connection; as the metric also takes into account individuals that possess multiple devices or sim cards.

figure 3(a) & 3(b) illustrate, while rural total tele density is strongly linked to economic growth over the past decade in India, this growth seems to have no impact on urban total tele density.

Figure 3: Link of economic development with urban and rural total tele density in India.



(a) **(b)**

Source: TRAI and National Accounts of India

However, proving that urban total tele density in India is not linked to economic development isn't enough for the validity of our instrument. Given, our analysis is undertaken using cross section data, we also need to conclusively show that within our dataset; richer or more developed states don't have higher urban tele density as those socio-economic features could also impact our outcome variable. We show this by plotting urban and rural total tele density with the average monthly consumption undertaken by households in a State's urban and rural areas respectively. This variable is created from the information available within our dataset. As figure A1 & A3 (in Appendix) show, rural areas of states with higher average consumption (a proxy for their income) have higher rural total tele density. The same impact is not seen for urban areas, where the states with higher urban consumption don't necessarily have higher total tele density. We check the robustness of this inference by now observing the relationship between urban and rural total tele density in a state with an exogenous variable to the dataset i.e., the respective states NSDP per capita at constant prices. As figure A2 & A4 (in Appendix) confirm, more developed states indeed have higher rural total tele density, however this economic development isn't associated with higher urban total tele density.

Another concern to the validity of our instrument could be that total tele density across a state is linked to its socio-cultural factors i.e., it could be that more socially conservative states give less importance to mobile devices, leading to lower total tele density. These socio-cultural factors could also impact the decision of a woman to participate in the labour force. To disparage this view, we first construct two variables in our dataset that estimate the sex ratio (to proxy socio-cultural factors) within urban and rural areas of each state. The assumption here is that a region with a higher sex ratio would be less socially conservative. As figure A5 & A6 (in Appendix) show, within rural areas of each state; there is a strong link between total tele density and socio-cultural factors. However, this impact of socio-cultural factors doesn't hold true in urban areas of each state. To check the robustness of these inferences, we plot the urban and rural total tele density in each state with the respective states sex ratio, a variable exogenous to our dataset. As figure A7 & A8 show, again there is a strong link between socio-cultural factors of a state and total tele density in rural areas but no such impact in urban areas of these states.

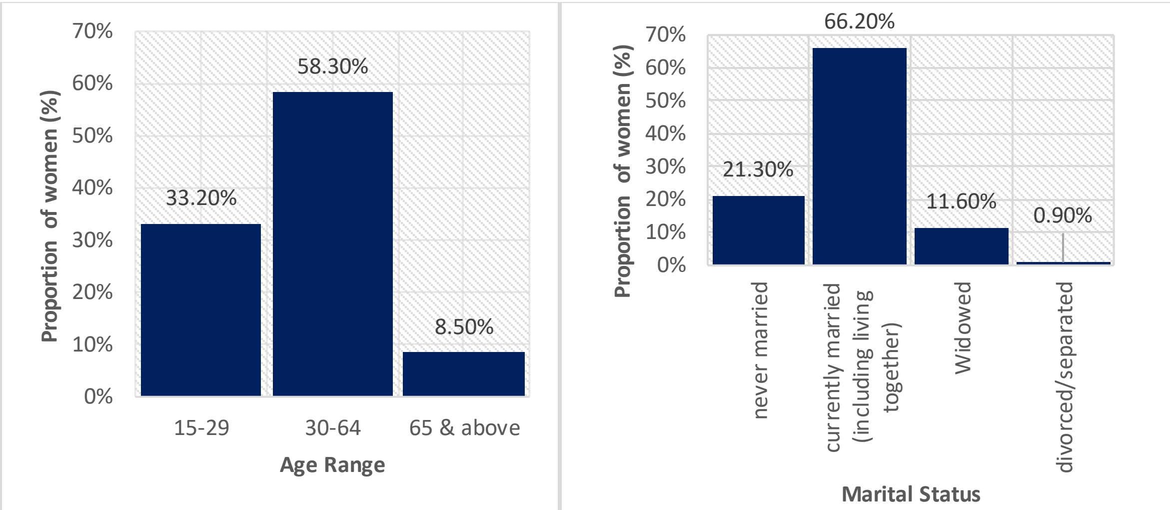
Finally, another straightforward method to check the exogeneity of our instrument is to include this variable (with the endogenous regressor) in the univariate probit as discussed in equation (1). We recognize that this is not a formal test since if the correct specification is a bivariate probit then the univariate model is mis specified, however it does offer a clear sense of the patterns in the data. As we observe in Table A1, all of the coefficients of State wise urban Total Tele Density (with primary explanatory variable as Access to Mobile, Exclusive Access to Mobile and Exclusive Access to Mobile & broadband in Household) are close to zero and statistically insignificant. As Evans & Schwab (1995) points out, although, this is not a direct test of the validity of the instrument, it does signify that our instrument is only significantly related to our outcome variable through our primary explanatory variable.

2.4 Descriptive Statistics

The descriptive statistics of our model illustrated below through Table 1 and Figures 4-7. These statistics include variables that we later use for sensitivity and sub-sample analysis of our estimates. Within our dataset, the mean FLPR (for women above 15) in urban India is 18.9%, with 73.4% of women having access to an active mobile phone in this area. However, this proportion falls for women having exclusive access to mobile (40.6%) and those using the digital features of their mobile phones (31%).

At an individual level, the largest proportion of women in our dataset are between the ages of 30 to 64 and the vast majority (66.2%) of women are currently married (Figure 4a & 4b).

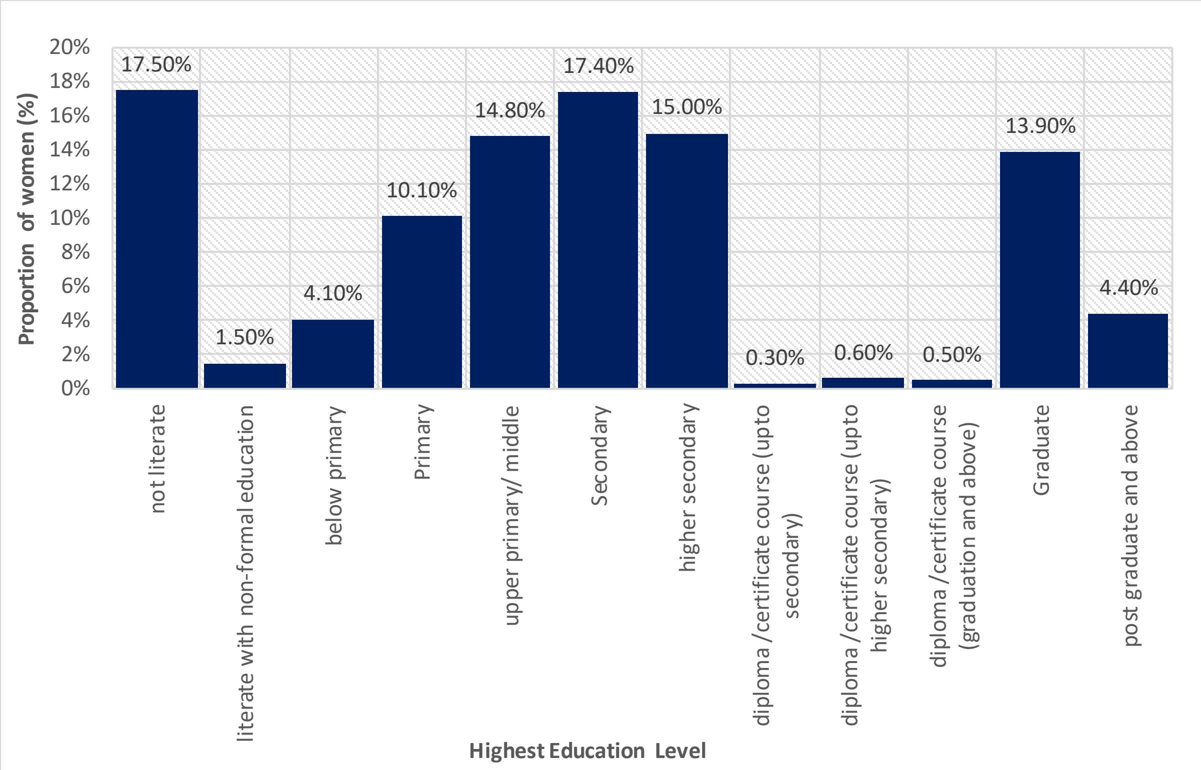
Figure 4: Age and Marital Status of women in Urban India



(a) **(b)**

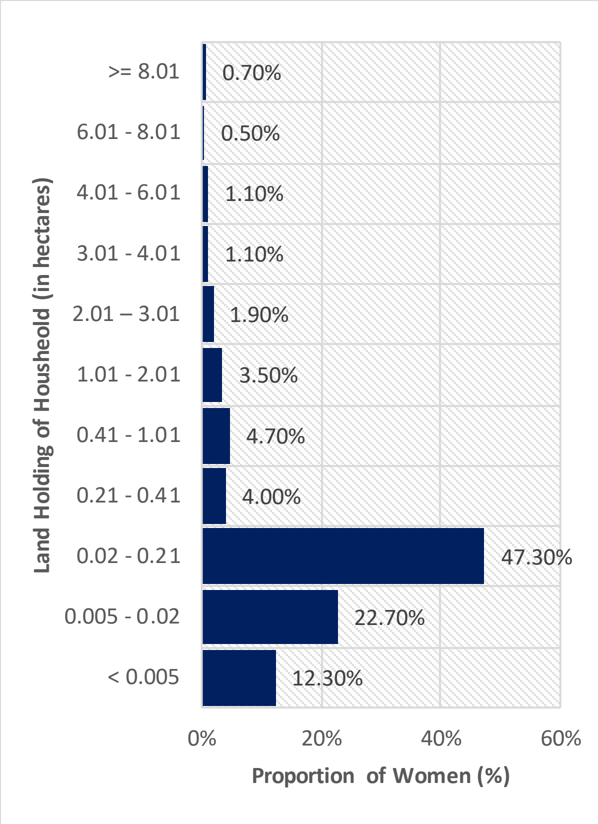
Further, only 18.3% of women have a graduate degree or above, with female illiteracy of 17.5% within urban India (Figure 5).

Figure 5: Highest Education level attained by women in Urban India

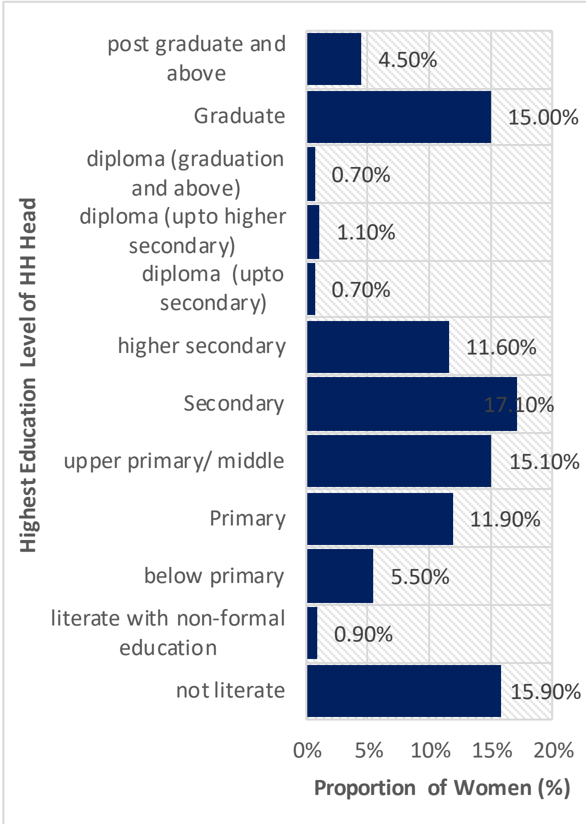


At a household level, the distribution of women is skewed towards households which possess less than 0.21 hectares of land. Nearly, 19.50% of women are part of households where the head has a graduate degree and above. The large majority of women (55.70%) in urban India are part of households where the head's highest education level is between primary and higher secondary (Figure 6a & 6b).

Figure 6: Land Holding of HH and Highest Education Level of HH head in Urban India



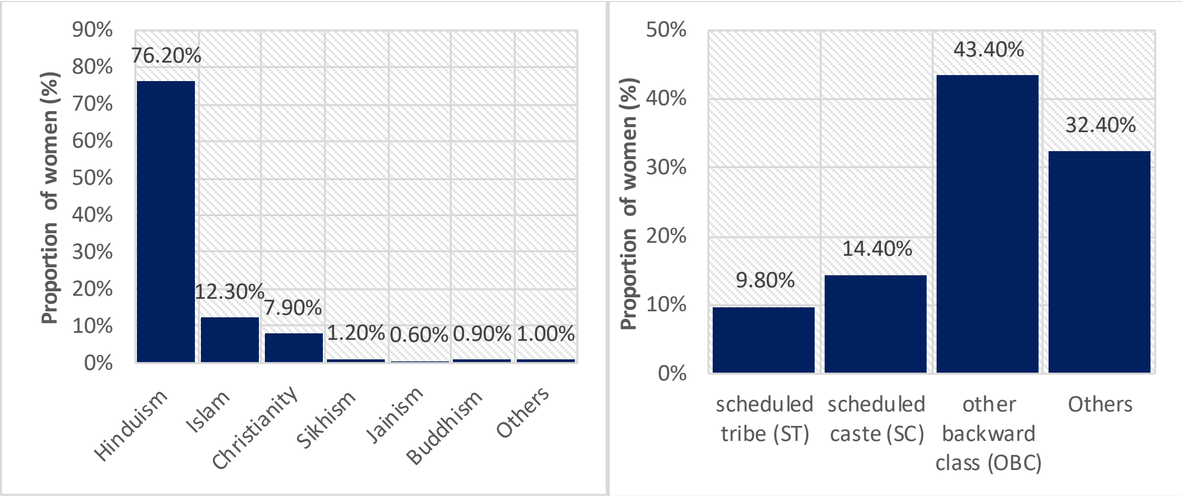
(a)



(b)

Looking at the religious distribution of the households, we find that 76.2% of women are from households identifying as practising Hinduism followed by Islam (12.30%) and Christianity (7.90%) [Figure 7a]. The dataset also elucidates responses on the social group affiliation of a household. It is seen that nearly 9.80% and 14.40% women in urban India (above the age of 15) belong to Schedule Tribes and Schedule castes, with the largest proportion of women (43.40%) belonging to the other backward castes (OBC). The MIS also has a category apart from all the social groups mention before, which is called the "others" category and refers to the general category castes in India [Figure 7b].

Figure 7: Religion and Social Group of Household



(a) **(b)**

Apart from the household characteristics illustrated above, there are some other household level and state level controls that are also part of our analysis as elucidated in Table 1. The mean age of the household head is 51.5, with 16.2% of these household being headed by a female. The average monthly consumption for households is INR 14388 (USD 173.16)[18] and 90.4% of these household live within 0.5km of an urban transport facility. The mean urban Total tele density is 143.5% indicating large availability of telephones and mobile devices in urban India.

Table 1: Descriptive Statistics

Variable	Obs	Mean	Std.Dev	Min	Max
Outcome Variable					
Female Labor Force Participation	128780	.189	.391	0	1
Primary Explanatory Variable					
Access to Mobile	128817	.734	.442	0	1

[18] Exchange rate is 1USD = 83.09 INR as of August 2023

Exclusive Access to Mobile	128817	.406	.491	0	1
Exclusive Access to Mobile & broadband in Household	128817	.31	.463	0	1
Individual and Household Controls					
Household Size	128817	4.88	2.124	1	23
Number of Children (aged 0-5)	128817	.353	.673	0	7
Age of Household Head	128817	51.466	13.213	13	100
Female Household Head	128817	.162	.368	0	1
State Level Controls					
Average household usual monthly consumer expenditure across Urban Areas of a State (INR)	128817	14387.85	3152.82	10092.42	29100.96
NSDP per capita of a State (constant prices) (INR)	127955	102361.7	46822.64	28127	298527
Availability of Power per capita in a State (Kilowatt-Hour)	127808	1099.08	846.184	292.5	13072.07
Bank Branches per 1000 people in urban areas of a State	128,817	.232	.062	.117	.637
State wise Sex Ratio at Birth	128817	936.06	37.452	817	1125
Share of HH within 0.5 km of nearest public transport facility	128817	.904	.051	.693	.992

in urban areas of a State					
Instrument					
State wise Urban Total Tele Density (%)	128817	143.466	37.538	65.947	466.5

Source: Authors' Computation of MIS data

3. Results and Analysis

3.1. Main Results

Table 2 represents the results of three different regression models. Column 1 illustrates the results using a univariate probit model. The univariate probit model is the standard model that is employed under a binary dependent variable scenario. We assess the robustness of the model estimates using the standard linear probability model (LPM), as shown in Column 3. Lastly, column 4 illustrates the estimates of a bivariate probit model. Within the bivariate probit regression, Rho (ρ) represents the correlation coefficient between the error terms of the simultaneous set of equations. The significance of this variable shows that there is endogeneity in our univariate probit estimates and thus the most suitable model is the bivariate probit model. Column 2 represents the marginal effects of the univariate probit model, while column 6 provides the marginal effects of the bivariate probit for easier interpretation.

Across all three models, we see that access to mobile phone causes female labour force participation to increase. In particular, on an average, access to mobile phone increases the probability of women joining the labour force by 29 percent. The exclusive access to a mobile phone increases the probability of women joining the labour force by 19 percent. Lastly, the combined effect of an exclusive ownership of mobile phone, along with broadband access increases the probability of a woman joining the labour force by 23 percent. In sum, it is seen that both mobile phone ownership, as well as broadband access increases the probability of female labour force participation in urban India. It is important to note the trend that the effect first declines as we move from mobile access to exclusive mobile access, but again increases as we include exclusive mobile access coupled with broadband access. This implies that as females get exclusive access to mobile phones, the labour enhancing effect is reduced, leading to a decline in the overall positive impact of mobile access. However, with the availability of broadband, the labour enhancing effect dominates and the probability of women participating in the labour force increases. Thus, the internet coupled with exclusive access to mobile phones enables women to participate in the labour force through better job search mechanisms, increasing information transparency, and improving the skills necessary to join the labour force.

Table 2: Effect of mobile and broadband access on female labour force participation[19]

	Univariate Probit		LPM	MLE estimates of Bivariate Probit		
	Coefficient	ME		Coefficient	ρ	ME
Access to mobile	.39***	.09***	.08***	1.19***	-.56***	.29***
	(.018)	(.004)	(.004)	(.14)	(.13)	(.040)
Exclusive Access to Mobile	.29***	.07***	.07***	.80***	-.32***	.19***
	(.016)	(.003)	(.004)	(.177)	(.12)	(.043)
Exclusive Access to Mobile & broadband in HH	.22***	.05***	.06***	.98***	-.44***	.23***
	(.014)	(.003)	(.004)	(.103)	(.06)	(.025)

Robust standard errors are in round brackets, LPM (Linear Probability Model) and ME (Marginal Effects)

**** p<.01, ** p<.05, * p<.1*

3.2.Sensitivity Analysis

In this section, we perform a host of sensitivity analysis to check whether our results our robust to any changes in our control variables. For the first four equations in Table 3, we substitute the control variable for development of a region i.e. we substitute mean consumption of the household with net state domestic product per capita (constant prices), availability of power per capita, state wise bank branches per capita, and the share of households within each state that live less than 0.5 km to a public transport facility within urban areas. For the next five equations in Table 3, we start adding controls at the household and state level within our model. These controls include the household size, the sex ratio at birth within each state, the age of the household head, the social group of the household, and the religion of the household. For the effect of mobile access, exclusive mobile access and exclusive mobile access with broadband on FLPR, the estimates range between 0.24 to 0.32, 0.11 to 0.20 and 0.20 to 0.24 respectively.

[19] Table A2 presents the full regression estimates of the univariate probit model and the LPM. Table A3 presents the full regression estimates of the bivariate probit model.

The estimates from the sensitivity tests are similar to those from the initial model in all the cases, showing the consistency of our results.

Table 3: Sensitivity analysis of Bivariate Probit Model

MLE estimates of Bivariate Probit Model						
	Access to mobile		Exclusive Access to Mobile		Exclusive Access to Mobile & broadband in HH	
	ρ	ME	P	ME	ρ	ME
(Net State Domestic Product per capita)	-.58***	.30***	-.19***	.14***	-.29***	.17***
	(.12)	(.04)	(.09)	(.04)	(.07)	(.03)
(Availability of power per capita)	-.57***	.32***	-.38***	.22***	-.50***	.26***
	(.07)	(.03)	(.09)	(.04)	(.05)	(.02)
(Bank branches per capita)	-.57***	.32***	-.37***	.21***	-.55***	.26***
	(.07)	(.03)	(.12)	(.04)	(.07)	(.02)
(Public Transportation Facility)	-.58***	.32***	-.42***	.23***	-.51***	.26***
	(.07)	(.03)	(.08)	(.03)	(.05)	(.02)
(Household size)	-.39***	.24***	-.11***	.11**	-.39***	.20***
	(.12)	(.05)	(.11)	(.04)	(.08)	(.03)
(Sex ratio at birth)	-.54***	.31***	-.31***	.19***	-.44***	.23***
	(.09)	(.04)	(.11)	(.04)	(.06)	(.03)
(Age of Household Head)	-.55***	.31***	-.33***	.20***	-.43***	.23***
	(.07)	(.03)	(.10)	(.04)	(.06)	(.02)
(Social Group)	-.53***	.30***	-.22	.15***	-.39***	.21***
	(.09)	(.04)	(.14)	(.05)	(.07)	(.03)
(Religion)	-.45***	.27***	-.31***	.19***	-.43***	.22***
	(.12)	(.05)	(.11)	(.04)	(.06)	(.03)

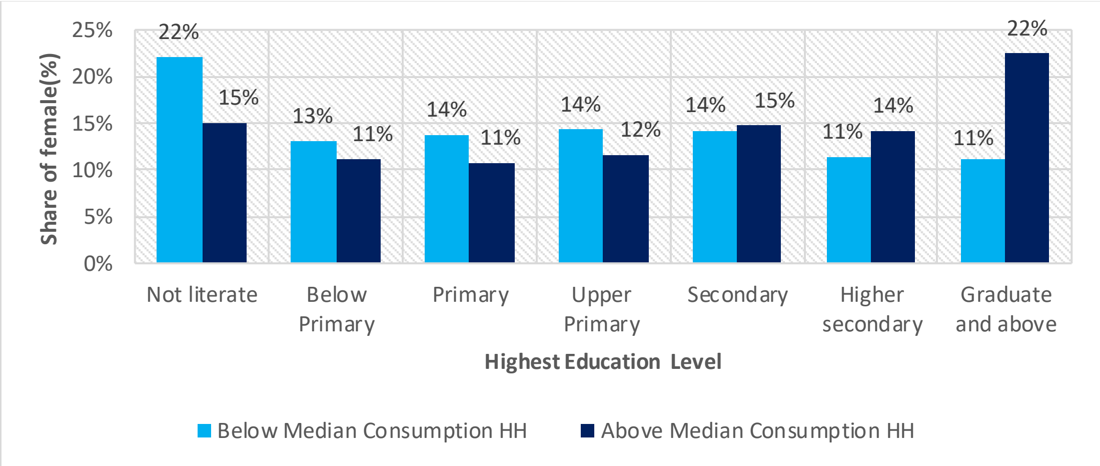
*Robust standard errors are in round bracket and ME (Marginal Effects) *** p<.01, ** p<.05, * p<.1*

3.3.Sub-sample analysis

In this section, we estimate the impact of our main independent variables across different sub-sets of the sample. We examine the impact of the three major explanatory variables on FLPR across six different categories (a) income levels (b) age (c) basic digital literacy (d) marital status, (e) number of children, & (f) social group

A. Income Level: We divide the sample into two halves, based on the median household consumption (a proxy for income), i.e. households having a consumption level higher than or below the median level[20]. It is seen that access to mobile increases the FLPR by 29 percent for richer households, but only 26 percent for households below the median consumption. With regard to exclusive mobile access, FLPR increases by 20 percent for women in richer households, and 16 percent for women in relatively poorer households. Lastly, the impact of mobile phone with broadband access increases FLPR by 27 percent for women in high-income households compared to 18 percent for women in low-income households. Given, there is a positive association between income levels and educational outcomes at a household level, a possible reason for the divergence in impact could be that females within higher income households tend to be more educated and thus are able to leverage digital infrastructure more conductively for employment opportunities. As Figure 8 illustrates, there is a significant gap in educational attainment for women in low-income households as compared to richer households.

Figure 8: Educational attainment of women in Urban India across Income level



Source: Author's computation of MIS data

B. Marital Status: Marital status is split into four categories: (a) never married (b) currently married (c) widowed (d) divorced. The results indicate that mobile access has a negative and significant impact on FLPR across all cohorts, except divorced women.

[20] The median monthly HH consumption in Urban India according to MIS is INR 12,367

On the other hand, exclusive mobile access has a positive impact only for married women, and a negative impact on FLPR for divorced women. For women who are never married, and for those who are widows, there is no impact of exclusive mobile access on FLPR. Lastly, the impact of exclusive mobile access and broadband service on FLPR is positive only for married women, and insignificant for the remaining cohorts. A possible reason married woman will benefit from exclusive use of mobile and access to broadband services is because digitalisation will expand their access to financial services, new entrepreneurial opportunities and afford them added security[21]. A reason why this exclusive use of mobile and broadband has not catalysed into increased labour force participation for never married women is because 92% of never married women are between the ages of 15 and 29, where in urban India the preferences are still towards attaining further education and not employment[22]. Another interesting finding is that shared access to mobile phone , which is captured in the access to mobile variable seems to be the driver of the negative (leisure effect) impact on the decision of a woman to join the labour force irrespective of the marital status .

C. Age: The sample is broadly divided into three categories. The first category are females who are in the age category 15-29. The second category are females within the age category 30-64, and the last category are females who are 65 and above. The results indicate that the access to mobile significantly increase the probability within the 15-29 age cohort to participate in the labour force. However, this positive impact is insignificant in exclusive access and exclusive mobile with broadband access. For the age cohort of 30-64, there is a significant increase in the probability of women participating in the labour force with exclusive mobile and broadband access. The results in this sub sample require a further understanding on the characteristics of women within the different age cohorts in urban India. Within the 30 - 64 age group, nearly 85% of the women are married which explains the similarity between the results of this sub sample and the currently married sub sample. However, within the 15-29 age group there is no clear defining trend. In this age cohort, 58.9% of the women have never been married and 40.5% are currently married (i.e., Nearly all never married women are in the 15-29 age cohort but within this cohort there is split between never married and

[21] World Bank Blogs (2021)

[22] In the 2021-22 round of the Periodic Labour Force Survey(PLFS), 47% of women in the age group 15-29 within urban India didn't participate in the labour force due to further educational aspirations.

currently married women). In both the age cohorts, the share of divorced and widowed women is negligible. Thus, within the 15-29 age cohort, the positive and significant impact of overall mobile access could be driven by either the never married or currently married sub sample or by a combination of both. From our results in the never married sub sample, it is clear the positive impact of digital infrastructure is not fully catalysed due to women pursuing further education. The results for currently married sub sample are more pronounced, with exclusive mobile and broadband access significantly increasing the probability of women to participate in the labour force. Further, the marital status sub sample analysis also implies that shares access to mobile is the major source of the leisure effect within both never married and currently married women. Thus, it is possible that the positive impact from exclusive mobile access and broadband overpowers the negative impact shared access which overall leads to digital infrastructure being a positive enabler for FLPR in the 15-29 age cohort.

D. **Basic digital literacy:** Basic digital literacy is defined as “individuals who can send electronic mails with an attached file”. We divide the sample into females who have basic digital literacy skills, and those who do not. It is seen that the impact of mobile access on FLPR is approximately similar for both cohorts. However, the difference is significant and higher for females with basic digital literacy that have exclusive access to mobile with broadband access as compared to those who do not possess basic digital literacy. This implies that digital literacy is important to leverage the digital infrastructure and to catalyse the impacts of digital inclusion.

E. **Number of children:** We divide the sample into three cohorts. The first cohort are those women who have no children. The second are those that have one child, and the last are those that have two or more children. The results indicate that the impact of mobile access on FLPR is positive and significant across all the three cohorts. However, the impact of exclusive mobile access on FLPR is positive for women having no children, but insignificant for the remaining two cohorts. Lastly, the impact of exclusive mobile access with broadband access is significant for women with no children or with one child, but insignificant for women with more than one child. The results broadly demonstrate the fact that the impact of digital infrastructure on FLPR is higher for women who either have no children or just one child. For women with more than one child, the motherhood penalty effect kicks in, which negates the positive impact of mobile phones and broadband access. The effects are similar to the broader literature on motherhood penalty and FLPR (Das and Zumbyte, 2017)

F. Social Group: We divide the sample into Scheduled Tribes (ST's), Scheduled Caste (SC's), other backward class (OBC's), and others. We examine the impact of our main explanatory variables across each social group. The results indicate that mobile access has a positive and significant impact on FLPR on all social groups, except ST's. Exclusive access to mobile phones has a positive and significant impact only on the general category social group. Lastly, exclusive access to mobile phones with broadband service has a positive and significant impact on FLPR for the general category. One important implication that emerges from this result is the high inequality that is still prevalent across caste groups. Digital inequality due to social exclusion has been a concern, not only in developing economies like India, but also in developed nations (Park, 2017). Hence, the governments and the social community should foster higher inclusion and bridge the digital divide across socio and ethnic lines.

Table 4: Sub-sample analysis of various socio-economic indicators on FLPR

		MLE estimates of Bivariate Probit					
		Access to mobile		Exclusive Access to Mobile		Exclusive Access to Mobile & broadband in HH	
		P	ME	P	ME	ρ	ME
Income	Below Median	-.42***	.26***	-.21***	.16***	-.29***	.18***
		(.16)	(.07)	(.11)	(.05)	(.08)	(.04)
	Above Median	-.50**	.29***	-.36	.20***	-.55***	.27***
		(.18)	(.08)	(.22)	(.08)	(.08)	(.03)
Marital Status	Never Married	.52***	-.09**	.13	.05	-.00	.07
		(.09)	(.04)	(.13)	(.04)	(.16)	(.05)
	Currently married (including living together)	.52***	-.17***	-.38***	.20***	-.43***	.22***
		(.08)	(.02)	(.12)	(.05)	(.07)	(.03)
	Widowed	.58***	-.12**	-.12	.09	-.18	.07
		(.08)	(.04)	(.28)	(.11)	(.28)	(.11)
	divorced/separated	-.48	.4*	.83	-.31***	.10	-.02
		(.49)	(.23)	(.23)	(.12)	(.31)	(.20)

Age	15-29	-.69*** (.23)	.31*** (.07)	-.05 (.12)	.06 (.04)	-.1 (.5)	.1 (.17)
	30-64	.38*** (.06)	-.09*** (.03)	-.24*** (.17)	.16** (.08)	-.41*** (.1)	.22*** (.04)
	65 & above	.57*** (.12)	-.05 (.03)	-.15 (.28)	.05 (.04)	.09 (.07)	-.00 (.05)
Basic Digital Literacy	No	-.61*** (.07)	.33*** (.03)	-.04 (.13)	.08 (.05)	-.24** (.08)	.14*** (.04)
	Yes	-.44* (.20)	.32*** (.09)	-.54** (.17)	.29*** (.07)	-.54*** (.16)	.29*** (.07)
No. of Children aged 0-5	No Children	-.78*** (.08)	.37*** (.02)	-.22*** (.14)	.16*** (.04)	-.40*** (.08)	.22*** (.03)
	One Child	.57*** (.14)	-.15*** (.05)	-.08 (.26)	.09 (.09)	-.37*** (.19)	.19*** (.07)
	Two Children and above	.41 (.30)	-.10 (.09)	.50* (.28)	-.11 (.08)	.28 (.32)	-.07 (.1)
Social Group	Scheduled Tribe (ST)	.54 (.16)	-.13 (.09)	.46 (.84)	-.11 (.43)	-.67*** (.09)	.39*** (.04)
	Scheduled Caste (SC)	-.65*** (.12)	.37*** (.05)	.15 (.25)	.02 (.10)	-.06 (.17)	.09 (.08)
	Other backward class (OBC)	-.67*** (.08)	.36*** (.03)	-.01 (.24)	.07 (.09)	-.14 (.17)	.10 (.07)
	Others	-.29* (.15)	.19*** (.06)	-.56*** (.11)	.28*** (.04)	-.64*** (.06)	.30*** (.02)

*Robust standard errors are in round bracket and ME (Marginal Effects) *** p<.01, ** p<.05, * p<.1*

4. Conclusion and Policy Recommendations

Mobile phones and digital infrastructure have been instrumental in improving development outcomes globally. We examine the causal impact of mobile phone access (shared and exclusive), and broadband access on FLPR in urban parts of India. Using an instrumental variable approach to examine the causal impact, we find that an increase in both, shared and exclusive mobile phone access increases FLPR. Disaggregating this impact on various cohorts of the sample, we find that the impact is strongest for households above the median level of income, and for women in the age cohort of 30-64. Furthermore, the effect is more pronounced for women with no children, and for those that belong to the general category.

This study has various policy implications, not only for India, but for many emerging economies across the globe. Digital infrastructure, including mobile phones and broadband connections have the power to increase employment opportunities for individuals. Countries should leverage on these technologies which could lead to higher employment rates and faster growth. Providing online training/skilling programs, expanding the reach of gig employment opportunities, and reducing the variable costs such as the cost of call rates, and internet data can lead to faster adoption of such technology. The results also indicate that digital literacy plays a vital role in increasing the impact of mobile and broadband access on labour market participation. Hence, governments and educational institutions should focus on improving basic digital literacy at the school level which will enable them to take up employment in productive sectors. While digital technologies have proven to be beneficial for labour market outcomes, it is also important that regulatory mechanisms are put in place to mitigate any risks that might emerge from the use of such technological devices.

One limitation of the study is that it is focused only on urban India at this stage. However, with the extensive reach of the internet and mobile phones into rural parts of the economy, future research can investigate the impact among the rural populace. Secondly, the availability of microdata at the household level restricts us to perform this analysis only for India. However, a cross country study would provide insights into how digital infrastructure impacts FLPR across the globe, and help countries learn from best practices.

References

1. Aker, J. C., & Mbiti, I. M. (2010). Mobile phones and economic development in Africa. *Journal of economic Perspectives*, *24*(3), 207-232.
2. Alozie, N. O., & Akpan-Obong, P. (2017). The digital gender divide: Confronting obstacles to women's development in Africa. *Development Policy Review*, *35*(2), 137-160.
3. Amber, H., & Chichaibelu, B. B. (2023). Narrowing the gender digital divide in Pakistan: Mobile phone ownership and female labor force participation. *Review of Development Economics*.
4. Angrist, J. D., & Pischke, J. S. (2009). *Mostly harmless econometrics: An empiricist's companion*. Princeton university press.
5. Anker, R. (1998). *Gender and jobs: Sex segregation of occupations in the world*. International Labour Organization.
6. Barboni, G., Field, E., Pande, R., Rigol, N., Schaner, S., & Moore, C. T. (2018). A Tough Call.
7. Bose, G., Jain, T., & Walker, S. (2022). Women’s labor force participation and household technology adoption. *European Economic Review*, *147*, 104181.
8. Bhalotra, S. R., & Fernández, M. (2021). *The rise in women's labour force participation in Mexico: Supply vs demand factors* (No. 2021/16). WIDER Working Paper.
9. Bhattacharya, J., Goldman, D., & McCaffrey, D. (2006). Estimating probit models with self-selected treatments. *Statistics in medicine*, *25*(3), 389-413.
10. Chiburis, R. C., Das, J., & Lokshin, M. (2012). A practical comparison of the bivariate probit and linear IV estimators. *Economics Letters*, *117*(3), 762-766.
11. Das, M., & Desai, S. (2003). *Why are educated women less likely to be employed in India?: Testing competing hypotheses*. Washington, DC: Social Protection, World Bank.
12. Das, M. B., & Zumbyte, I. (2017). The motherhood penalty and female employment in urban India.

13. Desai, S., & Jain, D. (1994). Maternal employment and changes in family dynamics: The social context of women's work in rural South India. *Population and Development Review*, 115-136.
14. Dettling, L. J. (2017). Broadband in the labor market: The impact of residential high-speed internet on married women’s labor force participation. *Ilr Review*, *70*(2), 451-482.
15. Dinkelman, T. (2011). The effects of rural electrification on employment: New evidence from South Africa. *American Economic Review*, *101*(7), 3078-3108.
16. Evans, W. N., & Schwab, R. M. (1995). Finishing high school and starting college: Do Catholic schools make a difference?. *The Quarterly Journal of Economics*, *110*(4), 941-974.
17. Fabbri, D., Monfardini, C., & Radice, R. (2004). Testing exogeneity in the bivariate probit model: Monte Carlo evidence and an application to health economics.
18. Fernández, R., & Fogli, A. (2009). Culture: An empirical investigation of beliefs, work, and fertility. *American economic journal: Macroeconomics*, *1*(1), 146-177.
19. Field, E., Pande, R., Rigol, N., Schaner, S., & Moore, C. T. (2016). On her account: Can strengthening women’s financial control boost female labor supply?. *Growth and labour markes in low income countries programme: Working. Paper*, (32).
20. Göksel, I. (2012). *The reasons of decreasing trend of female labour force participation in Turkey: The role of conservatism* (No. 12/05). Working Papers in Economics.
21. Golin, M. (2022). The effect of broadband Internet on the gender gap in mental health: Evidence from Germany. *Health Economics*, *31*, 6-21.
22. Goldin, C. (2006). The quiet revolution that transformed women's employment, education, and family. *American economic review*, *96*(2), 1-21.
23. Hossain, M. A., & Tisdell, C. A. (2005). Closing the gender gap in Bangladesh: inequality in education, employment and earnings. *International Journal of Social Economics*, *32*(5), 439-453.
24. Hilbert, M. (2011, November). Digital gender divide or technologically empowered women in developing countries? A typical case of lies, damned lies, and statistics. In *Women's studies international forum* (Vol. 34, No. 6, pp. 479-489). Pergamon.
25. Jaeger, U. (2010). *Working or stay-at-home mum? The influence of family benefits and religiosity* (No. 84). Ifo Working Paper.
26. Klasen, S., & Pieters, J. (2015). What explains the stagnation of female labor force participation in urban India?. *The World Bank Economic Review*, *29*(3), 449-478.

27. Klasen, S. (2019). What explains uneven female labor force participation levels and trends in developing countries?. *The World Bank Research Observer*, *34*(2), 161-197.
28. Klasen, S., Le, T. T. N., Pieters, J., & Santos Silva, M. (2021). What drives female labour force participation? Comparable micro-level evidence from eight developing and emerging economies. *The Journal of Development Studies*, *57*(3), 417-442.
29. Kleven, H., Landais, C., & Søgaard, J. E. (2019). Children and gender inequality: Evidence from Denmark. *American Economic Journal: Applied Economics*, *11*(4), 181-209.
30. Kroft, K., & Pope, D. G. (2014). Does online search crowd out traditional search and improve matching efficiency? Evidence from Craigslist. *Journal of Labor Economics*, *32*(2), 259-303.
31. Kuhn, P., & Mansour, H. (2014). Is internet job search still ineffective?. *The Economic Journal*, *124*(581), 1213-1233.
32. Lee, D., & Jayachandran, S. (2009). The impact of mobile phones on the status of women in India.
33. Lei, L., Desai, S., & Vanneman, R. (2019). The impact of transportation infrastructure on women's employment in India. *Feminist economics*, *25*(4), 94-125.
34. Ma, W., Grafton, R. Q., & Renwick, A. (2020). Smartphone use and income growth in rural China: Empirical results and policy implications. *Electronic Commerce Research*, *20*(4), 713-736.
35. Ostry, M. J. D., Alvarez, J., Espinoza, M. R. A., & Papageorgiou, M. C. (2018). *Economic gains from gender inclusion: New mechanisms, new evidence*. International Monetary Fund.
36. Park, S. (2017). Digital inequalities in rural Australia: A double jeopardy of remoteness and social exclusion. *Journal of Rural Studies*, *54*, 399-407.
37. Pennings, S. M. (2022). A Gender Employment Gap Index (GEGI).
38. Pieters, J., & Klasen, S. (2011). Drivers of female labour force participation in urban India during India's Economic Boom.
39. Rajkhowa, P., & Qaim, M. (2022). Mobile phones, off-farm employment and household income in rural India. *Journal of Agricultural Economics*, *73*(3), 789-805.
40. Rustagi, P. (2010). CONTINUING GENDER STEREOTYPES OR SIGNS OF CHANGE: OCCUPATIONAL PATTERN OF WOMEN WORKERS. *Indian Journal of Labour Economics*, *53*(3).

41. Salehan, M., & Negahban, A. (2013). Social networking on smartphones: When mobile phones become addictive. *Computers in human behavior*, *29*(6), 2632-2639.
42. Sarkar, S., Sahoo, S., & Klasen, S. (2019). Employment transitions of women in India: A panel analysis. *World Development*, *115*, 291-309.
43. Schaner, S., & Das, S. (2016). Female labor force participation in Asia: Indonesia country study. *Asian Development Bank Economics Working Paper Series*, (474).
44. Stock, J. H., & Yogo, M. (2002). Testing for weak instruments in linear IV regression.
45. Ureta, S. (2008). To move or not to move? Social exclusion, accessibility and daily mobility among the low-income population in Santiago, Chile. *Mobilities*, *3*(2), 269-289
46. Viollaz, M., & Winkler, H. (2022). Does the internet reduce gender gaps? The case of Jordan. *The Journal of Development Studies*, *58*(3), 436-453.
47. Wooldridge, J. M. (2008). Instrumental variables estimation of the average treatment effect in the correlated random coefficient model. In *Modelling and evaluating treatment effects in econometrics* (pp. 93-116). Emerald Group Publishing Limited.

APPENDIX

Section 1: Figures

Figure A1: Scatterplot Urban Total Tele Density and Average Urban HH UMCE

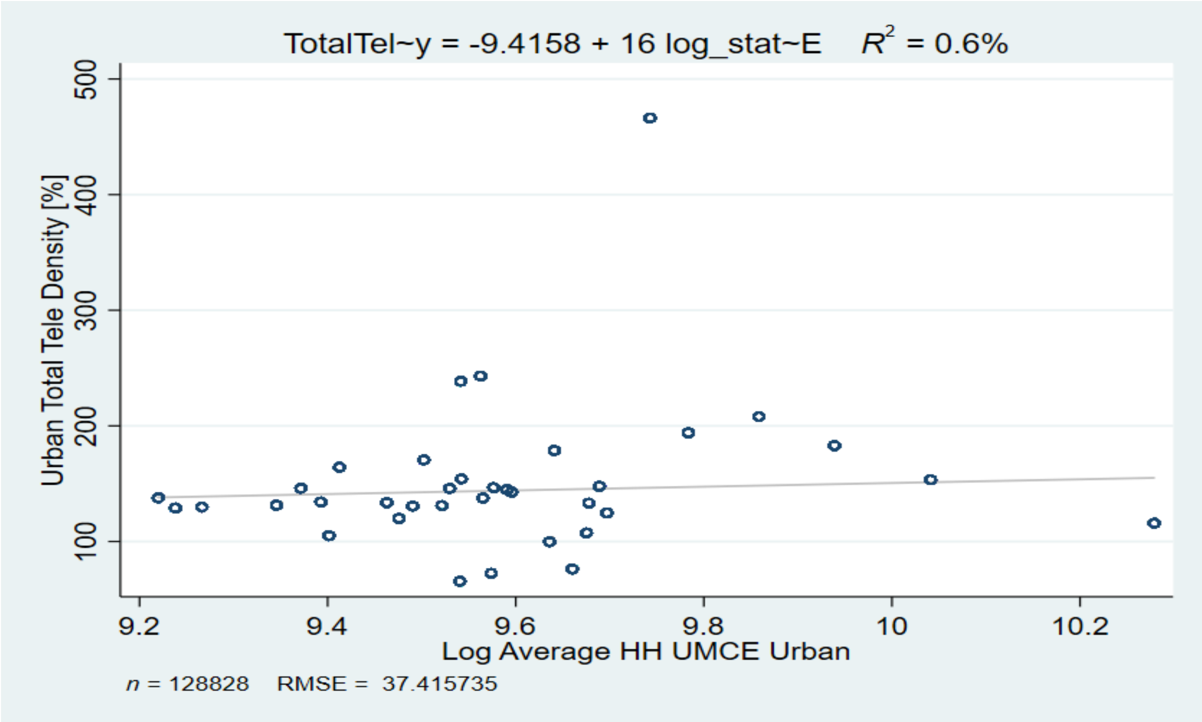


Figure A2: Scatterplot Urban Total Tele Density and NSDP per capita of each state (constant prices)

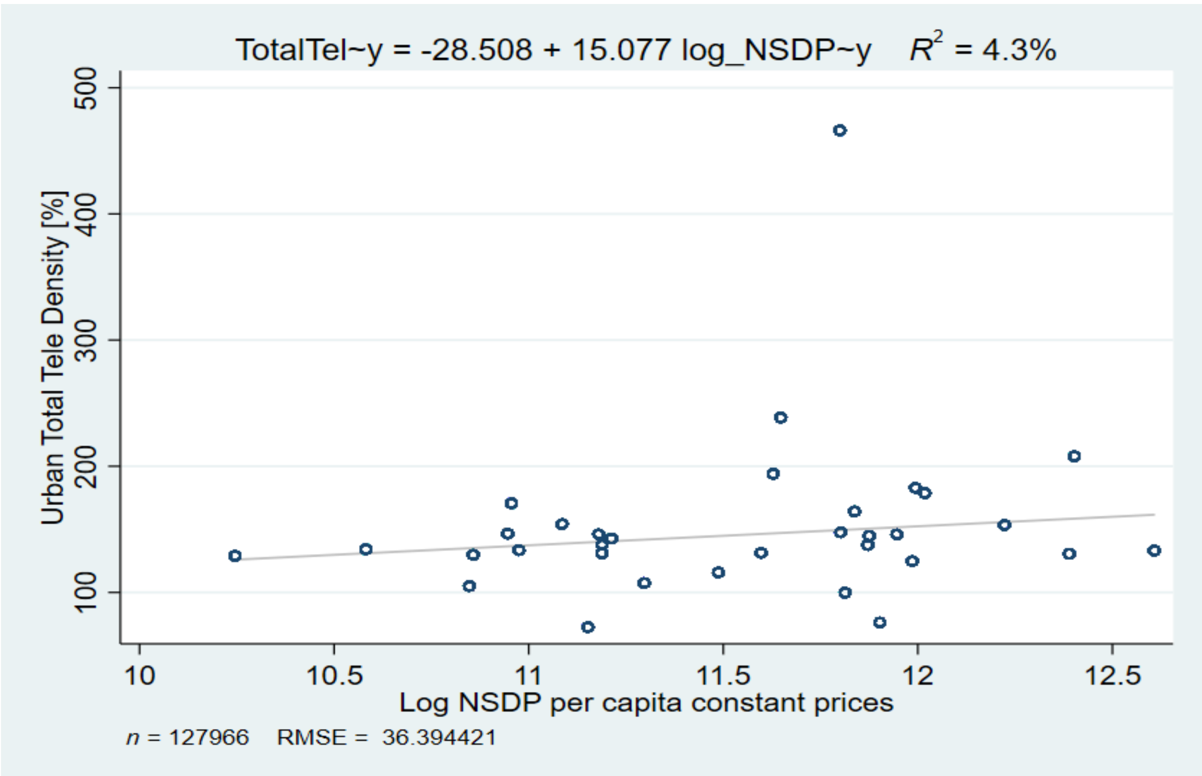


Figure A3: Scatterplot Rural Total Tele Density and Average Rural HH UMCE

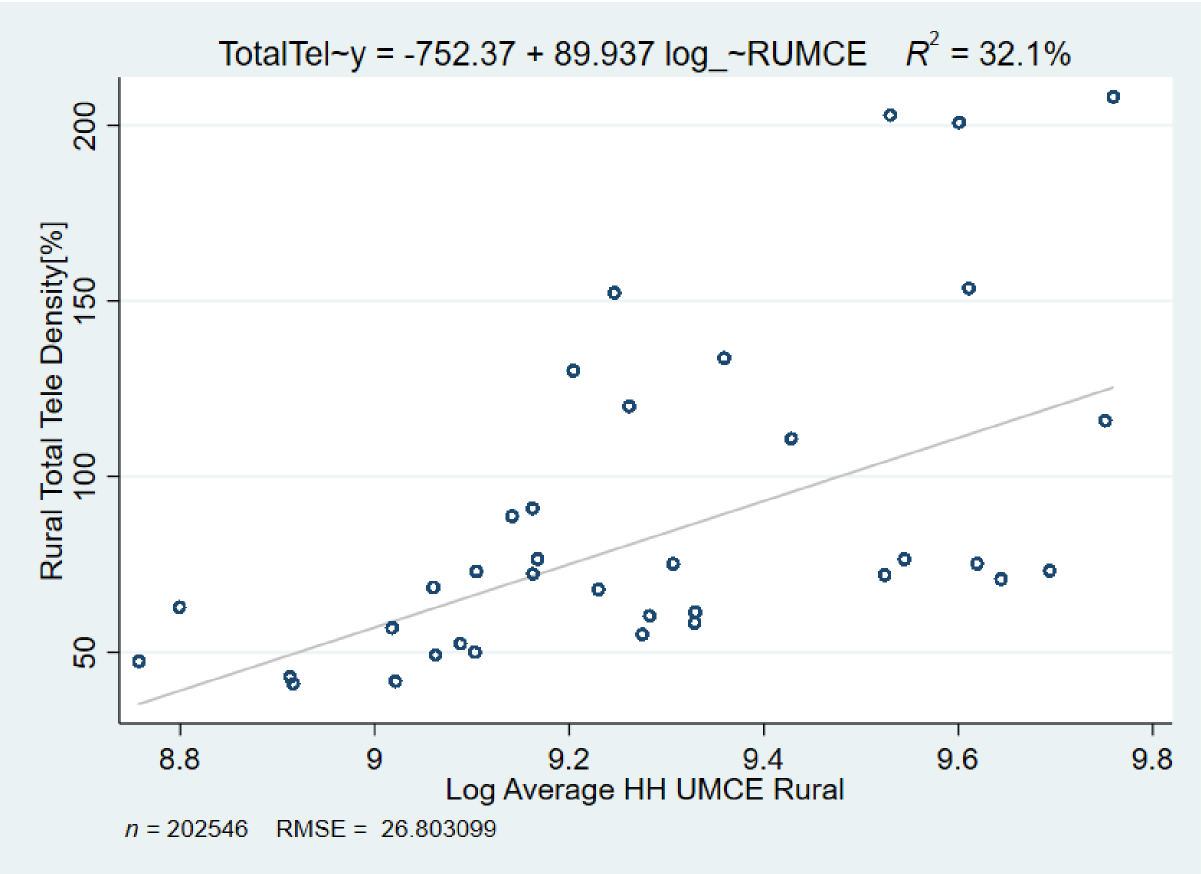


Figure A4: Scatterplot Rural Total Tele Density and NSDP per capita of each state (constant prices)

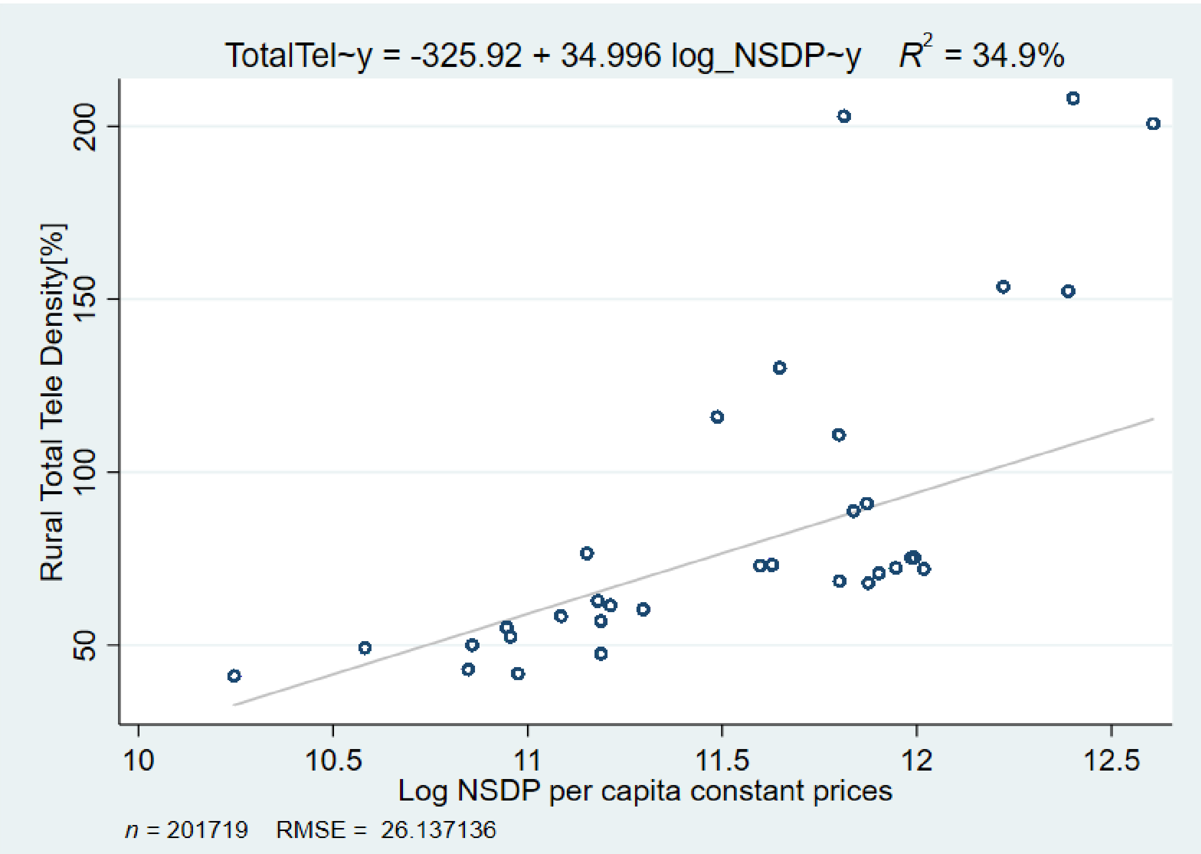


Figure A5: Scatterplot Urban Total Tele Density and Urban sex ratio of each state

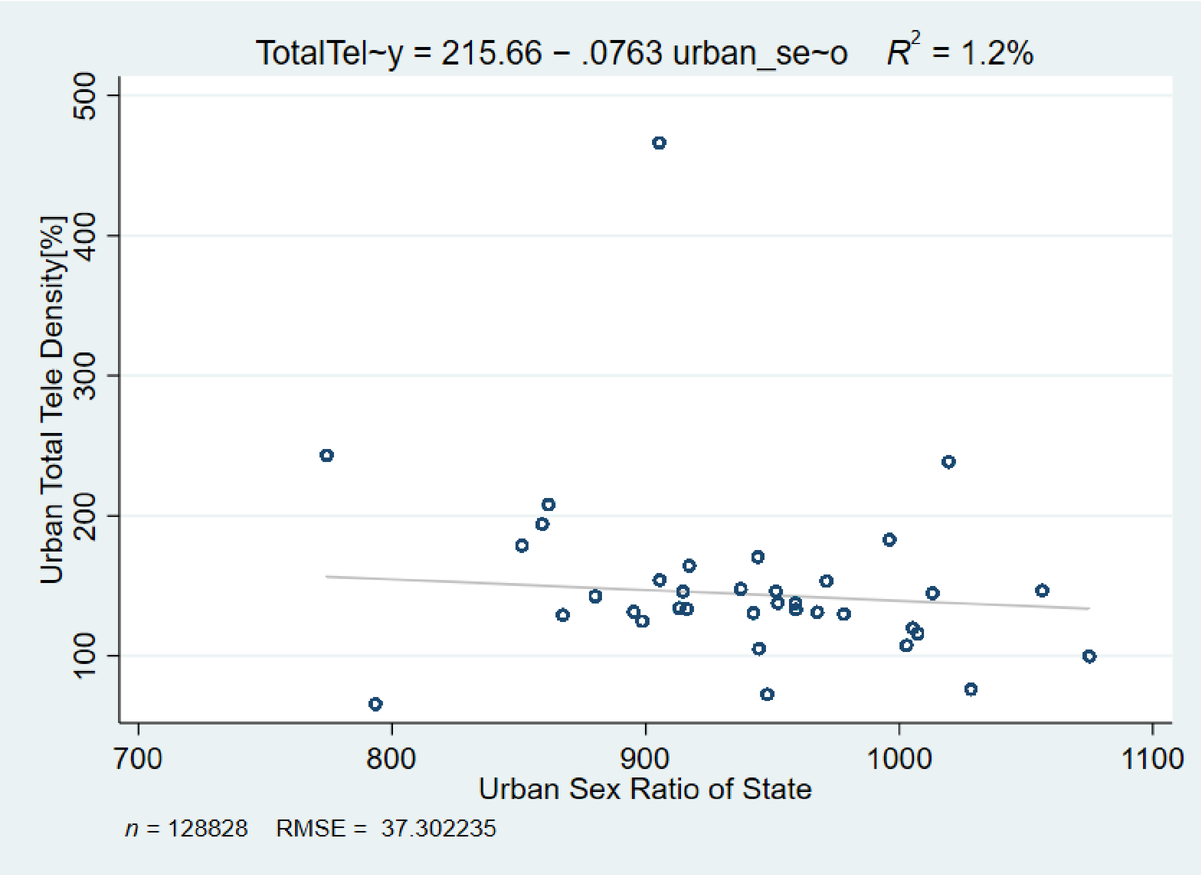


Figure A6: Scatterplot Rural Total Tele Density and Rural sex ratio of each state

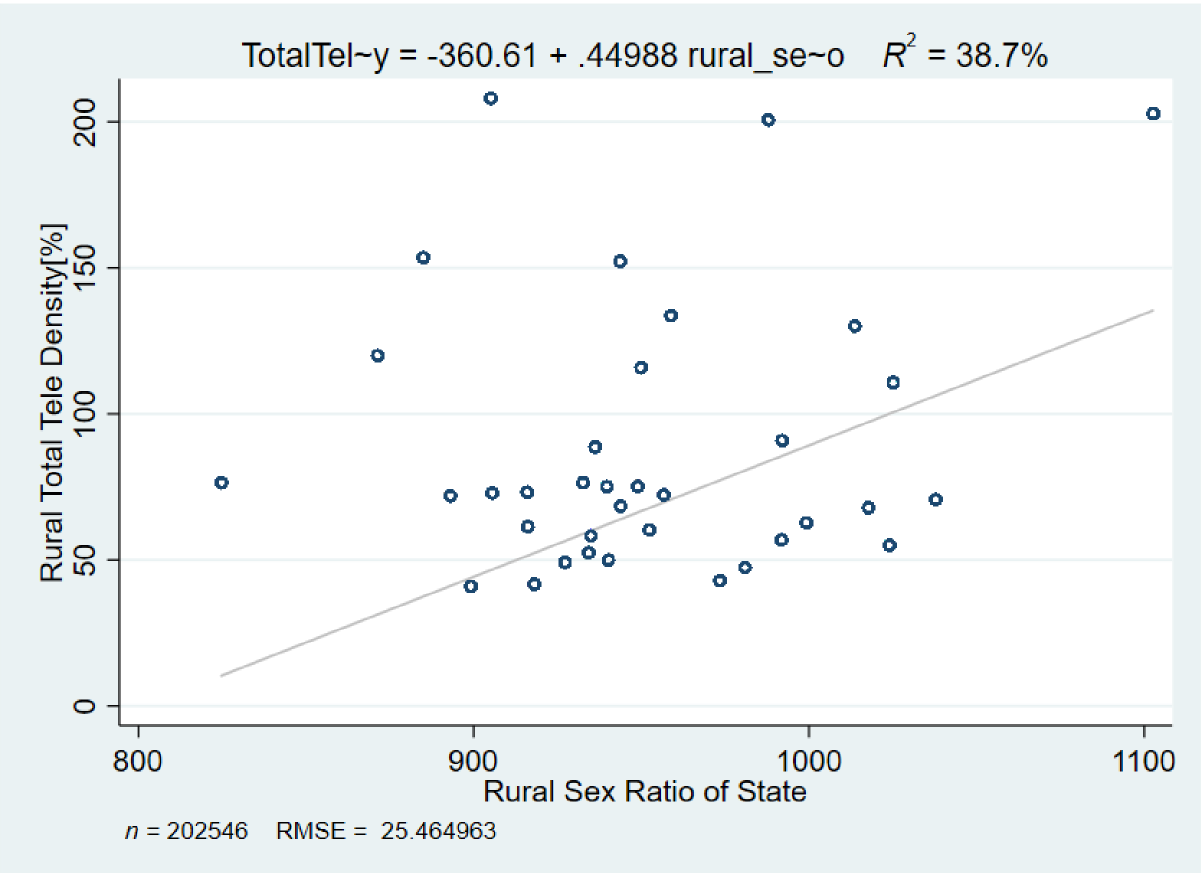


Figure A7: Scatterplot Urban Total Tele Density and sex ratio of each state

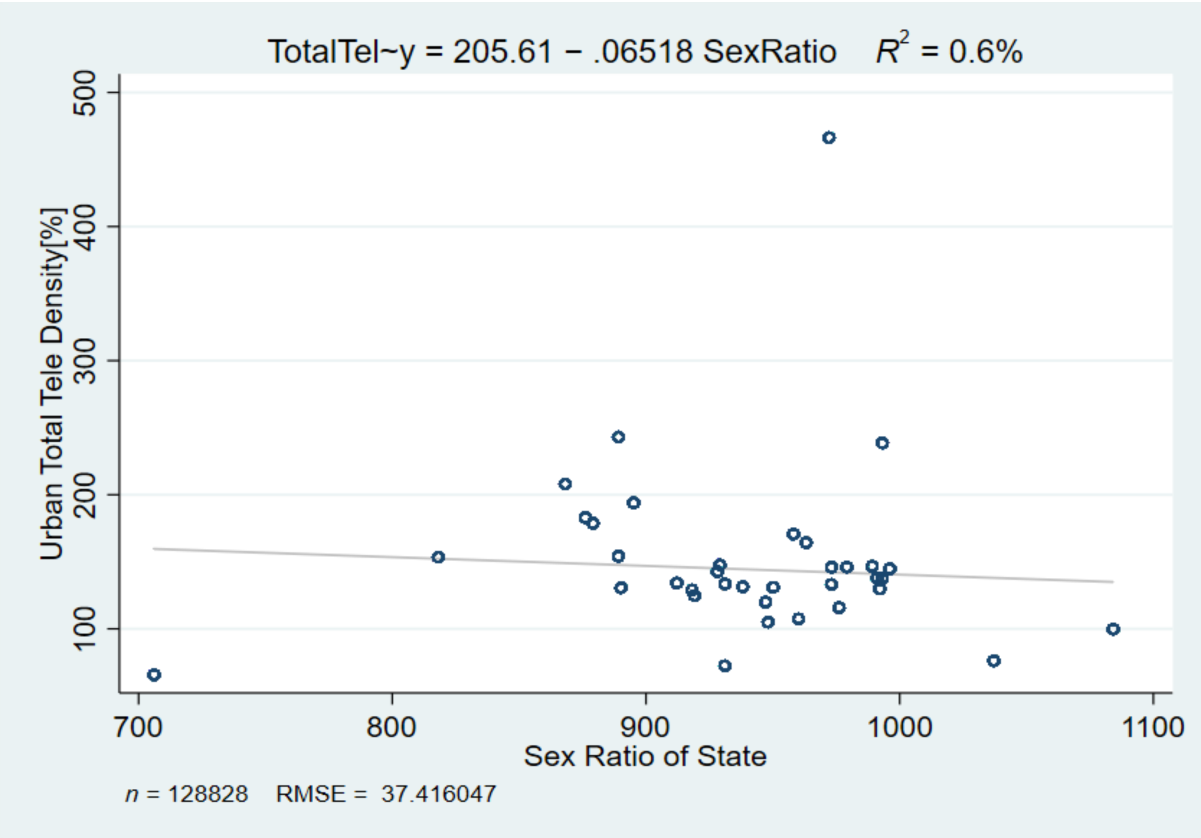


Figure A8: Scatterplot Rural Total Tele Density and sex ratio of each state