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RING OF PROGRESS: EXAMINING THE IMPACT OF THE INTENSITY OF MOBILE PHONE USE ON FEMALE LABOR FORCE PARTICIPATION IN INDIA

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Abstract

In this paper, we study the causal impact of the intensity of mobile phone use on female labor force participation in India. Using data from a large representative household survey, we employ an instrumental variable approach to estimate this causal impact. We decompose the intensity of mobile phone use into two channels, namely digital access (sharing a mobile phone) and digital inclusion (exclusively using a mobile phone). We find that while neither digital access nor inclusion has any significant impact on female labor force participation in India, the effect varies across different heterogeneous groups. The digital access effect is positive and significant for females residing in rural India, those with a basic level of education, and those belonging to the lower household consumption quartiles. Conversely, the digital inclusion effect is significant for females residing in urban India, those with higher levels of education, those residing in higher household consumption quartiles, and those belonging to the 15–24 years age group.

Keywords: digital, female labor force participation, rural, urban

JEL Classification: J21, O30, P25

Contents

1. INTRODUCTION

Over the decade from 2012 to 2021, India achieved rapid progress on some key socioeconomic indicators. Its gross domestic product (GDP) per capita grew at a compound annual growth rate (CAGR) of 3.9%, the fraction of the population with access to electricity increased from 79.9% to 99.6%, and tertiary education enrollment increased from 24% to 31% (World Bank 2022). As a result of this economic development, the proportion of the country's multidimensionally poor decreased from 24.85% in 2015–16 to 14.96% in 2019–21. Despite these remarkable advances, India's female labor force participation rate (FLPR) in 2022 stood at 24%, far lower than that of the People's Republic of China (PRC) (61%), Viet Nam (69.1%), Bangladesh (38%), and other neighboring and emerging economies. The FLPR in India saw a sustained increase from 23.3% in 2017–18 to 37% in 2022–23. The growth in the FLPR has been mostly driven by females in the rural economy, where the FLPR witnessed an increase from 24.6% (2017–18) to 41.5% (2022–23). The growth in the FLPR in urban areas has been relatively muted, with an increase from 20.4% in 2017–18 to 25% in 2022–23.

The reasons for the low FLPR in India can be broadly classified into two factors: demand-side factors and supply-side factors. Demand-side factors include structural changes in employment patterns, technological innovations, a lack of gender-inclusive policies, and gender wage gaps. There has been extensive research on the negative impact of gender segregation for jobs (Anker 1998; Swaminathan and Majumdar 2006; Rustagi 2010). On the supply side, marital status (Goldin 2006; Kleven, Landais, and Søgaard 2019) and the fertility rate (Bhalotra and Fernández 2021) are leading causes for the declining FLPR. Cultural factors also play a very significant role in determining female labor participation (Fernández and Fogli 2009). The effect of culture on the FLPR is more pronounced in the South Asian 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 labor force (Das and Desai 2003; Desai and Jain 1994; Göksel 2012; Jaeger 2010). Pieters and Klasen (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 labor force participation rate and showed that a higher social status has a negative impact on women's labor force participation in India.

The FLPR is an important socioeconomic indicator across the globe. Reducing gender gaps in employment has a significant positive effect on GDP (Klasen 2005; Klasen and Lamanna 2009). Pennings (2022) shows that narrowing the gender employment gap index (GEGI) in the Pacific Islands can increase GDP per capita by almost 20%. Hossain and Tisdell (2005) provide evidence that improving the -FLPR reduces gender earning differences and fosters self-esteem and equality within the household. Furthermore, including women in the workforce will have increased benefits 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 a higher FLPR. Evidence from South Africa shows that electrification improved the FLPR by 9% (Dinkelman 2011). Furthermore, safer public transportation can increase the likelihood of women joining the workforce (Lei, Desai, and Vanneman 2019). Second, access to finance is critical in supporting female entrepreneurship. The ownership of bank accounts and 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 labor force. For instance, countries such as Peru and Malawi have brought about significant changes in their legal frameworks that have significantly increased female labor participation (Gonzales et al. 2015).

Lately, mobile phones have become enablers towards employment as they have a positive association with various aspects of development. Extant research has provided evidence on the positive effects of mobile phone usage on off-farm employment (Rajkhowa and Qaim 2022), status, and well-being (Lee and Jayachandran 2009). The impact of access to and use of mobile phones on socioeconomic outcomes has attracted considerable research interest (Alozie and Akpan-Obong 2017; Dettling 2017; Hilbert 2011; Ma, Grafton, and Renwick 2020; Viollaz and Winkler 2022; Amber and Chichaibelu 2023). Mobile phone use affects female labor market participation through providing flexible work options, increased mobility for women, and enhanced information awareness about jobs (Nga and Ma 2008), as well as ease in digital transaction of wages (Aker and Mbiti 2010) and ease of communication while at the workplace (Ureta 2008).

There has been mixed evidence on the impact of mobile phones and labor participation in a cross-country context. Studies have illustrated the positive impacts of mobile phones and ICT usage on labor force participation. For instance, Amber and Chichaibelu (2023) find a positive and significant impact of mobile phone usage on female employment. Similarly, Rajkhowa and Qaim (2022) estimate the impact of mobile phone usage on off-farm employment and find that the impact is positive. Using a cross-country framework, Ngoa and Song (2021) and Asongu and Odhiambo (2019) find that ICT plays a critical role in improving the FLPR in the African region. While most studies believe there is a positive impact, Samargandi et al. (2019) find that ICT impedes the FLPR in the context of Saudi Arabia, owing to cultural factors.

Despite a high penetration of mobile phones, there still exists high gender inequality with regard to mobile phone use. The Mobile Gender Gap Report 2023 indicates that women are 19% less likely than men to use mobile Internet. In total, out of 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. Therefore, digital inclusion implies that women in households have equal access to mobile phones. Thus, while digital access is an enabler, digital inclusion reduces the inequality and improves women's decision-making empowerment.

Against this background, this paper addresses the effect of mobile phones on the FLPR in India. We focus on India for two specific reasons. First, India has recorded a massive increase in mobile phone adoption over the years. Smartphone penetration increased from 2.75% in 2010 to 66.2% in 2022. Second, almost 50% of the population, or 600 million individuals, have access to the Internet in India. Therefore, given the surge in both mobile phone and Internet penetration, this study assesses the causal impact of mobile phone usage on the female labor force participation rate.

We use the 78th round of the National Sample Survey (NSS) of India, which was undertaken in 2020–21, to examine this causal impact. The utility derived from a mobile phone can be assessed through the intensity of usage by a female, i.e., either the female shares her mobile with a household/non-household member or she exclusively uses the mobile phone. Accordingly, we define two effects with regard to mobile use. The first is the digital access effect, which is the effect of shared use of a mobile as compared to no use. The second is the digital inclusion effect, which is the effect of exclusive mobile use as compared to shared use. In our analysis, we investigate both these effects independently on the probability of a female joining the labor force. We examine this causality through an instrumental variable approach, where we exploit the exogeneous variation in the state/UT's dissemination of push SMS notifications by the Government of India's Mobile Seva Platform.

Our study's findings indicate that both the digital access and the digital inclusion effects have a positive statistically significant association with increasing the probability of a woman entering the labor force in India. However, on addressing endogeneity concerns, we do not find any causal impact. On assessing this impact across different heterogeneous groups, we find that the digital access effect is positive and significant across both rural and urban India. However, the digital inclusion effect is positive and significant only for urban India. Moreover, we find that the impact of digital access is positive for females with lower levels of educational attainment and those heading their respective households. The digital inclusion effect is positive for females that have higher levels of education attainment, those who have never married, and those in the 15–24 years age group.

Our study contributes to the existing literature at the intersection of labor force participation and digitalization. First, to the best of our knowledge, there is no previous literature on the causal impact of the intensity of mobile phone usage on the FLPR in India. Our work comes closest to that of Rajkhowa and Qaim (2022), who investigate the impact of women using a mobile phone on mobility for the rural nonfarm sector. Second, we also contribute to the literature on closing the gender gap in digital inclusion as we estimate the impact of exclusive mobile usage on the FLPR. Research on the barriers to the adoption of 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 digital divide can have positive labor market outcomes.

The rest of the paper is divided in the following way. Section 2 discusses the theoretical context behind this study. Section 3 looks at the methodology. Section 4 discusses the main results, along with robustness tests, and heterogeneity analysis. Section 5 concludes with policy implications and the limitations of this study.

2. MOBILE PHONES AND FLPR: THEORETICAL CONTEXT

Mobile phones can have both a positive and a negative effect on the FLPR (Figure 1). On the one hand, while the use of mobile phones leads to higher female labor force participation (employment effect), it can also lower the FLPR (leisure effect). The employment-inducing effects of mobile phone use are:

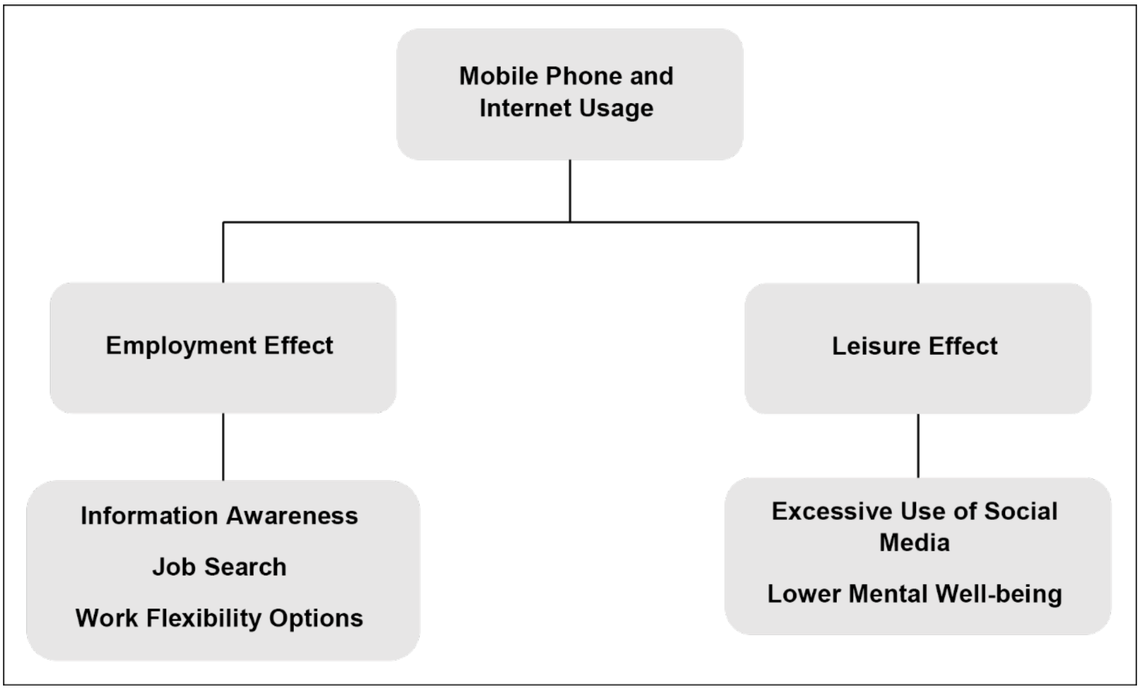
Informational awareness: Searching for jobs involves high transaction costs. Mobile phones reduce the transaction cost in a job search by facilitating informational awareness regarding job opportunities. Thus, mobile phones improve job search processes and the chances of women participating in the workforce.

Increased mobility: Access to mobile phones increases the chances of mobility for women. Extant research has shown that restrictions on female physical mobility directly affect women's participation in the labor force (Rani et al. 2022; Small and Rodgers 2023). Mobile phones enable women to communicate better with their family while traveling, as well as providing them with a sense of security. Therefore, access to, and the use of, mobile phones positively impact the decision for a female to participate in the labor force.

Work flexibility options: Access to, and the use of, mobile phones opens up a larger pool of work opportunities available for women. Using their mobile phones, women can now work from home. Extant research has shown that women's participation in entrepreneurship has increased with the presence of mobile phones. With access to digital infrastructure, the participation of women in the gig economy has also increased (Rani et al. 2022).

While mobile phones can improve the FLPR through better employment opportunities including access to information, improved mobility, enhanced communication, and flexible working opportunities, they can also act as inhibitors to employment by increasing the time for leisure activities. Greater use of digital infrastructure could lead to increased consumption of leisure, which would reduce the incentive and motivation to participate in employment. Leisure effects could include high consumption of social media (Salehan and Negahban 2013), online gaming, and other addictive activities that could possibly lead to the lowering of mental well-being (Golin 2022). Therefore, the impact of digital infrastructure and inclusion on the FLPR is ambiguous, and it is critical to examine which effect dominates more in this context. Hence, there is a labor-leisure trade-off that is seen with the availability of mobile phones (Figure 2).

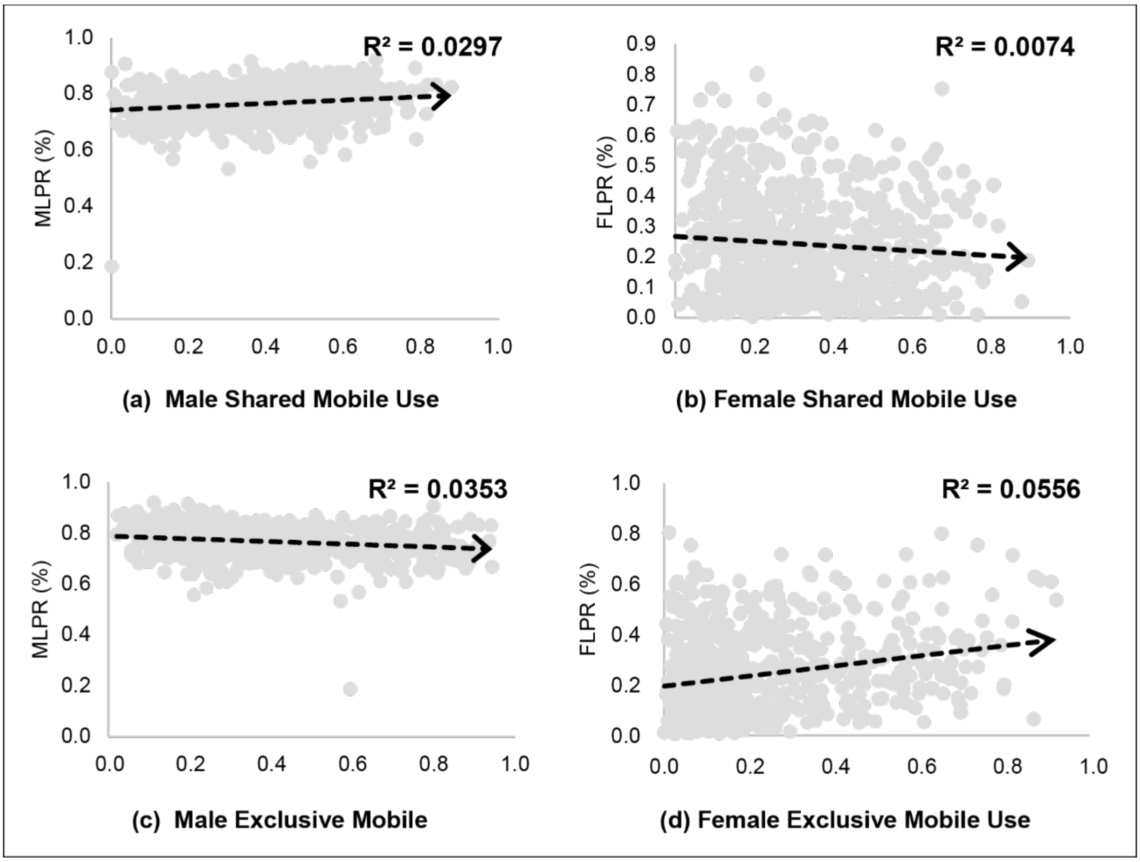
Figure 1: Possible Effects of the Use of Digital Infrastructure



Moreover, while mobile phone use is an important indicator in assessing socioeconomic development, it is equally important to assess the degree of use available to each individual. For instance, in India, the gender gap in the use of mobile phones is 31 percentage points, but this gap increases to 46 percentage points for exclusive mobile use. Thus, for our analysis, we categorize the use of a mobile phone by a female based on the degree of usage. We define three categories, namely: (a) no use; (b) shared use (sharing the mobile with a household/nonhousehold member); and (c) exclusive use (exclusively using the mobile phone). Using these three categories, we study two effects: (a) the digital access effect, which is the effect of shared use of a mobile phone as compared to no use; and (b) the digital inclusion effect, which is the effect of exclusive use of a mobile phone compared to shared use.

Does the degree of mobile phone use actually improve labor force participation rates? We check the association of shared and exclusive mobile use with labor force participation across males and females. Figures 2(a) to 2(d) illustrate the association between mobile use and labor force participation across males and females. While the correlation between labor force participation and shared mobile usage for males and females is positive, this relationship is weaker for females. On comparing the correlation between labor force participation and exclusive use of a mobile (Figures 2(c) and 2(d)), it can be seen that the association of labor force participation with regard to exclusive use is higher for females than for males. Thus, at an association level, it is seen that exclusive mobile use has a greater effect on FLPR than shared mobile use, indicating that the significance of the digital inclusion channel is greater than the digital access channel.

Figure 2: District-Wise Correlation between Degree of Mobile Use and Labor Force Participation Rates



3. METHODOLOGY

3.1 Estimation Strategy

The 78th round of the National Sample Survey (NSS) of India gathers information on the labor force participation status[1] of each individual surveyed. In our case, we are

[1] The labor 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).

concerned with the labor force participation status of working-age (between the ages of 15 and 64) females. We can only observe whether a surveyed female is within the labor force or not; hence our dependent variable is a function of a latent variable Y^*_{ihdsr}. This variable denotes the net benefit that a surveyed female "i" in household "h" in district "d" in state "s" in region "r" receives from entering the labor force.

Our explanatory variable of interest is an individual's use of a mobile phone.[2] This use can either be exclusive, shared with a household member, or shared with someone outside the household. The survey also records the responses of individuals that do not use a mobile phone. The distribution of our primary explanatory variable across working-age females is given in Table 1.

Table 1: Distribution of Mobile Use among Working-Age Females in India

Use of Mobile	**Share of Females** (%)
Exclusive Use	22.51
Shared Use with HH member	36.90
Shared Use with non-HH member	0.13
Does Not Use	40.46

Source: Author's computation of MIS data.

The underlying distribution that determines the use of a mobile by a female is also unobserved and can be described by a latent variable M^*_{ihdsr}. Suppose female "i" in household "h" in district "d" in state "s" in region "r" is sorted into "k" observable categories regarding their use of a mobile, with each category being denoted by "j," such that j = 1, 2 ,.., k. If the k different categories have a natural ordering, then we can create an ordered categorical variable. In our case, we use the information on our mobile use variable and divide it into three different ordered categories with each successive category increasing the use of a mobile for a female. Hence, category "1" denotes that a female does not use a mobile, category "2" denotes that a female shares her mobile with a household or non-household member, and category "3" denotes that a female has exclusive use of a mobile. Thus, we can observe the ordered categorical variable M_{ihdsr} but not the latent variable M^*_{ihdsr}.

Our choice problem is described by the latent variable model:

$$Y^*_{ihdsr} = X_{ihdsr}\alpha + M_{ihdsr}\theta + \varepsilon_{ihdsr}, \qquad (1)$$

where $Y_{ihdsr} = 1$ if $Y^*_{ihdsr} > 0$ and $Y_{ihdsr} = 0$ otherwise. ε_{ihdsr} is a random error.

Following the literature on the determinants of the FLPR in India, the vector X_{ihdsr} includes various individual, household, district, state, and regional characteristics that impact our dependant variable. At the individual level, we include controls like the age group, marital status, highest level of education[3], and highest digital literacy level[4] of a female. Previous literature has also emphasized the role of household income, wealth, and males' education in explaining the declining trend of the FLPR in India (Klasen and Pieters 2015; Sarkar, Sahoo, and Klasen 2019). We account for such

[2] The survey collects data on whether an individual used a mobile phone with an active SIM card in the three months preceding the date of the survey (National Statistics Office 2023).

[3] We categorize the highest education level attained by a female according to the ISCED-11 classification.

[4] We categorize digital literacy according to the International Telecommunication Union (ITU) (2020).

factors in our analysis. Firstly, we include the quartiles of per capita consumption of the household. By using consumption per capita, we control for heterogeneity in household size. Secondly, we also include a control for the security of household income via a dummy variable for having at least one male household member with salaried employment (Klasen and Pieters 2015). Thirdly, we include the landholding of the household to account for their wealth level. Fourthly, we include the type of house the female resides in, i.e., kutcha, semi-pucca, and pucca. Fifthly, we also include an indicator variable for having at least one air conditioner/air cooler to account for differences in wealth. Finally, we include the highest education attainment of a working-age male in the household. As per the previous research carried out on this subject, higher socioeconomic status, the education of male members, and the wealth of a household should all adversely impact a woman's decision to participate in the labor force. We also include other household-level controls that may adversely impact the decision of a female to participate in the labor force, such as the number of children in the household below the age of four and the number of elderly individuals in the household (those over the age of 64). We also include dummies to control for the position of the female within the household (an indicator for the cultural constraints at the intra-household level). These dummies include whether the female is the head of her household, the wife of the household head, the daughter-in-law of the household head, the unmarried daughter of the household head, and others. We also control for the caste and religion of a household to account for culturally or religiously imposed constraints on women. These constraints are expected to be strongest among upper-caste Hindus and Muslims (Klasen and Pieters 2015; Chen and Drèze 1992; Das and Desai 2003). Finally, at the household level, we also create a dummy variable that accounts for whether a household resides within 2 km of an all-weather road in rural India or within 0.5 km of a public transport facility in urban India. To control for the difference in urbanization of the local area, we include a dummy to control for the sectoral location (urban or rural) of a female. We also include the district share of male workers in agriculture, industry[5], and services[6] to account for the local labor demand factors that may impact the female decision to participate in the labor force. We further include the share of the literate population in a district to account for local labor supply factors. As pointed out in Klasen and Pieters (2015), we can expect that increasing the labor supply should reduce the probability of a female joining the labor force due to downward pressure on the wages within that district. At the state/UT level, we include the median household consumption and the child sex ratio to control for the socioeconomic characteristics of a state/UT that may impact the dependant variable. In addition to these controls, we also include regional[7] fixed effects to control for the culture differences and gender norms present in different regions of India.

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5 Industry comprises mining and quarrying, manufacturing, construction and electricity, gas and water supply.

6 Services comprise transport, storage and communication, trade, hotels and restaurants, banking and insurance, real estate, ownership of dwellings and business services, public administration, and other services.

7 We divide India into six different regions following the classification provided by the Ministry of Culture, Government of India, which divides India into different cultural zones. In the Northern Cultural Zone, we include the state/UTs of northern states, Ladakh, Himachal Pradesh, Uttarakhand, Punjab, Haryana, and Chandigarh [North Zone Cultural Center – AIMS and OBJECTIVES (culturenorthindia.com)]. In the Northern Central Zone, we include Uttar Pradesh, Madhya Pradesh, Bihar, Rajasthan and Delhi [About – NCZCC]. In the Northern Eastern Zone, we include Arunachal Pradesh, Assam, Manipur, Meghalaya, Mizoram, Nagaland, Sikkim, and Tripura [nezccindia.org.in/About/IntroNEZCC]. In the Eastern Zone, we include Jharkhand, Odisha, Chhattisgarh, and West Bengal [Eastern Zonal Cultural Center (ezcc-india.org)]. In the Western Zone, we include Gujarat, Maharashtra, Daman and Diu, Dadra and Nagar Haveli, and Goa [About West Zone Cultural Center – WZCC – West Zone Cultural Center

If M_{ihdsr} was an exogenous variable, i.e., E ($\varepsilon_{ihdsr}|M_{ihdsr}$) = 0, then we could directly isolate the impact of mobile phone use through Equation (1) using a standard probit model. In such a case, females would participate in the labor force if the expected net benefits of participation were positive, and thus the probability that a female participates in the labor force is:

$$\text{Prob}[Y_{ihdsr} = 1] = \text{Prob}[X_{ihdsr}\alpha + M_{ihdsr}\theta + \varepsilon_{ihdsr} > 0] = \phi[X_{ihdsr}\alpha + M_{ihdsr}\theta], \quad (2)$$

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

However, M_{ihdsr} can suffer from endogeneity. The 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 women's decision to participate in the labor force. For instance, it is possible that women that use mobile phones are from households that positively encourage them to participate in the labor force. Furthermore, mobile phone use or access and participation in the labor 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.

To rectify the endogeneity in the variable M_{ihdsr} we use a control function (CF) approach, which is described in Wooldridge (2014). Now, suppose the latent variable M^*_{ihdsr} is determined as:

$$M^*_{ihdsr} = X_{ihdsr}\pi_1 + Z_{ihdsr}\pi_2 + \mu_{ihdsr} \quad (3)$$

$$\text{with } M_{ihdsr} = \begin{Bmatrix} 1 & if\ a_0 < M^*_{ihdsr} \leq a_1 \\ 2 & if\ a_1 < M^*_{ihdsr} \leq a_2 \\ 3 & if\ a_2 < M^*_{ihdsr} < a_3 \end{Bmatrix},$$

where $a_1\ and\ a_2$ are unobserved cutoffs dividing the use of a mobile; $a_0 \equiv -\infty$ and $a_3 \equiv \infty$. X_{ihdsr} is the same vector of observables as in (1) and Z_{ihdsr} is an additional vector of observables that impacts the dependant variable. μ_{ihdsr} is a random error with zero mean and unit variance.

Within an ordered probit model as in (3), an underlying score is estimated as a linear function of the explanatory variables and the set of cutoffs. The probability of observing category "j" corresponds to the probability that the estimated linear function, plus random error, is within the range of the cutoffs estimated for the category, i.e., $\text{Prob}[M_{ihdsr} = \text{j}] = \text{Prob}[a_{j-1} < X_{ihdsr}\pi_1 + Z_{ihdsr}\pi_2 + \mu_{ihdsr} \leq a_j]$.

To operationalize the CF approach, we first estimate the generalized residuals $\widehat{gr_{ihdsr}}$ from (3) and then include the estimated generalized residuals as an explanatory variable in (1). For the CF approach to produce consistent estimates, we assume that D ($\varepsilon_{ihdsr}|X_{ihdsr}, M_{ihdsr}$) = D ($\varepsilon_{ihdsr}|gr_{ihdsr}$), where D(.) is a conditional distribution function. This means that gr_{ihdsr} acts as a kind of sufficient statistic for capturing the endogeneity of M_{ihdsr} (Wooldridge 2014: 7). Further, we also need to have $\pi_2 \neq 0$ to ensure that gr_{ihdsr} has variation that is not determined entirely by (X_{ihdsr}, M_{ihdsr}).

(wzccindia.com)]. In the Southern Zone, we include Andhra Pradesh, Telangana, Karnataka, Kerala, Tamil Nadu, Andaman and Nicobar Islands, Lakshadweep, and Puducherry [Szcc Annual Report (szccindia.org)].

The average marginal effects on the FLPR of using "j" category of mobile phone compared to "j-1" category of mobile phone can then be calculated as $\text{Prob}[Y_{ihdsr} = 1 \mid M_{ihdsr} = \text{j}] - \text{Prob}[Y_{ihdsr} = 1 \mid M_{ihdsr} = \text{j} - 1] = \Phi[X_{ihdsr}\alpha + \theta_{jihdsr}] - \Phi[X_{ihdsr}\alpha + +\theta_{(j-1)ihdsr}]$.

As described in Chiburis and Lokshin (2007) and Vella (1993), the generalized residuals for the model in (3) are of the following form:

$$E(\mu_{ihdsr} \mid M_{ihdsr}, X_{ihdsr}, Z_{ihdsr}) = \frac{\phi(a_{j-1} - \pi_1 X_{ihdsr} - \pi_2 Z_{ihdsr}) - \phi(a_j - \pi_1 X_{ihdsr} - \pi_2 Z_{ihdsr})}{\Phi(a_j - \pi_1 X_{ihdsr} - \pi_2 Z_{ihdsr}) - \Phi(a_{j-1} - \pi_1 X_{ihdsr} - \pi_2 Z_{ihdsr})},$$

where M_{ihdsr}=j, and $\phi(.)\ and\ \Phi(.)$ are the standard normal density and distribution function, respectively. As Vella (1993: 449) points out, the form above represents the score of the likelihood function of model (3) with respect to the intercept.

Using the form discussed above, the estimated generalized residual is calculated as:

$$\widehat{\mathrm{gr}_{\imath hdsr}} = \frac{\phi(\widehat{a_{j-1}} - \widehat{M^*_{\imath hdsr}}) - \phi(\widehat{a_j} - \widehat{M^*_{\imath hdsr}})}{\Phi(\widehat{a_j} - \widehat{M^*_{\imath hdsr}}) - \Phi(\widehat{a_{j-1}} - \widehat{M^*_{\imath hdsr}})},$$

where M_{ihdsr}=j and $\widehat{M^*_{\imath hdsr}} = \widehat{\pi_1}X_{ihdsr} + \widehat{\pi_2}Z_{ihdsr}$.

For our Instrument Z_{ihdsr} we use the state/UT-wise number of Total Push SMS Sent per capita through Mobile Seva. Total Push SMS Sent per capita is constructed by dividing the number of Push SMS sent in each state/UT through Mobile Seva (until June 2021) with the total population in each state/UT as of March 2021. In section A1 of the appendix, we give a detailed justification of the validity of our instrument.

3.2 Data Sources and Variables

We use the unit-level household and individual 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 enumerating information for 1,163,416 individuals. We further refine the dataset by including households that were in the original sample frame (not substituted due to nonresponse) and the informants within these households were cooperative and capable. As mentioned earlier, we also restrict our analysis to the working-age cohort of women within this sample, i.e., women between the ages of 15 and 64[8]. In addition, we use datasets exogenous to the MIS survey, which include data on certain state-level variables used in our model. The data for our instrument on the states/UT-wise number of Total Push SMS Sent through Mobile Seva[9] were taken from a question answered by the GOI in the upper house of the Indian parliament. The data on states/UT-wise total population were obtained from the report of the technical group on population projections that was published by the National Commission on Population in July 2020. The data on NSDP per capita were obtained from the Reserve Bank of India's (RBI) *Handbook of Statistics on Indian States* (RBI, 2020–21). The data on states/UT-wise literacy rates were obtained from the Periodic Labor Force Survey

[8] We further removed 18,478 observations due to there being no working-age male present in certain households. This exclusion is equivalent to 6% of our pre-modified sample.

[9] Rajya Sabha Session – 254 Unstarred Question No. 2001.

of India 2020–21. The data on states/UT-wise sex ratio at birth are taken from the National Health Family Survey (NFHS)-5, which was conducted between 2019 and 2021. We exclude the states/UTs of Tripura, Dadra and Nagar Haveli, Daman and Diu, Lakshadweep, and Ladakh due to the lack of availability of data within these regions on certain state-level variables. Thus, our final dataset for analysis contains a total of 276,451 working-age females distributed across India.

Table 2 provides the descriptive statistics of the variables used in our study. In our dataset, approximately 24% of working-age females are in the labor force. Female mobile phone use decreases with increasing intensity of use. Nearly 40% of Indian females do not use a mobile phone, 37% share one, and only 23% use one exclusively. The majority of females (71%) work in the rural cohort of the economy. There is also a high prevalence of marriage (74% across the country), with a negligible proportion of females being divorced. The educational attainment among working-age females remains poor, with 34% and 44% of all females having either a less-than-basic or basic level of education, respectively. Only 10% of females in the country have attained an advanced level of education, i.e., have a graduate degree or above. At the household level, 24% of females are in households where at least one person is in a regular salaried job. Nearly 4% of all females in our dataset are the heads of their respective households. A majority of working-age females (57%) belong to non-SCST Hindu households, followed by SCST Hindu households (27%) and Islamic households (10%).

Table 2: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
FLPR	276,451	0.24	0.42	0	1
Mobile Use					
Does Not Use	276,451	0.40	0.49	0	1
Shared Use	276,451	0.37	0.48	0	1
Exclusive Use	276,451	0.23	0.42	0	1
Age Group					
15–24	276,451	0.27	0.44	0	1
25–34	276,451	0.24	0.43	0	1
35–44	276,451	0.22	0.42	0	1
45–54	276,451	0.16	0.37	0	1
55–64	276,451	0.11	0.31	0	1
Marital Status					
Never Married	276,451	0.20	0.40	0	1
Currently Married	276,451	0.74	0.44	0	1
Widowed	276,451	0.05	0.23	0	1
Divorced	276,451	0.00	0.07	0	1
Highest Education Level					
Less than Basic	276,451	0.34	0.47	0	1
Basic	276,451	0.44	0.50	0	1
Intermediate	276,451	0.12	0.33	0	1
Advanced	276,451	0.10	0.30	0	1
Highest Digital Literacy Level					
None	276,451	0.78	0.42	0	1
Basic	276,451	0.06	0.24	0	1
Intermediate	276,451	0.15	0.35	0	1
Advanced	276,451	0.01	0.11	0	1

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Table 2 *continued*

Variable	Obs	Mean	Std. Dev.	Min	Max
Highest Education of Working-Age Male in HH					
Less than Basic	276,451	0.13	0.34	0	1
Basic	276,451	0.48	0.50	0	1
Intermediate	276,451	0.20	0.40	0	1
Advanced	276,451	0.20	0.40	0	1
At least One Male in the HH is a Salaried Employee	276,451	0.24	0.43	0	1
HH Per Capita Consumption Quartile					
Q1	276,451	0.24	0.42	0	1
Q2	276,451	0.25	0.43	0	1
Q3	276,451	0.26	0.44	0	1
Q4	276,451	0.26	0.44	0	1
Landholding of HH (in hectares)					
Less than 0.005	276,451	0.06	0.23	0	1
0.005–0.02	276,451	0.12	0.33	0	1
0.02–0.21	276,451	0.34	0.47	0	1
0.21–0.41	276,451	0.05	0.21	0	1
0.41–1.01	276,451	0.11	0.32	0	1
1.01–2.01	276,451	0.12	0.33	0	1
Greater than 2.01	276,451	0.20	0.40	0	1
House Type					
Kutcha	276,451	0.03	0.18	0	1
Semi-Pucca	276,451	0.11	0.31	0	1
Pucca	276,451	0.86	0.35	0	1
HH Has Possession of at Least One Air Conditioner/Air Cooler	276,451	0.20	0.40	0	1
Number of Children in the HH Aged Zero to Four	276,451	0.40	0.72	0	6
Number of Elderly in the HH Aged Over 65	276,451	0.24	0.51	0	5
Caste and Religion of HH					
Non-SCST Hindu	276,451	0.57	0.50	0	1
SCST Hindu	276,451	0.27	0.45	0	1
Islam	276,451	0.10	0.31	0	1
Other	276,451	0.05	0.22	0	1
Relation of Female to HH Head					
HH Head	276,451	0.04	0.20	0	1
Wife	276,451	0.54	0.50	0	1
Daughter-in-Law	276,451	0.17	0.37	0	1
Unmarried Daughter	276,451	0.18	0.38	0	1
Other	276,451	0.08	0.27	0	1
HH Accessibility of Roads in Rural Areas and Public Transport in Urban Areas	276,451	0.92	0.27	0	1
Sector					
Rural	276,451	0.71	0.45	0	1
Urban	276,451	0.29	0.45	0	1
District Male Employment Shares					
Agriculture	276,451	0.40	0.17	0	1
Industry	276,451	0.27	0.09	0	1
Services	276,451	0.33	0.12	0	1
District Share of Literate Workers	276,451	0.79	0.09	0	1
State/UT-Wise Child Sex Ratio	276,451	919.30	52.89	752	1,124
State/UT-Wise Log of Median HH Consumption	276,451	9.15	0.21	9	10

Source: Author’s computation of MIS data.

4. RESULTS AND ANALYSIS

4.1 Results

Table 3 reports the average marginal effects of the different independent variables, including mobile use, on the FLPR. These results are estimated using the probit model in Equation (1) (reported in Column A) and the CF method outlined in the previous section (reported in Column B). We estimate the average marginal effects over three dimensions. First, we calculate the incremental change in the probability of a working-age female entering the labor force if she shares the use of a mobile phone compared to no mobile phone. Second, we estimate a similar change in probability for a working-age female who exclusively uses a mobile phone compared to no use. Finally, we estimate this change for a female who uses a mobile phone exclusively compared to shared use. The results of the probit model (Column A) indicate that there is a positive and statistically significant association between increasing mobile use and the FLPR across all three dimensions. We estimate that using a shared mobile phone compared to no mobile phone increases the probability of a female participating in the labor force by 5 percentage points (pp). On transitioning from shared mobile use to exclusive use, a female increases her probability of labor force participation by 3.6 pp. Both of these effects are statistically significant. Thus, using an exclusive mobile phone compared to no use increases the probability of a female participating in the labor force by 8.6 pp. As mentioned in Section 2, the first effect is the digital access effect while the latter elucidates the digital inclusion effect. However, on addressing the endogeneity concerns, both the digital access and the digital inclusion effect become statistically insignificant (Column B).

On examining the effect of the control variables, we find that the results from the probit model (Column A) are similar to those from the CF approach (Column B), thus showing the robustness of our results. The results indicate that the probability of participating in the labor force is the highest for females within the age group 35 to 44. We also find that the relationship between the FLPR and the highest educational attainment of a female follows a U-shaped distribution, with the highest- and lowest-educated female having the highest probability of being in the labor force. On examining the impact of marital status on the FLPR, we find there is no statistically significant impact of mobile phone use on FLPR for married females as compared to never-married females. This effect is different for divorced females, where the effect of mobile phone use on FLPR is positive and significant. Our results show that all indicators of household income, wealth, and male education have a negative and statistically significant impact on the FLPR. This finding is similar to previous research on this subject in India (Klasen and Pieters 2015; Sarkar, Sahoo, and Klasen 2019). Looking at geographical controls, we find that the effect of mobile phone use on FLPR is lower in urban than in rural India. Finally, we observe that labor supply indicators lower the probability of a female joining the labor force, labor demand indicators increase the probability of FLPR towards services and agriculture sectors. These findings are similar to the existing trends of the FLPR in India (Fernández and Puri 2023).

Table 3: Average Marginal Effects of Determinants of FLPR

	(A) Probit	(B) Control Function	(C) Control Function	(D) Joint MLE
	FLPR	FLPR	FLPR	FLPR
Mobile Use (Ref. = Does Not Use)				
Shared Use	0.050***	0.040	0.038	0.027
	(0.0053)	(0.035)	(0.035)	(0.094)
Exclusive Use	0.086***	0.066	0.067	0.039
	(0.0055)	(0.076)	(0.077)	(0.19)
Age Group (Ref. = 15–24)				
25–34	0.12***	0.12***	0.12***	0.12***
	(0.0048)	(0.0063)	(0.0063)	(0.0100)
35–44	0.17***	0.17***	0.17***	0.17***
	(0.0058)	(0.0065)	(0.0065)	(0.0059)
45–54	0.15***	0.15***	0.15***	0.14***
	(0.0063)	(0.0074)	(0.0074)	(0.0098)
55–64	0.046***	0.045***	0.044***	0.042**
	(0.0063)	(0.0099)	(0.0098)	(0.017)
Marital Status (Ref. = Never Married)				
Currently Married	–0.0069	–0.0045	–0.0046	–0.0013
	(0.013)	(0.016)	(0.016)	(0.027)
Widowed	0.0090	0.011	0.011	0.013
	(0.014)	(0.015)	(0.015)	(0.022)
Divorced	0.14***	0.15***	0.15***	0.15***
	(0.026)	(0.030)	(0.029)	(0.041)
Highest Education Level of the Woman (Ref. = Less than Basic)				
Basic	–0.079***	–0.077***	–0.077***	–0.074***
	(0.0041)	(0.0090)	(0.0090)	(0.022)
Intermediate	–0.095***	–0.091***	–0.090***	–0.084*
	(0.0060)	(0.018)	(0.018)	(0.045)
Advanced	0.095***	0.10***	0.10***	0.11
	(0.0079)	(0.029)	(0.029)	(0.073)
Highest Digital Literacy Level of the Woman (Ref. = No Digital Literacy)				
Basic	–0.018***	–0.017**	–0.017**	–0.016
	(0.0063)	(0.0070)	(0.0070)	(0.0100)
Intermediate	0.0021	0.0034	0.0031	0.0050
	(0.0043)	(0.0067)	(0.0067)	(0.013)
Advanced	0.039**	0.041**	0.040**	0.043*
	(0.020)	(0.018)	(0.018)	(0.026)
Highest Education of Working-Age Male in the HH (Ref. = Less than Basic)				
Basic	–0.031***	–0.031***	–0.031***	–0.031***
	(0.0058)	(0.0060)	(0.0060)	(0.0058)
Intermediate	–0.066***	–0.066***	–0.065***	–0.065***
	(0.0066)	(0.0075)	(0.0075)	(0.0074)
Advanced	–0.095***	–0.095***	–0.095***	–0.094***
	(0.0070)	(0.0082)	(0.0082)	(0.0090)
At least One Male in the HH Is a Salaried Employee	–0.017***	–0.016***	–0.016***	–0.015**
	(0.0042)	(0.0041)	(0.0041)	(0.0071)
HH Per Capita Consumption Quartile (Ref. = Q1)				
Q2	–0.018***	–0.018***	–0.017***	–0.017**
	(0.0060)	(0.0059)	(0.0059)	(0.0080)
Q3	–0.013*	–0.012	–0.012	–0.011
	(0.0067)	(0.0080)	(0.0080)	(0.012)
Q4	–0.038***	–0.036***	–0.036***	–0.033
	(0.0078)	(0.012)	(0.012)	(0.023)
Landholding of the HH in Hectares (Ref. = less than 0.005–01)				
0.005–0.02	0.0058	0.0055	0.0055	0.0051
	(0.0083)	(0.0085)	(0.0085)	(0.0089)
0.02–0.21	–0.0049	–0.0048	–0.0049	–0.0048
	(0.0077)	(0.0073)	(0.0073)	(0.0077)
0.21–0.41	0.00026	0.00040	0.00022	0.00058
	(0.011)	(0.011)	(0.011)	(0.011)

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Table 3 *continued*

	(A) Probit	(B) Control Function	(C)	(D) Joint MLE
	FLPR	FLPR	FLPR	FLPR
0.41–1.01	0.027***	0.026***	0.026***	0.026***
	(0.0094)	(0.0092)	(0.0092)	(0.0098)
1.01–2.01	0.062***	0.061***	0.061***	0.060***
	(0.0092)	(0.0097)	(0.0097)	(0.011)
Greater than 2.01	0.100***	0.099***	0.099***	0.098***
	(0.0097)	(0.010)	(0.010)	(0.013)
HH Type (Ref. = Katcha)				
Semi–Pucca	0.058***	0.059***	0.058***	0.059***
	(0.011)	(0.012)	(0.012)	(0.012)
Pucca	–0.015	–0.014	–0.014	–0.013
	(0.0096)	(0.011)	(0.011)	(0.013)
HH Has Possession of at Least One Air Conditioner/Air Cooler	0.0074	0.0077	0.0076	0.0082
	(0.0061)	(0.0057)	(0.0057)	(0.0069)
Number of Children in the HH Aged Zero to Four	–0.014***	–0.014***	–0.014***	–0.014***
	(0.0026)	(0.0029)	(0.0029)	(0.0030)
Number of Elderly in the HH Aged over 65	0.00066	0.00080	0.00080	0.00099
	(0.0031)	(0.0036)	(0.0036)	(0.0034)
Caste and Religion of HH (Ref. = Non-SC-ST Hindu)				
SC-ST Hindu	0.060***	0.059***	0.059***	0.058***
	(0.0053)	(0.0065)	(0.0064)	(0.0088)
Muslim	–0.078***	–0.079***	–0.079***	–0.079***
	(0.0077)	(0.0079)	(0.0079)	(0.0078)
Others	0.038***	0.039***	0.039***	0.041***
	(0.0085)	(0.0091)	(0.0092)	(0.013)
Relation of Female to HH Head (Ref. = female is the HH head)				
Wife of HH Head	–0.16***	–0.16***	–0.16***	–0.16***
	(0.010)	(0.017)	(0.017)	(0.029)
Daughter-in-Law of HH Head	–0.23***	–0.23***	–0.23***	–0.24***
	(0.011)	(0.017)	(0.017)	(0.030)
Unmarried Daughter of HH Head	–0.17***	–0.18***	–0.18***	–0.18***
	(0.015)	(0.020)	(0.020)	(0.032)
Other Relation to HH Head	–0.20***	–0.20***	–0.20***	–0.21***
	(0.0099)	(0.016)	(0.016)	(0.030)
HH Access to Roads in Rural Areas and Public Transport in Urban Areas	0.014	0.014*	0.014*	0.015
	(0.0084)	(0.0081)	(0.0081)	(0.0095)
Sector (Ref. = Rural)				
Urban	–0.054***	–0.054***	–0.054***	–0.053***
	(0.0058)	(0.0060)	(0.0060)	(0.0072)
District Male Employment Shares (Ref. = Agriculture)				
Industry	–0.067**	–0.064**	–0.064**	–0.061
	(0.033)	(0.032)	(0.032)	(0.042)
Services	0.062**	0.064**	0.064**	0.067**
	(0.027)	(0.026)	(0.026)	(0.032)
District Share of Literate Workers	–0.19***	–0.18***	–0.18***	–0.17*
	(0.046)	(0.062)	(0.062)	(0.088)
State/UT-Wise Child Sex Ratio	0.00032***	0.00032***	0.00032***	0.00032***
	(0.000065)	(0.000066)	(0.000066)	(0.000066)
State/UT-Wise Log of Median HH Consumption	0.16***	0.16***	0.16***	0.16***
	(0.021)	(0.021)	(0.021)	(0.021)
Control Function Residual		0.0076	0.0081	
		(0.029)	(0.029)	
Rho				0.067
				(0.28)
Controls	Yes	Yes	Yes	Yes
Regional Fixed Effects	Yes	Yes	Yes	Yes
Pseudo R Square	0.139	0.139	0.139	
N	276,451	276,451	276,451	276,451

Notes: (i) Standard errors in parentheses are clustered at the primary sampling units, * p < 0.1, ** p < 0.05, *** p < 0.01.

(ii) The standard errors for the control function estimates are based on 100 bootstrap replications with seed 1234, clustered at the primary sampling units.

4.2 Robustness Checks

To check the robustness of our results, we estimate two more models. In Column C we estimate the CF model as in Column B but also include the square of the generalized residual to control for the nonlinearity present within the residual (Wooldridge 2015). In Column D, we estimate a joint maximum likelihood estimation of Equations (1) and (3). In this case, we assume that the unobserved determinants of a woman's decision to use a mobile phone and the unobserved determinants of a woman's decision to participate in the labor force are correlated, with ε_{ihdsr} and μ_{ihdsr} following bivariate normal distribution, with E [ε_{ihdsr}] = E [μ_{ihdsr}] = 0, var [ε_{ihdsr}] = var [μ_{ihdsr}] = 1, and cov [$\varepsilon_{ihdsr}, \mu_{ihdsr}$] = ρ. If the error terms ε_{ihdsr} and μ_{ihdsr} are correlated, then the outcomes are endogenously determined (Fabbri, Monfardini, and Radice, 2004). In Columns C and D of Table 3, we see that the effects of mobile use and other controls on the FLPR are similar to those estimated in our initial CF approach, thereby showing the robustness of our results.

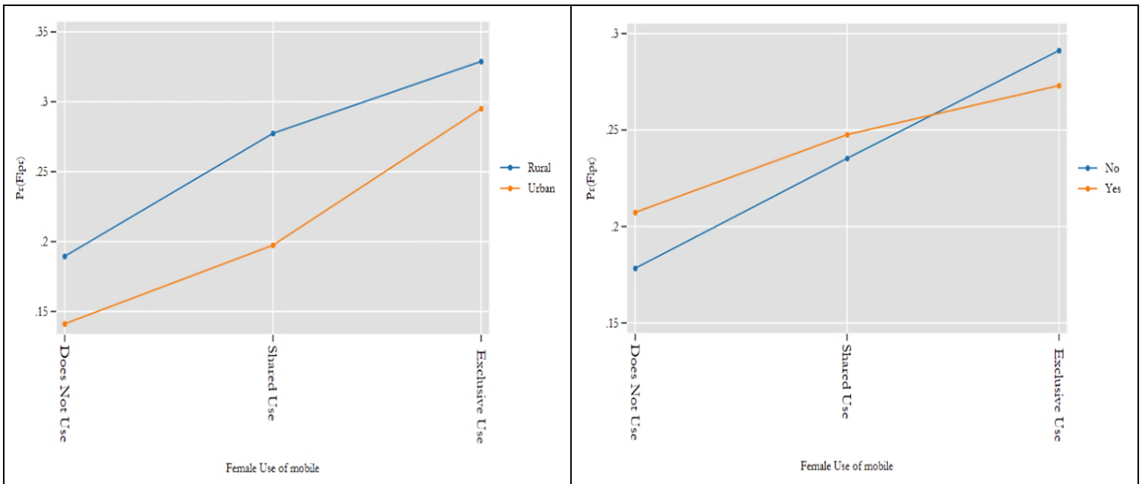
4.3 Heterogeneity Analysis

4.3.1 Location

Figure 3(a) shows the impact of mobile use across sectoral location on the probability of a female joining the labor force. Figure 3(b) shows the same impact across households located within 2 km of an all-weather road in rural India or within 0.5 km of a public transport facility in urban India. Table A2 elucidates in detail the average marginal effects across these heterogeneous groupings.

We find that for both rural and urban cohorts of the Indian economy, the digital access effect is positive and significant. However, the digital inclusion effect is only positive and significant for the urban cohorts. This is in contrast to rural India, wherein the effect of mobile phones on FLPR is primarily driven by the digital inclusion channel (exclusive use of mobile phones). Furthermore, we find that the impact of mobile phone on FLPR is not affected by the access to transportation infrastructure.

Figure 3: Average Marginal Effects of Mobile Use on FLPR across Locations



(a) Sector **(b) Accessibility**

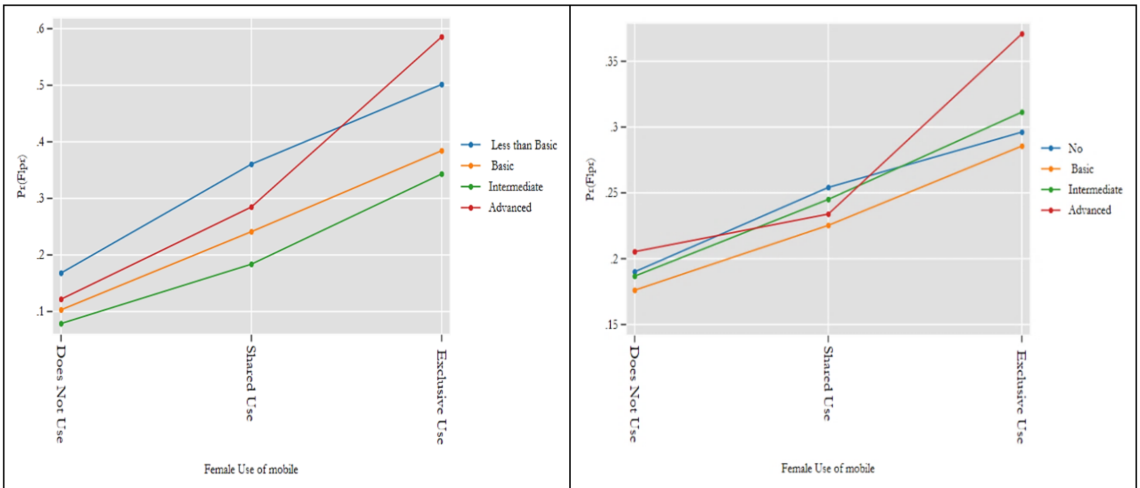
Source: Author's computation of MIS data.

4.3.2 Literacy

Figure 4(a) shows the impact of mobile use across the foundational literacy of a female on the probability of a female joining the labor force. Figure 4(b) shows the same impact across female digital literacy attainment. Table A2 elucidates in detail the average marginal effects across these heterogeneous groupings.

We find that the digital access effect is more dominant for less-than-basic and basic levels of foundational literacy, while the digital inclusion effect is more dominant for intermediate and advanced levels of foundational literacy. This implies that as females become more educated, they are better able to leverage the benefits from exclusive mobile use in determining their labor force participation status. However, the levels of digital literacy do not seem to have a significant impact on their labor force participation decision, particularly for females possessing lower levels of digital literacy. Furthermore, we find that females with intermediate levels of digital literacy begin to leverage mobile phones for the FLPR, with this effect becoming more prominent with advanced levels of digital literacy.

Figure 4: Average Marginal Effects of Mobile Use on FLPR across Literacy



(a) Foundational Literacy **(b) Digital Literacy**

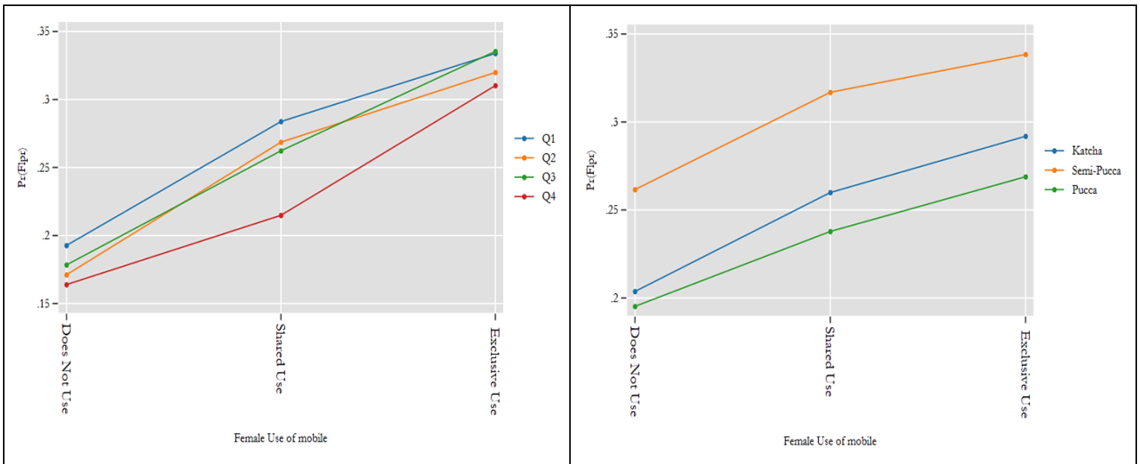
Source: Author's computation of MIS data.

4.3.3 Prosperity

Figure 5(a) shows the impact of mobile use across household consumption quartiles on the probability of a female in that household joining the labor force. Figure 5(b) shows the same impact across the wealth of the households indicated by the type of material used in household construction. Table A2 elucidates in detail the average marginal effects across these heterogeneous groupings.

We find that females residing in households within the top quartile of consumption per capita are able to leverage the digital inclusion effect for increasing their probability of labor force participation. For females belonging to households in all other quartiles, the digital access effect dominates their decision to join the labor force. This effect is not surprising given that nearly 52% of women in the top quartile have an exclusive mobile phone, which is much higher than the average for all three preceding quartiles. In contrast, the effect of mobile use on the FLPR is insignificant across the wealth categories of households.

Figure 5: Average Marginal Effects of Mobile Use on FLPR across Prosperity



(a) Income (b) Wealth

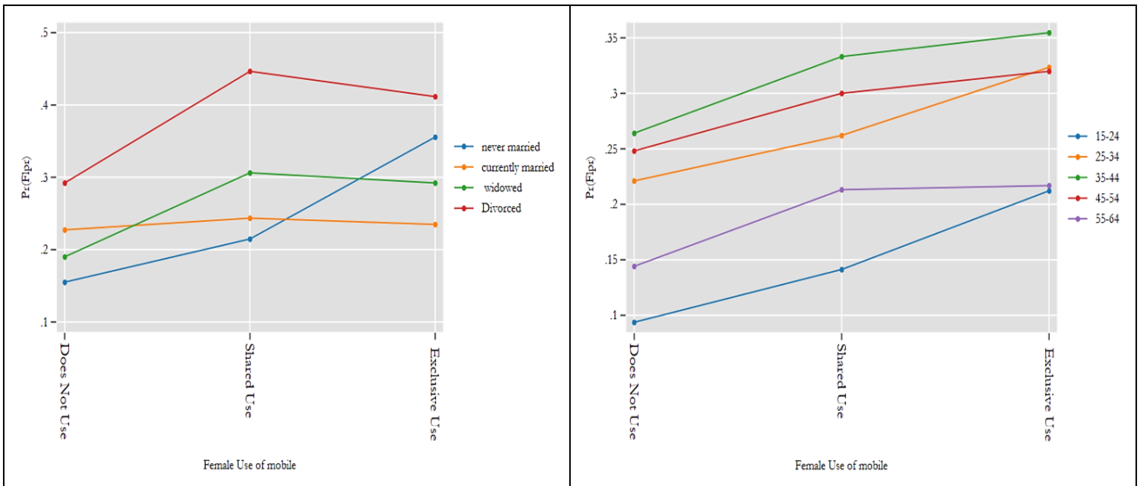
Source: Author's computation of MIS data.

4.3.4 Demography

Figure 6(a) shows the impact of mobile use across female marital status on the probability of a female joining the labor force. Figure 6(b) shows the same impact across the different age groups for a female. Table A2 elucidates in detail the average marginal effects across these heterogeneous groupings.

We find that the impact of mobile use on the FLPR is only significant for women that have never been married, with the digital inclusion effect being dominant. A similar result is found for women within the age group 15 to 24. Therefore, never-married females between the ages of 15 and 24 are the most likely to leverage an exclusive mobile phone to increase their chances of being in the labor force.

Figure 6: Average Marginal Effects of Mobile Use on FLPR across Demography



(a) Marital Status (b) Age Group

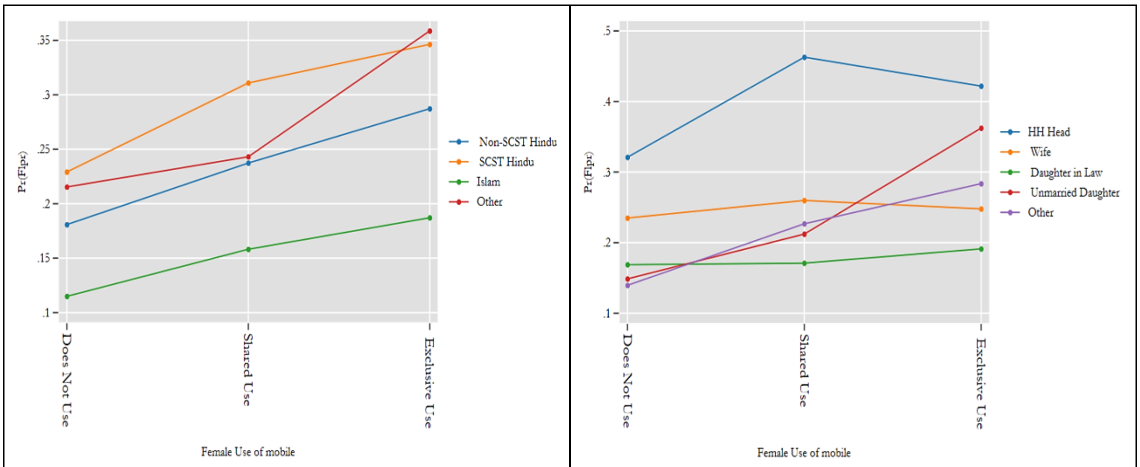
Source: Author's computation of MIS data.

4.3.5 Culture

In this subsection, we see the impact of mobile use on the probability of joining the labor force through cultural channels. We proxy these channels through two indicators mentioned below. Figure 7(a) shows the impact of mobile use by females belonging to different religions and castes on the probability of those females joining the labor force. Figure 7(b) shows the same impact across females that are in different positions in their respective households. These positions may impose different cultural constraints on a female, thereby impacting her ability to leverage the mobile phone to participate in the labor force. Table A2 elucidates in detail the average marginal effects across these heterogeneous groupings.

We find that digital access has a positive and significant impact on the decision of females to be in the labor force for those belonging to both non-SCST and SCST Hindu households. However, this impact is missing for females belonging to Islamic households, where culture restrictions are known to be more prominent (Klasen and Pieters 2015). Furthermore, the impact of digital inclusion is negligible for all three of the cohorts mentioned above, with the exception of females belonging to households in other religious groups. We find that females in this cohort significantly leverage exclusive mobile use to increase their probability of labor force participation. On looking at the position of females in the household, we find the digital inclusion effect is the strongest for unmarried daughters, while the digital access effect is strongest for female household heads.

Figure 7: Average Marginal Effects of Mobile Use on FLPR across Demography



(a) Caste and Religion **(b) Position in Household**

Source: Author's computation of MIS data.

5. CONCLUSION AND POLICY RECOMMENDATIONS

Mobile phone use has been instrumental in improving development outcomes globally. We examine the causal impact of mobile phone use (shared and exclusive) on the FLPR in India. We decompose the impact into two channels, namely a digital access channel (shared versus no use) and a digital inclusion channel (exclusive versus shared access). Using an instrumental variable approach, we find that there is no significant impact of either digital access or inclusion on the FLPR in India. Disaggregating this impact on various cohorts of the sample, we find that the digital access impact is strongest for households in the rural economy, for females residing in households within the lower consumption quartile, for women with basic and less-than-basic levels of education, and for households with a female head. Moreover, the digital inclusion effect is more pronounced for females residing within the urban economy, for those that belong to households that are within the higher consumption quartiles, and for unmarried daughters in the household.

This study has various policy implications, not only for India but for many emerging economies across the globe. While digital access to mobile phones, among other digital infrastructure assets, has increased over the years, the power to leverage these assets becomes larger only when women are provided with exclusive use of a mobile phone. Furthermore, there is huge inequality in the ability to leverage mobile phones for labor force participation across urban and rural India, with women in rural India having a much lower digital inclusion effect. Hence, improving the digital literacy in rural India will have promising benefits in terms of female labor force participation. However, providing a mobile phone is only half the battle won, as users need to be equipped to use them appropriately. Hence, governments and policymakers should focus on providing increasing levels of digital literacy to enable women to leverage the power of digital infrastructure. Second, policymakers should invest in firms that provide gig employment opportunities to complement the effect of mobile use on labor participation. Expanding the reach of gig employment opportunities can have a positive spillover effect on labor force participation, especially for females. While digital infrastructure has proven to be beneficial for labor 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 India. A similar analysis at a cross-country level would be promising as it could provide insights that would facilitate understanding how technology plays a role in fostering labor market participation in emerging and developed countries.

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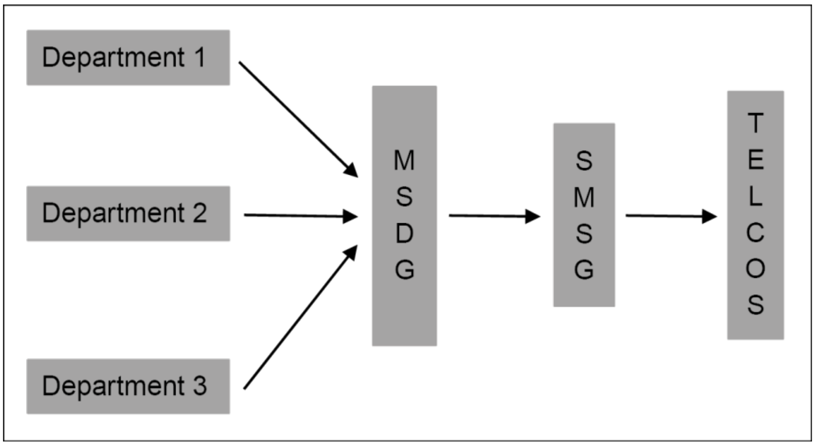
APPENDIX

Section A1: Validity of Instrument

Our instrument measures the cumulative number of Push SMS Sent per capita (until June 2021) at the state/UT level through Mobile Seva. The Mobile Seva project was launched by the Government of India (GOI) in July 2011 as the country's first federally hosted cloud-based platform for all government departments and agencies to deliver mobile-based services via various channels, such as SMS, USSD, IVRS, and mobile apps (Kumar 2014). Under this project, the GOI developed and currently maintains a Mobile Services Delivery Gateway (MSDG) to enable public services to be delivered through mobile devices. This infrastructure is shared by both federal and state government departments and agencies at a nominal cost. While the MSDG is used to disseminate several Mobile Seva services to mobile devices, we are particularly interested in the role of the SMS Gateway (SMSG) component, which supports both push- and pull-based messaging services. According to the GOI, push services can be a significant channel through which common informational services can be disseminated to citizens as a group. These Push SMS notifications can be sent to specific individuals/groups or in bulk (using their respective mobile numbers) by each department at the federal/state level. For our instrument Z_{ihdsr} we specifically look at the cumulative SMS dissemination per capita undertaken by different government departments within each state/UT. As of June 2021, 3,530 state/UT-level government departments and agencies were integrated within the MSDG.[1] Figure A1 exhibits the flow of Push SMS sent by a government department/agency to Telecom operators (TELCOS), which then disseminate them to their subscribers.

Figure A1: Flow of Push SMS through MSDG in Mobile Seva



[1] Rajya Sabha Session – 254 Unstarred Question No. 2001.

If our instrument is valid, then (i) it must be sufficiently correlated with female mobile phone use, i.e., Corr $(M_{ihdsr}, Z_{ihdsr}) \neq 0$, but (ii) it must not be a determinant of the decision of a female to participate in the labor force, i.e., it must not be correlated with the error term ε_{ihdsr}.

The first part is relatively easy to prove. Our primary goal is to exploit the inter-state/UT variation in the total SMS sent per capita, as we hypothesize that states/UTs with higher SMS sent per capita would have greater mobile use among their population. For this instrument to be relevant, it should be positively correlated to the use of mobiles among females in India. First, we check this relevance by calculating the correlation of our instrument with mobile phone use in India across males and females. We find that our instrument has a positive correlation of 5.48% and 9.96% with mobile phone use by males and females, respectively. Thus, not only does the instrument have a sufficiently high correlation with mobile phone use among both males and females, but it's particularly high for females. Second, we statistically test the significance of π_2 in Equation (3). As we observe in Table A3 of the appendix, π_2 is positive and statistically significant for all the models estimated in our study, further showcasing the instrument's relevance.

The second part is trickier to prove through any specific statistical tests, leading us to rely primarily on economic theory for the proof. All of the infrastructure costs for setting up and maintaining the MSDG are borne by the federal government, thus making the setup cost for state governments effectively nil. However, the dissemination of SMS is still the prerogative of state departments/agencies. Thus, to prove that the exclusion restriction holds, we would need to prove that the dissemination of SMS is not determined by any unobserved state/UT-level characteristics that may impact the FLPR in that state/UT. A major concern regarding the validity of our instrument is that the quality of institutions/governance in a states/UT could impact the dissemination of SMS through Mobile Seva. Another concern is that the demand for information and knowledge could determine SMS dissemination in states/UTs. Given that the demand for information could be linked to the level of education and knowledge in the population, it is important to test whether more SMS are being disseminated in more literate states/UTs. Finally, given the urban-rural divide in mobile phone penetration[2] in India, the share of the population living in the rural area of a state/UT could also be a determinant of SMS dissemination. If any of the three determinants mentioned above had a statistically significant impact on our instrument, it could violate the exclusion restriction. To check this statistically, we estimate a simple ordinary least squares (OLS) model:

$$SMS\_PerCapita_{sr} = D_{sr}\beta + X_{sr}\alpha + \gamma_r + w_{sr}, \quad (1)$$

where D_{sr} is one of the three determinants mentioned above in state "s" and region "r," X_{sr} is a vector of observable state/UT-level socioeconomic characteristics, γ_r are the regional fixed effects, and w_{sr} is a random error.

[2] According to the MIS survey, nearly 50% of Indians in rural India and 67% of Indians in urban India have some sort of access to mobile phones.

In Table A1 we show the results of the four models that we estimate to test the exclusion restriction of our instrument. In Column (A), we test whether the strength of institutions/governance in states/UTs impacts our instrument. We use the state/UT-wise Good Governance Index (GGI)[3] score for 2020–21 for this purpose. In Column (B), we include the basic literacy level of each state/UT to check whether that could impact the dissemination of our instrument. In Model (C), we check whether the degree of rural population in each state/UT (or alternatively urbanization) impacts our instrument. Finally, in Model (D), we include all three determinants mentioned above to check their impact on our instrument. As we observe in Table A1, none of these factors have a statistically significant relation with our instrument, thus showcasing its exogeneity.

Table A1: OLS Estimates of Determinants of State/UT-wise No. of Total Push SMS Sent per Capita

	(A) State/UT-wise SMS per Capita Sent through Mobile Seva	(B) State/UT-wise SMS per Capita Sent through Mobile Seva	(C) State/UT-wise SMS per Capita Sent through Mobile Seva	(D) State/UT-wise SMS per Capita Sent through Mobile Seva
State/UT-Wise Good Governance Index 2020–21	4.76			4.45
	(6.45)			(5.90)
State/UT-Wise Log of NSDP per capita at constant prices	–2.15	–2.26	–4.06	–5.01
	(3.12)	(3.75)	(6.77)	(6.86)
State/UT-Wise Sex Ratio at Birth 2019–21 (NFHS-5)	–0.11	–0.11	–0.10	–0.10
	(0.067)	(0.066)	(0.069)	(0.069)
State/UT-Wise Literacy Rate above age of 7		0.36		0.22
		(0.76)		(0.78)
State/UT-Wise Rural Share of Population			–10.6	–6.75
			(20.6)	(18.7)
_cons	109.3	102.9	155.7*	127.4
	(73.5)	(82.3)	(80.9)	(110.7)
Controls	Yes	Yes	Yes	Yes
Regional Fixed Effects	Yes	Yes	Yes	Yes
N	32	32	32	32
R^2	0.387	0.389	0.384	0.402
adj. R^2	0.174	0.176	0.170	0.118
VIF	2.41	2.34	2.33	2.98

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

[3] GGI 2020–21 was released by the Department of Administrative Reforms and Public Grievances, Government of India. It is "a comprehensive and implementable framework to assess the State of Governance in all the States and UTs" (GGI Report 2020–21).

Section A2: Other Tables

Table A2: Average Marginal Effects of Mobile Use on FLPR in India

		Digital Access	Digital Inclusion
Sector	Rural	0.09**	0.05
		(0.036)	(0.044)
	Urban	0.06**	0.10**
		(0.028)	(0.046)
Per Capita Consumption Quartile	Q1	0.09**	0.05
		(0.041)	(0.045)
	Q2	0.10***	0.05
		(0.036)	(0.046)
	Q3	0.08**	0.07
		(0.036)	(0.047)
	Q4	0.05*	0.10*
		(0.030)	(0.049)
Age Group	15–24	0.05*	0.07*
		(0.024)	(0.041)
	25–34	0.04	0.06
		(0.039)	(0.051)
	35–44	0.07	0.02
		(0.019)	(0.052)
	45–54	0.05	0.02
		(0.045)	(0.048)
	55–64	0.07*	0.004
		(0.038)	(0.037)
Marital Status	Never Married	0.06*	0.14***
		(0.035)	(0.051)
	Currently Married	0.02	–0.01
		(0.039)	(0.041)
	Widowed	0.12***	–0.01
		(0.041)	(0.044)
	Divorced	0.15**	–0.03
		(0.071)	(0.078)
Highest Education Level	Less than Basic	0.19***	0.14***
		(0.044)	(0.049)
	Basic	0.14***	0.14***
		(0.029)	(0.052)
	Intermediate	0.10***	0.16***
		(0.021)	(0.052)
	Advanced	0.16***	0.30***
		(0.024)	(0.053)

continued on next page

Table A2 *continued*

		Digital Access	Digital Inclusion
Caste and Religion	Non-SCST Hindu	0.06*	0.05
		(0.034)	(0.045)
	SCST Hindu	0.08*	0.04
		(0.041)	(0.045)
	Islam	0.04	0.03
		(0.030)	(0.035)
	Other	0.03	0.12**
		(0.038)	(0.051)
Relation to HH Head	HH Head	0.14***	–0.04
		(0.049)	(0.053)
	Wife of HH Head	0.02	–0.01
		(0.040)	(0.041)
	Daughter-in-Law of HH Head	0.002	0.02
		(0.033)	(0.037)
	Unmarried Daughter of HH Head	0.06*	0.15***
		(0.034)	(0.051)
	Other relation to HH Head	0.09**	0.06
		(0.034)	(0.047)
Access Mobility	No	0.06	0.06
		(0.037)	(0.043)
	Yes	0.04	0.025
		(0.035)	(0.041)
Digital Literacy	No	0.06*	0.04
		(0.038)	(0.045)
	Basic	0.05	0.06
		(0.034)	(0.049)
	Intermediate	0.06*	0.07
		(0.033)	(0.049)
	Advanced	0.03	0.14*
		(0.054)	(0.073)
House Type	Kutcha	0.06	0.03
		(0.045)	(0.048)
	Semi-Pucca	0.06	0.02
		(0.045)	(0.046)
	Pucca	0.04	0.03
		(0.035)	(0.043)
Controls		Yes	Yes
Regional Fixed Effects		Yes	Yes

The standard errors for the estimates are based on 100 bootstrap replications at seed 1234, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Determinants of FLPR in India

	Probit	Control Function		Control Function		Joint MLE	
	FLPR	Mobile Use	FLPR	Mobile Use	FLPR	Mobile Use	FLPR
Mobile Use (Ref. = Does Not Use)							
Shared Use	0.19***		0.16		0.15		0.10
	(0.021)		(0.14)		(0.14)		(0.37)
Exclusive Use	0.32***		0.25		0.25		0.15
	(0.021)		(0.28)		(0.28)		(0.72)
Age Group (Ref. = 15–24)							
25–34	0.50***	0.14***	0.50***	0.14***	0.50***	0.14***	0.51***
	(0.021)	(0.015)	(0.025)	(0.015)	(0.025)	(0.015)	(0.031)
35–44	0.67***	–0.013	0.67***	–0.013	0.67***	–0.013	0.67***
	(0.024)	(0.018)	(0.027)	(0.018)	(0.027)	(0.018)	(0.026)
45–54	0.59***	–0.14***	0.58***	–0.14***	0.58***	–0.14***	0.58***
	(0.026)	(0.020)	(0.030)	(0.020)	(0.030)	(0.020)	(0.043)
55–64	0.21***	–0.37***	0.21***	–0.37***	0.21***	–0.37***	0.20**
	(0.029)	(0.024)	(0.044)	(0.024)	(0.044)	(0.023)	(0.077)
Marital Status (Ref. = Never Married)							
Currently Married	–0.026	0.43***	–0.017	0.43***	–0.017	0.43***	–0.0048
	(0.047)	(0.040)	(0.059)	(0.040)	(0.059)	(0.038)	(0.10)
Widowed	0.033	0.30***	0.040	0.30***	0.040	0.30***	0.049
	(0.050)	(0.041)	(0.056)	(0.041)	(0.056)	(0.041)	(0.082)
Divorced	0.48***	0.52***	0.49***	0.52***	0.49***	0.52***	0.50***
	(0.083)	(0.059)	(0.095)	(0.059)	(0.094)	(0.066)	(0.13)
Highest Education Level of the Woman (Ref. = Less than Basic)							
Basic	–0.30***	0.32***	–0.29***	0.32***	–0.29***	0.32***	–0.28***
	(0.015)	(0.013)	(0.031)	(0.013)	(0.031)	(0.013)	(0.078)
Intermediate	–0.37***	0.79***	–0.35***	0.79***	–0.35***	0.79***	–0.32*
	(0.024)	(0.019)	(0.071)	(0.019)	(0.071)	(0.018)	(0.18)
Advanced	0.30***	1.10***	0.33***	1.10***	0.33***	1.10***	0.36
	(0.025)	(0.021)	(0.092)	(0.021)	(0.093)	(0.021)	(0.23)
Highest Digital Literacy Level of the Woman (Ref. = No Digital Literacy)							
Basic	–0.069***	0.14***	–0.066**	0.14***	–0.066**	0.14***	–0.062
	(0.025)	(0.019)	(0.028)	(0.019)	(0.028)	(0.019)	(0.039)
Intermediate	0.0081	0.22***	0.013	0.22***	0.012	0.22***	0.019
	(0.016)	(0.012)	(0.025)	(0.012)	(0.025)	(0.013)	(0.047)
Advanced	0.14**	0.33***	0.15**	0.33***	0.14**	0.34***	0.15*
	(0.068)	(0.047)	(0.064)	(0.047)	(0.064)	(0.044)	(0.089)
Highest Education of Working-Age Male in the HH (Ref. = Less than Basic)							
Basic	–0.11***	0.0032	–0.11***	0.0032	–0.11***	0.0030	–0.11***
	(0.020)	(0.016)	(0.021)	(0.016)	(0.021)	(0.016)	(0.020)
Intermediate	–0.24***	0.050***	–0.24***	0.050***	–0.24***	0.050***	–0.24***
	(0.024)	(0.019)	(0.027)	(0.019)	(0.027)	(0.019)	(0.028)
Advanced	–0.36***	0.11***	–0.36***	0.11***	–0.36***	0.11***	–0.36***
	(0.026)	(0.022)	(0.030)	(0.022)	(0.030)	(0.021)	(0.037)
At least One Male in the HH Is a Salaried Employee	–0.064***	0.11***	–0.061***	0.11***	–0.061***	0.11***	–0.058**
	(0.016)	(0.013)	(0.015)	(0.013)	(0.015)	(0.013)	(0.027)
HH Per Capita Consumption Quartile (Ref. = Q1)							
Q2	–0.068***	0.096***	–0.066***	0.096***	–0.065***	0.096***	–0.063**
	(0.022)	(0.021)	(0.022)	(0.021)	(0.022)	(0.019)	(0.030)
Q3	–0.048*	0.17***	–0.044	0.17***	–0.043	0.17***	–0.039
	(0.025)	(0.022)	(0.029)	(0.022)	(0.029)	(0.021)	(0.045)
Q4	–0.14***	0.39***	–0.14***	0.39***	–0.14***	0.39***	–0.12
	(0.030)	(0.026)	(0.044)	(0.026)	(0.044)	(0.024)	(0.090)
Landholding of the HH in Hectares (Ref. = less than 0.005–01)							
0.005–0.02	0.023	–0.053	0.022	–0.053	0.022	–0.054*	0.020
	(0.033)	(0.033)	(0.034)	(0.033)	(0.034)	(0.033)	(0.036)
0.02–0.21	–0.020	0.0036	–0.020	0.0036	–0.020	0.0040	–0.019
	(0.031)	(0.031)	(0.030)	(0.031)	(0.030)	(0.032)	(0.031)
0.21–0.41	0.0011	0.027	0.0016	0.027	0.00088	0.027	0.0023
	(0.044)	(0.039)	(0.044)	(0.039)	(0.044)	(0.039)	(0.044)
0.41–1.01	0.10***	–0.047	0.10***	–0.047	0.10***	–0.047	0.10***
	(0.037)	(0.035)	(0.036)	(0.035)	(0.036)	(0.036)	(0.039)

continued on next page

Table A3 *continued*

	Probit	Control Function		Control Function		Joint MLE	
	FLPR	Mobile Use	FLPR	Mobile Use	FLPR	Mobile Use	FLPR
1.01–2.01	0.23***	–0.10***	0.23***	–0.10***	0.23***	–0.10***	0.23***
	(0.036)	(0.034)	(0.037)	(0.034)	(0.037)	(0.035)	(0.045)
Greater than 2.01	0.36***	–0.13***	0.36***	–0.13***	0.36***	–0.13***	0.35***
	(0.036)	(0.036)	(0.039)	(0.036)	(0.039)	(0.035)	(0.050)
HH Type (Ref. = Katcha)							
Semi-Pucca	0.20***	0.061*	0.21***	0.061*	0.21***	0.062	0.21***
	(0.041)	(0.037)	(0.045)	(0.037)	(0.045)	(0.038)	(0.042)
Pucca	–0.056	0.18***	–0.052	0.18***	–0.052	0.18***	–0.048
	(0.036)	(0.033)	(0.040)	(0.033)	(0.040)	(0.034)	(0.049)
HH Has Possession of at Least One Air Conditioner/Air Cooler	0.028 (0.023)	0.056*** (0.017)	0.029 (0.022)	0.056*** (0.017)	0.029 (0.022)	0.056*** (0.017)	0.031 (0.026)
Number of Children in the HH Aged Zero to Four	–0.053*** (0.0097)	–0.031*** (0.0087)	–0.054*** (0.011)	–0.031*** (0.0087)	–0.053*** (0.011)	–0.031*** (0.0083)	–0.054*** (0.011)
Number of Elderly in the HH Aged over 65	0.0025 (0.012)	0.024** (0.011)	0.0030 (0.014)	0.024** (0.011)	0.0030 (0.014)	0.024** (0.010)	0.0037 (0.013)
Caste and Religion of HH (Ref. = Non-SC-ST Hindu)							
SC-ST Hindu	0.22***	–0.12***	0.21***	–0.12***	0.21***	–0.12***	0.21***
	(0.019)	(0.017)	(0.023)	(0.017)	(0.023)	(0.016)	(0.033)
Muslim	–0.34***	–0.034	–0.34***	–0.034	–0.34***	–0.034	–0.34***
	(0.038)	(0.026)	(0.039)	(0.026)	(0.039)	(0.023)	(0.038)
Others	0.14***	0.15***	0.14***	0.15***	0.14***	0.16***	0.15***
	(0.030)	(0.029)	(0.032)	(0.029)	(0.032)	(0.029)	(0.044)
Relation of Female to HH Head (Ref. = female is the HH head)							
Wife of HH Head	–0.50***	–0.40***	–0.51***	–0.40***	–0.51***	–0.40***	–0.52***
	(0.032)	(0.030)	(0.051)	(0.030)	(0.051)	(0.028)	(0.080)
Daughter-in-Law of HH Head	–0.80***	–0.41***	–0.81***	–0.41***	–0.81***	–0.41***	–0.82***
	(0.035)	(0.033)	(0.054)	(0.033)	(0.054)	(0.031)	(0.081)
Unmarried Daughter of HH Head	–0.57***	–0.43***	–0.58***	–0.43***	–0.58***	–0.43***	–0.59***
	(0.051)	(0.040)	(0.064)	(0.040)	(0.064)	(0.041)	(0.091)
Other Relation to HH Head	–0.67***	–0.44***	–0.68***	–0.44***	–0.68***	–0.44***	–0.69***
	(0.031)	(0.029)	(0.049)	(0.029)	(0.048)	(0.028)	(0.083)
HH Access to Roads in Rural Areas and Public Transport in Urban Areas	0.052 (0.032)	0.092*** (0.023)	0.054* (0.030)	0.092*** (0.023)	0.054* (0.030)	0.093*** (0.027)	0.056 (0.036)
Sector (Ref. = Rural)							
Urban	–0.21***	0.081***	–0.21***	0.081***	–0.21***	0.081***	–0.21***
	(0.023)	(0.019)	(0.024)	(0.019)	(0.024)	(0.020)	(0.030)
District Male Employment Shares (Ref. = Agriculture)							
Industry	–0.25**	0.52***	–0.24**	0.52***	–0.24**	0.52***	–0.23
	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.11)	(0.16)
Services	0.23**	0.32***	0.24**	0.32***	0.24**	0.32***	0.25**
	(0.10)	(0.088)	(0.098)	(0.088)	(0.098)	(0.091)	(0.12)
District Share of Literate Workers	–0.70***	1.40***	–0.67***	1.40***	–0.68***	1.41***	–0.64*
	(0.17)	(0.16)	(0.24)	(0.16)	(0.24)	(0.15)	(0.34)
State/UT-Wise Child Sex Ratio	0.0012***	0.00028	0.0012***	0.00028	0.0012***	0.00026	0.0012***
	(0.00025)	(0.00023)	(0.00025)	(0.00023)	(0.00025)	(0.00026)	(0.00025)
State/UT-Wise Log of Median HH Consumption	0.60*** (0.078)	0.062 (0.076)	0.60*** (0.079)	0.062 (0.076)	0.60*** (0.080)	0.065 (0.074)	0.60*** (0.079)
CF Residual/Rho			0.029		0.033		0.067
			(0.11)		(0.11)		(0.28)
CF Residual # CF Residual					–0.019**		
					(0.0084)		
State/UT-Wise SMS Sent per Capita		0.0037***		0.0037***		0.0035**	
		(0.00076)		(0.00076)		(0.0015)	
_cons	–6.61***		–6.65***		–6.60***		–6.69***
	(0.69)		(0.70)		(0.70)		(0.74)
cut1		2.73***		2.73***		2.74***	
		(0.66)		(0.66)		(0.65)	
cut2		3.98***		3.98***		3.99***	
		(0.66)		(0.66)		(0.65)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	276,451	276,451	276,451	276,451	276,451	276,451	276,451

Notes: (i) Standard errors in parentheses are clustered at the primary sampling units, * p < 0.1, ** p < 0.05, *** p < 0.01.

(ii) The standard errors for the control function estimates are based on 100 bootstrap replications with seed 1234, clustered at the primary sampling units.