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Narrowing the gender digital divide in Pakistan: Mobile phone ownership and female labor force participation

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Abstract

The unprecedented growth in access to mobile phones and smartphones has opened up new possibilities in the way people live and work. However, women in developing countries are unable to take advantage of this growth due to certain factors and socio-cultural norms that give rise to the gender digital divide. In this study, using the nationally representative Pakistan Social and Living Standards Measurement Survey (2019–2020), we investigate the gender and rural–urban (female) digital divide in a country with one of the most considerable digital divides. Furthermore, we employ an instrumental variable approach to study the effect of mobile or smartphone ownership on female labor force participation. The results indicate that institutional and sociocultural norms explain most of the ownership gap of mobile or smartphones between men and women. The instrumental variable approach demonstrates that mobile or smartphone ownership increases the participation of women in the labor force. We also find that the differences between observable characteristics, especially literacy and education, explain the rural–urban digital divide among females. Considering the importance of mobile or smartphone ownership in facilitating

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women's labor supply decisions, providing women with digital tools and upskilling them has wider implications for their economic well-being.

KEYWORDS

decomposition, female labor force, gender digital divide, instrumental variable, mobile or smartphone, rural–urban divide

JEL CLASSIFICATION

J16, J21, J71

1 | INTRODUCTION

In the second half of the 20th century, the world has witnessed a convergence in the economic status of men and women (Ponthieux & Meurs, 2015). However, the gender gap in economic participation and opportunities continues to widen; it is estimated to take 151 years to close this gap (World Economic Forum, 2022). Developing countries have specific characteristics and sociocultural norms that lead to significant gender gaps in employment, education, health, and autonomy (Jayachandran, 2014). These gaps are more pronounced in the labor markets. Legal restrictions to undertake economic activities, for example, opening a bank account, women's right to inheritance, and maternity leave, are associated with larger gender gaps in labor force participation in developing countries (Gonzales et al., 2015). On average, women in developing countries are more likely to be unemployed, have fewer employment opportunities, and are more likely to work in the informal sector (Antonio & Tuffley, 2014). Additionally, most women work as contributing family workers, constituting 82% of all females in informal employment (Bonnet et al., 2019).

The gender inequality in the physical world is also apparent in the digital world. Globally, around 52% of women are offline compared to 44% of men (International Telecommunication Union, 2020). However, the gender digital divide is more pronounced in the developing world, where women are 7% less likely to own a mobile phone and 18% less likely to own a smartphone (Global System for Mobile Communication, 2022). Computer access is also low in developing countries, where 54% of households in urban areas have access, while access in rural areas is only 17%. There are noticeable regional differences in the gender digital divide. South Asia is the region with the highest gender digital divide, with the widest gaps in mobile phone ownership and mobile Internet use.

Considering the pace of the fourth industrial revolution, the digital gender divide has been determined as a critical challenge to achieving gender equality (Kuroda et al., 2019). The impact of digitalization on gender equality, income, and employment has attracted considerable research interest (Alozie & Akpan-Obong, 2017; Bayes, 2001; Dettling, 2017; Hilbert, 2011; Ma, Grafton, et al., 2020; Ma et al., 2023; Rotondi et al., 2020; Viollaz & Winkler, 2022). For example, mobile phone technology in rural Uganda improves household income, gender equality, and nutrition (Sekabira & Qaim, 2017). A study on the Grameen Bank's village phone scheme shows that owning a mobile phone contributes to the generation of income through increased business transactions and information dissemination (Aminuzzaman et al., 2003). Puspitasari

and Ishii (2016) put more emphasis on information and telecommunication (ICT) literacy to narrow gender inequality in low- and middle-income countries. Therefore, knowledge and access to digital technologies can reduce gender inequality by improving women's economic status.

Mobile and smartphones have brought new possibilities and opportunities to the developing world (Aker & Mbiti, 2010). They are an important economic asset for the poor as they are more valuable than landline phones in terms of ease of carrying and using and require lower fixed costs in physical infrastructure (Lee & Jayachandran, 2009). These attributes make mobile phones a reasonable and affordable proxy for other digital devices (e.g. computers, laptops, tablets, etc.) for the poor and marginalized. Many researchers have shown a positive impact of mobile phones on the economic growth of developing countries (Andrianaivo & Kpodar, 2012; Lee et al., 2012; Waverman et al., 2005). Mobile phones affect various aspects of development such as gender equality and nutrition (Sekabira & Qaim, 2017), women physical mobility and contraceptive use (Rajkhowa & Qaim, 2022b), efficiency in agriculture (Islam & Grönlund, 2007), market performance (Jensen, 2007), individual wealth (Krell et al., 2021), income growth and subjective well-being (Ma, Nie et al., 2020; Nie et al., 2021), the status of women (Lee & Jayachandran, 2009), rural livelihoods (Sife et al., 2010), farm performance and agrochemical expenditures (Ma & Zheng, 2022; Zheng & Ma, 2021), off-farm employment, and household income (Rajkhowa & Qaim, 2022a).

Considering the importance of ICT in today's world, the study aims to achieve three objectives: (1) to examine the gender divide in traditional mobile or smartphone ownership¹ and identify the contribution of individual covariates to explaining the divide in Pakistan, (2) to investigate the effect of traditional mobile or smartphone ownership on the participation of the female labor force in Pakistan, and (3) to analyze the rural–urban divide in traditional mobile or smartphone ownership of the female sample to gain some important insights that can help policy makers understand the dynamics of participation of the female labor force in Pakistan and its relation to digital tools. We endeavor to achieve these objectives using the Social and Living Standards Measurement Survey (2019–2020), which includes a section on ICT indicators. We employ the Oaxaca Blinder decomposition to quantify the gender (objective 1) and rural–urban divide (objective 3) in traditional mobile or smartphone ownership into explained (covariate effect) and unexplained (coefficient effect) parts. Furthermore, we use the district-wise “number of mobile network franchises” as an instrument to see the effect of traditional mobile or smartphone ownership on the participation of women in the labor force.

There is a dearth of literature finding the relationship between mobile telephony and female labor force participation. Empirical literature addressing the gender digital divide and women's labor force participation focusses primarily on the use of internet (Galperin & Arcidiacono, 2021; Jiang & Luh, 2017; Viollaz & Winkler, 2022). However, the requirement for digitalization varies with the level of development and mobile phones facilitate cheap and effective communication and access to information on several services, including education, employment, health, markets, and the economy (Rotondi et al., 2020). Furthermore, different uses of mobile phones lead to differential impacts on female labor supply decisions. It depends on how much females use mobile phones for work, leisure, and home production. This study fills this gap in the literature by assessing the effect of traditional mobile or smartphone ownership on the female labor force participation in a country with the most considerable digital gender divide.

The remainder of the paper is divided into five sections. Section 2 explains the context of the study area chosen for the analysis. Section 3 briefly talks about the theoretical and conceptual framework describing how ownership of a mobile or a smartphone affects the labor force

participation of women. Section 4 describes the data and construction of the variables, and the methods we employ to perform the analysis. Section 5 discusses the results and interpretations. Finally, Section 6 provides conclusions, recommendations, and limitations.

2 | CONTEXT OF THE STUDY

Pakistan is one of the poor performers in gender equality, as it joins the lower category of countries in the Global Gender Gap Report (2022). In terms of economic participation and opportunities, the country slipped from 112th (2006) to 145th (2022). Looking at Figure A1, we can see huge differences in the labor force participation rates of men and women in Pakistan over the last three decades. Many researchers find several factors that contribute to women's low labor force participation rates. For example, Field and Vyborny (2016) found that restrictions on physical mobility outside the home pose a major obstacle to women's inclusion in Pakistan's labor market, especially in urban areas. Family size and the number of children in the household are associated with lower female labor force participation (Ejaz, 2007). Additionally, marital status and household income are found to be negatively associated with female labor force participation in Pakistan (Batool et al., 2019).

The gender digital divide is not much different from the gender divide in the labor force participation. According to GSMA (2022), South Asia has the largest difference in the ownership of mobile phones in all regions, and these differences are the largest in Pakistan. Figure 1 shows gender disparities based on access to different digitalization indicators. In terms of access to various digital tools, households have more access to mobile devices/smartphones compared to computers/laptops/tablets and the use of the Internet. Furthermore, there are noticeable gender differences in the use of the Internet and in the ownership of mobile/smart phones. However, the gender digital divide is more pronounced in rural areas than in urban areas. Jamil (2021), using qualitative analysis, identifies certain contextual factors responsible for the increased digital divide in Pakistan. These factors include educational and income inequalities, religious and cultural barriers, gender inequality, and the urban–rural divide. Furthermore, inequitable access to mobile phones and the internet in Pakistan is responsible for widening gender-based development gaps and demands the collective efforts of all stakeholders (Shahid & Arfeen, 2021).

Over the years, there has been an increase in mobile cellular subscriptions worldwide (Figure A2). Pakistan's telecommunication statistics have shown impressive growth over the last few years. Pakistan also faces a surge in mobile cellular subscriptions, accelerating from fewer than 10 inhabitants per 100 in 2005 to more than 82 inhabitants in 2021.² Along with the expansion of 3G and 4G services (Figure A3), there are around 110 million broadband subscribers in 2021. However, there is a flip side to this growth in the ICT sector.

Regarding gender disparities, the Pakistan Telecommunication Authority (2021) reports that of 182 million mobile subscriptions, only 38 million are taken by women. Considering the importance of digitalization in the financial sector and its role in grabbing economic opportunities, women make only 3.3% of the total online transactions in Pakistan. A total of 18.8 million women have branchless banking accounts for digital financial services compared to 55.7 million males.

Considering the importance of ICT in today's world, our objective is to examine the effect of ownership of traditional mobile devices or smartphones on female labor force participation in Pakistan, along with finding the factors responsible for the large gender and rural–urban (female) digital divide.



FIGURE 1 Gender digital divide in the ownership and use of different digital tools (2019–2020). [Colour figure can be viewed at wileyonlinelibrary.com]

3 | CONCEPTUAL FRAMEWORK

The conceptual framework of this study relies on the neoclassical labor supply model, which attempts to identify the determinants of individual labor supply decisions. According to this framework, an individual tries to maximize utility by allocating time between work and leisure. Therefore, the individual must allocate his time between the market and home to maximize current utility (Dettling, 2017). The theory of the allocation of time proposed by Becker (1965) argues that time spent at home is not only leisure time, but also used productively to perform different duties related to home production, for example, cooking, cleaning, shopping, caring for children and the elderly, etc. The production of commodities depends on various combinations of purchased inputs and the time used to make the final product (Dettling, 2017). For example, an individual faces a trade-off between preparing a meal and ordering ready-made food. Thus, labor supply decisions involve a trade-off between the time spent in the market (wage) and the time consumed at home. The time consumed at home is divided between leisure and home production (reservation wage). The reservation wage suggests that an individual will not work if the market wage is less than the reservation wage and vice versa (Borjas & Van Ours, 2010).

The emergence of new technologies, especially mobile and smartphones, has led to various new activities that can affect the reservation wage, for example, making calls, text messages, visiting social networks, playing games, watching videos, listening to music, and so forth. Individuals who find these activities enjoyable would want to exchange for time spent in leisure, increasing their reservation wage, and decreasing their labor market participation. According to a survey (Statista, 2022) conducted in the United States (USA), 46% of the respondents stated that on average, they spent 5–6 h on their phones, which does not include work-related activity. Sylvester (2016) uses quantitative and qualitative methods covering six developing countries

(including Pakistan) and finds that women tend to overuse (for leisure activities) mobile phones more than men. Furthermore, the results suggest that men use the mobile phone primarily for employment purposes and to make and nurture social connections. Excessive use of a mobile phone or smartphone can also lead to addiction. Various studies on mobile and smartphone addiction report a higher prevalence of addiction in boys than in girls (Basu et al., 2018; Chen et al., 2017; Gangadharan et al., 2022; Nikhita et al., 2015).

Moreover, with the help of mobile or smartphones, individuals can find information about goods and services, pay bills, use online banking, access government services, use maps and traffic information, use a ride-hailing app, and so forth. These activities facilitate females in home production and decrease their reservation wage, increasing their participation in the labor force. According to Robinson and Godbey (1997), mobile technologies enable people to program their tasks in advance; hence, this time-shifting property expands the possibility of multitasking. Facilitating coordination among multiple demands of work and home is vital given the mismatch between work, school, transport, and shopping hours (Wajcman, 2008). Mobile phones allow working mothers to stay connected with their children back at home, reducing the nonmonetary cost (psychic cost of being away from children) of working. Palen and Hughes (2007), following the work of Rakaw (1992), show that mobile phones allow mothers to be predictably available without being physically available, allowing remote mothering. With the emergence of ride-hailing platforms (using mobile applications), female drivers working with Uber and Careem report the flexible nature of the job as an important motivation to enter the labor market along with financial obligation (Rizk et al., 2018).

Mobile or smartphones as job search tools can directly impact labor force participation. Mobile phones increase people's socialization skills and help create external social networks from home (Chen, 2007). Social network mobilization facilitates job search activity and success (Wanberg et al., 2020). Furthermore, ownership of mobile phones contributes to the inclusion of the labor market by reducing the cost of acquiring information related to job search activity. Rajkhowa and Qaim (2022a) show that the ownership of mobile phones increases off-farm employment in rural India by reducing the transaction cost of acquiring information and also by reducing search and negotiation costs. Furthermore, they report a higher association between mobile phone ownership and off-farm employment for female-headed households. Previous empirical literature has also examined the importance of the internet as a job search tool. Viollaz and Winkler (2022) find a positive and significant relationship between internet adoption and participation of women in the labor force in Jordan. They show that older and more experienced women experience an increase in employment in response to the adoption of the internet. Furthermore, the increase in online job search explains some, but not all, of the total increase in the participation of female labor force in Jordan. Glassdoor (Zhao, 2018) research reveals that women are more likely to use mobile phones as job search devices than men.

Mobile phones can indirectly contribute to the participation of women in the labor force by improving women's bargaining power through channels such as financial autonomy, freedom of movement, and increased decision-making power. Aker et al. (2011) determine that the mobile money cash transfer program in Niger is positively associated with changes in intra-household decision-making for women. Physical mobility is considered an obstacle to women's economic participation, especially in developing countries due to conservative social norms and harassment in public places (Field & Vyborny, 2022). The acquisition of a mobile phone gives women a sense of security when traveling without accompanying a male family member. Rajkhowa and Qaim (2022b) find that the use of a mobile phone is associated with a 5% increase in the physical mobility of women in India.

Different uses of mobile devices or smartphones lead to an indecisive prediction of the net effect of mobile or smartphone ownership on female labor supply. It depends on many factors, including the degree to which individuals use mobile or smartphones for home production, leisure, work, and job search. It also depends on interpersonal differences in tastes and preferences. In this study, we aim to quantify the net effect of the likelihood of traditional mobile or smartphone ownership on female labor force participation in a developing country context.

4 | DATA AND METHODS

4.1 | Data

We used a nationally representative Pakistan Social and Living Standards Measurement (PSLM) District Level Survey, which was conducted in 2019–2020. The survey covered 176,790 households in rural and urban areas. The data provide information on various sociodemographic characteristics of the households along with individual-level labor market outcomes, education, income, and use of ICT. The questionnaire includes a section on ICTs, reporting the ownership and use of different digital technologies. The survey adopts a two-stage stratified random sampling design.³ Since the analysis focusses on labor market outcomes, we restrict our sample to the working-age (between age 15 and 64 years) individuals and construct variables based on individual and household characteristics. Table A1 provides information on the sample used for the analysis. Data on the number of mobile franchises in each district were obtained from the websites of the major mobile service providers in Pakistan (Figure A4).

The first variable of interest is the ownership and use (MS) of traditional mobile or smartphones. MS is a dummy variable with “1” for people who owned and used a traditional mobile or smartphone and “0” otherwise. For the sake of brevity, we will use the ownership of mobile phones synonymously with traditional mobile or smartphone ownership and use. As described by Ma et al. (2018), traditional mobile phones provide simplified core functions such as voice calls and text messages; smartphones, however, provide wider functionality due to the possibility to install various software applications. Taking into account that more females own a mobile phone rather than a smartphone, we combine the ownership and use of the mobile and smartphone. Another variable of interest is labor force participation, which includes employed and unemployed individuals. Employed individuals are those who worked for pay, profit, or family gain during the last month for at least for 1 h on any day during the survey period. These also include individuals who have had a job or enterprise, such as a shop, business, farm, or service establishment during the last month. Unemployed people are the ones who are not employed but are seeking work during the survey period. Labor force participation (LFS) is a dummy variable with “1” for individuals who are either employed or unemployed and “0” otherwise. Table A2 presents information on the construction of other variables (individual and household characteristics) used in the analysis.

4.2 | Methods

4.2.1 | Nonlinear Oaxaca–Blinder decomposition

To investigate the existing digital gender divide in Pakistan, we apply an extension of the Oaxaca–Blinder decomposition proposed by Yun (2005) and further elaborated by Powers et al.

(2011). The technique was originally developed by Oaxaca (1973) and Blinder (1973) to explain the differences in the mean value of an outcome variable (based on linear regression models) between two groups into different components, that is, explained and unexplained. Yun (2005) generalizes the decomposition technique to consider the functional form. The method provides estimates for overall decomposition and detailed decomposition, which helps to identify the contribution of each covariate to the different components of the overall gap (Powers et al., 2011). For our analysis, the decomposition analysis helps determine the differences in the likelihood of mobile phone ownership between men and women by decomposing the digital gender gap into two components. The first component, the explained component, captures the differences attributable to individual and household characteristics (covariates). The selection of covariates is based on the existing literature (Alozie & Akpan-Obong, 2017; Antonio & Tuffley, 2014; Galperin & Arcidiacono, 2021; Hilbert, 2011) on the gender digital divide (especially in the context of developing countries), including labor force participation, age, age square, marital status, literacy, different levels of education, individual's income, different income quintiles, household size, number of children between 0 and 4 years of age, location, wealth index, and ownership of agricultural land, nonagricultural land, and residence. The second component reports the differences caused by the differences in coefficients due to institutional factors and prevailing social and cultural norms that hinder women from taking advantage of digital technologies.

In the first step, we estimate the effect of individual- and household-level characteristics on the likelihood of mobile phone ownership by employing Logit regression. Following this, we apply an extension of the Oaxaca–Blinder decomposition proposed by Yun (2005) and further elaborated by Powers et al. (2011).

In the context of our study, taking males as the comparison group and females as the reference category, the gender digital divide can be decomposed as follows:

$$\bar{Y}^m - \bar{Y}^f = \left[F(\overline{X^m \beta^m}) - F(\overline{X^f \beta^m}) \right] + \left[F(\overline{X^f \beta^m}) - F(\overline{X^f \beta^f}) \right] \tag{1}$$

where $\bar{Y}^m - \bar{Y}^f$ represents the difference in the likelihood of mobile phone ownership between females and males. The first term in the parenthesis $\left[F(\overline{X^m \beta^m}) - F(\overline{X^f \beta^m}) \right]$ is attributable to gender differences due to the difference in characteristics or endowments. The second term $\left[F(\overline{X^f \beta^m}) - F(\overline{X^f \beta^f}) \right]$ reports gender differences in the ownership and use of mobile or smartphones due to differences in coefficients.

In addition, the model estimates the detailed decomposition to capture the contribution of all individual and household covariates to the differences in the likelihood of ownership of mobile phones between males and females. Yun (2005) proposed a two-stage method to assign weights to each variable included in the model. The first stage evaluates the function using mean characteristics, and in the second stage, a first-order Taylor expansion rule linearizes the endowment and coefficient effects. The following equation shows the weighted total of each factor's contribution:

$$\bar{Y}^m - \bar{Y}^f = \sum_{i=1}^k w_{\delta X}^i \left[F(\overline{X^m \beta^m}) - F(\overline{X^f \beta^m}) \right] + \sum_{i=1}^k w_{\delta X}^i \left[F(\overline{X^f \beta^m}) - F(\overline{X^f \beta^f}) \right] \tag{2}$$

where $w_{\delta X}^i$ in Equation (2) is the decomposition weight calculated separately for characteristics and coefficients.

4.2.2 | Instrumental variable approach

The second objective of this paper is to estimate the effect of mobile phone ownership on female labor force participation in Pakistan. The following equation estimates the proposed relationship:

$$lfp_{ij} = \beta_0 + \beta_1 MS_{ij} + \beta_2 X_{ij} + \beta_3 P_j + \varepsilon_{ij} \quad (3)$$

where subscripts i and j denote the female i living in district j . MS_{ij} is the main explanatory variable and lfp_{ij} is the outcome variable. The construction of variables has been described in Section 4.1. We include a vector of individual and household characteristics (X_{ij}) to consider the confounding factors that can influence both the explanatory and the outcome variables. These characteristics include age, age square, marital status, education level, literacy, female head of the household, education of household head, income quintiles, location, wealth index, ownership of agricultural land, ownership of nonagricultural land, own residence, household income security, and district male employment rates (Afridi et al., 2018; Ejaz, 2007; Klasen, 2019; Klasen et al., 2021; Klasen & Pieters, 2012; Sarkar et al., 2019; Schaner & Das, 2016). We include provincial fixed effects (P_j) to control for the regional differences. We estimate Equation (3) by clustering standard errors at the district level and household level.

The ownership of a mobile phone is potentially endogenous because women decide to own and use a phone based on observed and unobserved characteristics. Furthermore, mobile phone ownership and participation in the labor force can be jointly determined by specific factors that are not observed. Hence, we use a two-stage least-squares instrumental variable approach to overcome these challenges. According to Chiburis et al. (2012), researchers use two common approaches to measure the causal impact in a model with binary endogenous and outcome variables. Standard linear IV estimation ignores the binary nature of the outcome and the endogenous variable. The second approach is based on the maximum likelihood estimation of a bivariate probit model. The existing literature provides mixed advice on either method (Angrist, 2001; Bhattacharya et al., 2006). The coefficients for both methods differ substantially when the sample size is less than 5000. For our analysis, the sample size is 245,254 females. The method requires a variable that is not present in the primary regression estimation and is uncorrelated with the error term, but is correlated with the endogenous explanatory variable (Murray, 2006; Ullah et al., 2021). In the presence of many covariates, misspecification of the bivariate probit leads to biased estimates (Chiburis et al., 2012). Therefore, we use linear two-stage least squares (2SLS) to estimate the impact of mobile phone ownership on female labor force participation in Pakistan.

To estimate Equation (3), we follow a 2SLS procedure. In the first stage, we regress our endogenous explanatory variable MS_{ij} on the instrument MF_{ij} and other variables used in the Equation (3). The first-stage equation is given by:

$$MS_{ij} = \gamma_0 + \gamma_1 MF_{ij} + \gamma_2 X_{ij} + \gamma_3 P_j + \varepsilon_{ij} \quad (4)$$

where MF_{ij} in Equation (4) is the number of mobile phone franchises in each district where female i lives. This is a good instrument for several reasons. First, it is correlated with the likelihood of owning a mobile phone, as mobile phone franchises facilitate the provision of different services. In the context of Pakistan, these services include post and prepaid connection sales, billing services, sim or duplicate sim, easy load, mobile accessories, repair services, and internet connection. Ullah et al. (2021) argue that choosing an instrument outside your unit of analysis increases the chances that the instrument satisfies the exogeneity condition. Our instrument, the number of mobile phone franchises, is a district-level variable, while our unit of analysis is individual females. One concern about the instrument's validity is that these mobile franchises generate employment opportunities and there is a possibility of correlation with labor force participation. However, considering Pakistan's prevailing social and cultural norms, it is implausible that women work in these franchises. Our instrument shows a positive and significant association with mobile phone ownership (first-stage regression) and passes the validity test (see Table 3). However, we cannot rule out the possibility that mobile network franchises might co-drive some vital economic variables, as the franchises would be located where there is more economic activity and a higher capacity to pay for the services. Therefore, we report our results as an association rather than as a causality.

In the second stage, we obtain the fitted values \widehat{MS}_{ij} from Equation (4) and use it as an explanatory variable with other covariates (X_{ij}, P_j) to estimate the primary Equation (3). The procedure will give us a consistent estimate of β_1 , which quantify the effect of mobile or smartphone ownership and use on female labor force participation through the instrument.

5 | RESULTS AND DISCUSSION

5.1 | Descriptive statistics

Table A3 reports the summary statistics for the variables of interest and other digital indicators for the sample disaggregated by gender. Statistics show that there are substantial gender gaps in different digital technologies along with labor force participation. Around 79% of men own a mobile phone compared to 28% of women. However, the table also shows that there exist negligible gender differences in the use of mobile phones. The reason is mobile sharing within poor households; Porter et al. (2020) find that in sub-Saharan Africa, phone usage surpasses ownership due to the high frequency of sharing among family, friends, and neighbors. It could also be because of the type of question the survey asked from the respondents without giving them any time window. The question asked them to report whether they had used a mobile phone, a smartphone, or none.

Table A4 further disaggregates the participation of the labor force and mobile phone ownership by gender and location. The results show a considerable gender digital divide between rural and urban areas in Pakistan. It indicates that the gender digital divide drives the rural–urban digital divide. However, one can also observe a significant rural–urban digital divide between women. Urban women are much more likely to own a mobile phone than rural females.

Table 1 shows the summary statistics of the control and outcome variables used in the Oaxaca Blinder decomposition disaggregated by gender. The results indicate that there are significant differences between men and women for all the variables except age. On average, males are more educated and literate, earning more and participating more in the labor force. On the

other hand, more females belong to lower-income quintile households, and most females are married compared to males. Finally, we see a significant difference in the ownership and use of mobile phones between men and females, where on average, males are more likely to own and use mobile phones.

Table A5 reports the summary statistics of the outcome and control variables of the female sample disaggregated by females who own mobile phones and those who do not own mobile phones. On average, females who own mobile phones are more educated, literate, and are more likely to live in urban areas. They also live in households where the head of the family is female and more educated. Females who do not own mobile phones are likely to be from lower-income households. In addition, we can see significant differences in the outcome variables between the two groups; women who own mobile phones are more likely to participate in the workforce. Table A6 lists the summary statistics of the rural–urban digital divide for the female sample. We can observe that women who reside in urban areas are less likely to participate in the labor force than women who live in rural areas. However, this is a surprising result because women in urban areas are more likely to own a mobile phone, and females that own a mobile phone are more likely to participate in the labor market. To examine whether these differences in labor force participation are due to the differences in the ownership of mobile phones, we employ 2SLS, and the results are presented in Section 5.3.

5.2 | Nonlinear Oaxaca–Blinder decomposition

Table 3 reports the results of the gender digital divide between men and women in Pakistan based on the estimation results of the logit regression given in Table 2. The average marginal effects for men and women reveal some important information. First, the significant and positive effect of tertiary education and individual income is more distinct for women. Regarding household characteristics, women belonging to lower-income quintiles are less likely to own a mobile phone. The calculated marginal effects for location show that women in urban areas are more likely to have a mobile phone. However, the results are insignificant for the male sample.

Table 3 presents the aggregate and detailed decomposition of the gender digital divide and further separates that into covariate and coefficient effects. The results show that men, on average, are more likely to own a mobile phone, making them an advantaged group in our analysis. The total differences in the covariates explain only 0.094 unit of the 0.500 unit gap in the likelihood of MS ownership between males and females. This means that if women had the same characteristics as men, they would be more likely to own a mobile phone. Among the covariates, literacy and individual income turn out to be the most significant contributors to the explained part.

Table 3 shows that the coefficient effect (the unexplained part) is primarily responsible for the observed differences in MS ownership for men and women. The coefficient effect explains 0.397 unit of the 0.5 unit gap in the MS ownership between males and females. Two potential explanations can be provided for the coefficient effect on the gender divide in MS ownership. The first is the case of unobserved factors in which the model may have not included (due to unavailability of information) significant predictors of MS ownership. For example, the language of the content of mobile or smartphone is an essential factor that should also be taken into account. Using a mobile phone requires basic English skills, as 90% of the online content is in English (United Nations e-Government Survey, 2012). The PSLM survey includes a question about the literacy of individuals without focusing on their English language skills.

TABLE 1 Summary statistics by gender.

| | Male Mean | Female Mean | Difference | SE |
|-----------------------------------|-----------|-------------|------------|-------|
| MS ownership and use | 0.769 | 0.269 | 0.501*** | 0.001 |
| Labor force participation | 0.805 | 0.151 | 0.654*** | 0.001 |
| Age | 33.096 | 33.068 | 0.029 | 0.038 |
| Age square | 1277.915 | 1260.508 | 17.407*** | 2.792 |
| Marital status | 0.637 | 0.758 | -0.121*** | 0.002 |
| Literacy | 0.677 | 0.429 | 0.247*** | 0.002 |
| Primary education level | 0.261 | 0.17 | 0.091*** | 0.001 |
| Secondary education level | 0.226 | 0.134 | 0.092*** | 0.001 |
| Tertiary education level | 0.075 | 0.052 | 0.023*** | 0.001 |
| No formal education | 0.436 | 0.643 | -0.207*** | 0.002 |
| Log of individual's income | 8.332 | 0.7 | 7.632*** | 0.013 |
| First income quintile | 0.152 | 0.216 | -0.064*** | 0.001 |
| Second income quintile | 0.182 | 0.188 | -0.006*** | 0.001 |
| Third income quintile | 0.201 | 0.196 | 0.005*** | 0.001 |
| Fourth income quintile | 0.218 | 0.196 | 0.022*** | 0.001 |
| Fifth income quintile | 0.247 | 0.204 | 0.043*** | 0.001 |
| HH size | 6.348 | 6.384 | -0.036*** | 0.009 |
| Children (0-4) | 0.633 | 0.703 | -0.07* | 0.003 |
| Location | 0.324 | 0.308 | 0.015*** | 0.002 |
| Ownership of agricultural land | 0.248 | 0.259 | -0.011*** | 0.001 |
| Ownership of nonagricultural land | 0.042 | 0.043 | -0.002*** | 0.001 |
| Own residence | 0.845 | 0.851 | -0.005*** | 0.001 |
| Wealth index | 77.481 | 77.148 | 0.332*** | 0.105 |
| Observations | 244,663 | 245,254 | | |

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

The second reason is the sociocultural and institutional factors responsible for the digital gender divide. According to Antonio and Tuffley (2014), the amalgamation of policies, laws, and societal customs in developing countries prohibits women from owning assets and obtaining loans for technology acquisitions. This discrimination leads to a vicious circle that hinders women from getting financial independence to afford digital technologies that can improve their economic well-being (Hafkin & Taggart, 2001). Restrictive social and gender norms help to explain the gender gap in the ownership of a mobile phone. Acquisition of technology is often considered a realm of men, and gender norms about men's access to and use of technology limit women's prospects to learn, use, and benefit from technology (Hafkin & Taggart, 2001). As pointed out by Kabeer (2012), gender inequalities are determined by unjust structures and practices rather than choices made by individuals. Women

TABLE 2 Average marginal effects of the total sample and also the sample disaggregated by male and female.

| | Total sample | Male | Female |
|--------------------------------|---------------------|-------------------|-------------------|
| MS ownership and use | Coefficient | Coefficient | Coefficient |
| Gender | −0.308*** (0.008) | – | – |
| Labor force participation | 0.042*** (0.009) | 0.086*** (0.008) | −0.020 (0.014) |
| Age | 0.033*** (0.001) | 0.032*** (0.001) | 0.033*** (0.001) |
| Age square | −0.000*** (0.000) | −0.000*** (0.000) | −0.000*** (0.000) |
| Marital status | 0.108*** (0.005) | 0.081*** (0.004) | 0.133*** (0.001) |
| Literacy | 0.088*** (0.008) | 0.069*** (0.007) | 0.150*** (0.001) |
| Primary level of education | 0.022*** (0.007) | 0.029*** (0.006) | −0.050*** (0.009) |
| Secondary level of education | 0.091*** (0.006) | 0.081*** (0.006) | 0.020** (0.009) |
| Tertiary level of education | 0.187*** (0.009) | 0.118*** (0.013) | 0.160*** (0.012) |
| Log of individual's income | 0.009*** (0.001) | 0.006*** (0.001) | 0.010*** (0.001) |
| Second income quintile | −0.055*** (0.006) | −0.015** (0.007) | −0.091*** (0.008) |
| Third income quintile | −0.027*** (0.006) | 0.002 (0.007) | −0.056*** (0.008) |
| Fourth income quintile | −0.018** (0.006) | 0.009 (0.007) | −0.045*** (0.008) |
| Fifth income quintile | 0.016*** (0.008) | 0.035*** (0.008) | −0.002 (0.010) |
| Household size | −0.014*** (0.001) | −0.008*** (0.001) | −0.021*** (0.001) |
| Children (aged 0–4 years) | 0.010*** (0.001) | 0.009*** (0.001) | 0.009*** (0.002) |
| Location | 0.006 (0.006) | −0.006 (0.006) | 0.014* (0.008) |
| Ownership of agricultural land | 0.012*** (0.004) | 0.023*** (0.005) | 0.004 (0.005) |
| Ownership nonagricultural land | 0.021*** (0.008) | 0.012 (0.009) | 0.032*** (0.009) |
| Own residence | −0.004*** (0.004) | −0.002 (0.004) | −0.005 (0.005) |
| Wealth index | 0.002*** (0.000) | 0.001*** (0.000) | 0.002*** (0.000) |
| Provincial fixed effects | Yes | Yes | Yes |
| Pseudo R-square | 0.3711 | 0.2395 | 0.2310 |
| No. of observation | 489,917 | | |

Note: Numbers in brackets represent standard errors.

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

in different societies make choices based on limits imposed by rules, norms, and resources (Kabeer, 2012). The actual and perceived benefits of digital tools are also determined by socio-cultural factors (Ono & Zavodny, 2007), making women unaware of the benefits of using these tools.

An interesting finding regarding the coefficient effect is the significant contribution of the constant term that derives this gender digital divide. The constant term represents the base category which includes the most disadvantaged individuals, that is, the individuals (men and women) from rural areas with no formal education, illiterate, and belonging to households with low income and with no ownership of land and property. The results reveal that disadvantaged males are much more likely to own a mobile phone than females with the prevailing socio-

TABLE 3 Decomposition of the gender divide in the ownership of mobile or smartphones.

| MS ownership | Coefficients | | Standard errors | |
|--|--------------|----------------|-----------------|----------------|
| Overall decomposition | | | | |
| Male | 0.769*** | | 0.007 | |
| Female | 0.269*** | | 0.013 | |
| Total difference | 0.500*** | | 0.009 | |
| Covariates effect | 0.094*** | | 0.006 | |
| Coefficients effect | 0.379*** | | 0.008 | |
| Interaction effect | 0.026*** | | 0.008 | |
| | Covariates | | Coefficients | |
| | Coefficients | Standard error | Coefficients | Standard error |
| Detailed decomposition | | | | |
| Labor force participation | -0.016 | 0.011 | 0.021*** | 0.003 |
| Age | 0.001 | 0.002 | 0.065 | 0.052 |
| Age square | -0.009*** | 0.002 | -0.006 | 0.024 |
| Marital status | -0.019*** | 0.001 | -0.041*** | 0.008 |
| Literacy | 0.045*** | 0.003 | -0.039*** | 0.005 |
| Primary level of education | -0.005*** | 0.001 | 0.017*** | 0.002 |
| Secondary level of education | 0.002** | 0.000 | 0.011*** | 0.001 |
| Tertiary level of education | 0.003*** | 0.000 | 0.000 | 0.001 |
| Log of individual's income | 0.095*** | 0.012 | -0.003*** | 0.001 |
| Second income quintile | 0.001*** | 0.000 | 0.017*** | 0.002 |
| Third income quintile | -0.000*** | 0.000 | 0.013*** | 0.002 |
| Fourth income quintile | -0.001*** | 0.000 | 0.012*** | 0.002 |
| Fifth income quintile | -0.000 | 0.000 | 0.010*** | 0.002 |
| Household size | 0.001** | 0.000 | 0.099*** | 0.009 |
| Number of children in the HH (0-4 age) | -0.001*** | 0.000 | 0.000 | 0.002 |
| Location | 0.0002 | 0.000 | -0.008** | 0.003 |
| Ownership of agricultural land | -0.000 | 0.000 | 0.006*** | 0.001 |
| Ownership of nonagricultural land | -0.000 | 0.000 | -0.001** | 0.000 |
| Own residence | 0.000 | 0.000 | 0.003 | 0.005 |
| Wealth index | 0.001 | 0.000 | -0.092*** | 0.015 |
| Constant | None | | 0.267*** | 0.033 |
| Provincial fixed effects | Yes | | | |

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

cultural norms in Pakistan. Hence, the constant term depicts the extent to which the gap in the likelihood of mobile phone ownership among the most disadvantaged females would disappear if they faced the same socio-cultural norms as their male counterparts.

5.3 | Two-stage least squares

Table 4 reports the results of the effect of mobile ownership on female labor force participation. The results of logit regression show a positive and statistically significant effect of mobile phone

TABLE 4 Regression results of the effect of mobile phone on female labor force participation.

| Labor force participation | Average marginal effects (logit) | IV2SLS first stage | IV2SLS second stage |
|--|----------------------------------|----------------------|---------------------------|
| | Labor force participation | MS ownership and use | Labor force participation |
| MS ownership and use | 0.03*** (0.006) | | 0.362** (0.188) |
| Mobile network franchise | | 0.001*** (0.0002) | |
| Age | 0.017*** (0.001) | 0.026*** (0.001) | 0.007 (0.004) |
| Age square | -0.000*** (0.000) | -0.0003*** (0.000) | -0.000 (0.000) |
| Marital status | -0.067*** (0.008) | 0.146*** (0.009) | -0.113*** (0.028) |
| Age of the head | -0.001*** (0.000) | 0.0002 (0.000) | -0.001*** (0.000) |
| Female head | -0.010 (0.007) | 0.224*** (0.009) | -0.062 (0.043) |
| Education of the head | -0.003*** (0.000) | 0.006*** (0.000) | -0.005*** (0.001) |
| Literacy | -0.060*** (0.009) | 0.099*** (0.008) | -0.070*** (0.022) |
| Primary | 0.041*** (0.007) | -0.006 (0.007) | 0.019*** (0.006) |
| Secondary | 0.063*** (0.008) | 0.092*** (0.007) | 0.003 (0.017) |
| Tertiary | 0.342*** (0.016) | 0.280*** (0.013) | 0.154*** (0.053) |
| Second income quintile | -0.019* (0.011) | -0.025*** (0.007) | -0.014 (0.014) |
| Third income quintile | -0.047*** (0.012) | 0.005 (0.007) | -0.058*** (0.013) |
| Fourth income quintile | -0.059*** (0.013) | 0.016** (0.007) | -0.070*** (0.014) |
| Fifth income quintile | -0.076*** (0.014) | 0.055*** (0.008) | -0.094*** (0.018) |
| Household size | 0.001* (0.008) | -0.013*** (0.000) | 0.006** (0.002) |
| Children (0–4) | -0.003* (0.001) | 0.004* (0.001) | -0.004** (0.002) |
| Nuclear family | 0.010*** (0.003) | 0.028*** (0.003) | 0.001 (0.006) |
| Location | 0.009 (0.008) | -0.016* (0.008) | -0.016 (0.010) |
| Ownership of agriculture land | 0.046*** (0.008) | 0.001 (0.004) | 0.050*** (0.011) |
| Ownership of nonagriculture land | 0.010 (0.009) | 0.020*** (0.008) | 0.001 (0.011) |
| Own residence | -0.027*** (0.006) | -0.001 (0.004) | -0.023*** (0.006) |
| Wealth index | -0.001*** (0.000) | 0.002*** (0.000) | -0.001*** (0.000) |
| Employment rate of males (district wise) | 0.905*** (0.161) | -0.351*** (0.119) | 1.022*** (0.240) |
| Household income security | -0.009** (0.004) | -0.021*** (0.002) | -0.016 (0.005) |
| Provincial FE | Yes | Yes | Yes |
| R-Square | 0.121 | - | 0.127 |
| First stage F-statistic | - | - | 22.501 |
| Number of observations | 245,254 | | |

Note: Numbers in brackets represent standard errors.

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

ownership on female labor force participation. Furthermore, the results of the second stage (2SLS) suggest a significant and much larger positive association with female labor force participation. On average, women who own mobile phones have a 36.2% point higher probability of participating in the labor force than females who do not own mobile phones. Our results are consistent with other quantitative studies that explored the same relationship with different digital tools (Dettling, 2017; Non et al., 2021; Viollaz & Winkler, 2022; Zheng et al., 2023). From the coefficients of individual and household controls, we can observe that women who reside in urban areas are less likely to participate in the labor force than females who live in rural areas; however, the coefficient is not significant. A plausible reason for the lower participation in the labor force of urban females who are more likely to own mobile phones could be the time spent on mobile phones on activities that increase their leisure time (as described in the conceptual framework). On the other hand, rural women use mobile phone for more work-related activities. For example, Islam and Slack (2016) study the use of mobile phones among rural women in Bangladesh and find that 71% of the respondents use mobile phones to access information on economic opportunities. Furthermore, women in rural India use mobile phones for a range of activities including social networking, employment, education, and health-related services (Mehta & Mehta, 2014).

5.3.1 | Robustness checks

As explained in Section 4.2.2, in the presence of an endogenous regressor, the instrumental variable approach is the appropriate method by which the instrument controls for unobservable variables, reverse causality, and self-selection into owning a mobile phone (Wooldridge, 2010). To confirm the validity of our estimates, we apply some robustness checks including inverse probability-weighted regression adjustment (IPWRA) and control function approach of IV. The average treatment effect and average treatment effect on the treated for IPWRA are consistent with logit estimates as IPWRA cannot account for selection bias related to unobserved heterogeneity (Lu et al., 2021; Zheng et al., 2023); however, control function approach estimates are consistent with 2SLS estimates.⁴

5.4 | Nonlinear Oaxaca–Blinder decomposition for female rural–urban divide

An important insight from the above analysis shows a significant digital divide between rural and urban women in Pakistan (Figure 1, Tables A4 and A6). To further probe this insight, we perform a decomposition analysis of the rural–urban digital divide for the female sample. Summary statistics (Table A6) show that on average, urban females are more educated and literate, earn a higher income, belong to higher-income households, and are more likely to own a mobile phone.

The results of the Oaxaca–Blinder decomposition for the female sample (Table 5) indicate significant differences in rural–urban MS ownership. As shown, the differences in the ownership of mobile phones between rural and urban females are driven by observable characteristics. If women in rural areas had the same characteristics as those in urban areas, the digital divide would disappear. The differences in literacy, education, income, and wealth index are the main contributors to the observed digital divide.

TABLE 5 Decomposition results of mobile phone or smartphone ownership by location.

| MS ownership and use | Coefficients | | Standard error | |
|---------------------------|--------------|----------------|----------------|----------------|
| Overall decomposition | | | | |
| Urban females | 0.411*** | | 0.018 | |
| Rural females | 0.205*** | | 0.010 | |
| Total difference | 0.205*** | | 0.019 | |
| Covariates effect | 0.152*** | | 0.021 | |
| Coefficients effect | -0.006 | | 0.010 | |
| Interaction effect | 0.059*** | | 0.021 | |
| | Covariates | | Coefficients | |
| | Coefficients | Standard error | Coefficients | Standard error |
| Detailed decomposition | | | | |
| Labor force participation | 0.003*** | 0.001 | 0.034 | 0.089 |
| Age | 0.010** | 0.004 | -0.094 | 0.260 |
| Age square | -0.007* | 0.004 | 0.042 | 0.118 |
| Marital status | -0.007*** | 0.001 | -0.084 | 0.216 |
| Literacy | 0.042*** | 0.004 | 0.034 | 0.085 |
| Primary education | -0.001** | 0.000 | -0.017 | 0.045 |
| Secondary education | 0.006*** | 0.002 | -0.009 | 0.024 |
| Tertiary education | 0.014*** | 0.002 | -0.003 | 0.008 |
| Log of income | 0.002** | 0.001 | -0.006 | 0.017 |
| Second income quintile | 0.009*** | 0.001 | -0.004 | 0.010 |
| Third income quintile | -0.001 | 0.0004 | 0.002 | 0.008 |
| Fourth income quintile | -0.003*** | 0.0005 | 0.003 | 0.001 |
| Fifth income quintile | -0.003** | 0.001 | 0.016 | 0.041 |
| Household size | 0.012*** | 0.003 | -0.109 | 0.281 |
| Children (0-4) | -0.002*** | 0.0005 | 0.006 | 0.017 |
| Own agricultural land | 0.001 | 0.002 | 0.009 | 0.027 |
| Own nonagricultural land | 0.0003 | 0.0002 | -0.000 | 0.001 |
| Own residence | -0.002 | 0.001 | -0.035 | 0.088 |
| Wealth index | 0.118*** | 0.013 | 0.009 | 0.024 |
| Constant | None | | 0.077 | 0.244 |
| Provincial fixed effects | Yes | | | |

*** $p < 0.01$. ** $p < 0.05$. * $p < 0.1$.

6 | CONCLUSIONS, IMPLICATIONS, AND LIMITATIONS

In this study, we examine the gender dimension of the mobile phone ownership divide and its relevance for female labor force participation in the context of developing countries, that is, Pakistan. Using the Oaxaca-Blinder decomposition, we find a significant gender digital gap in Pakistan that is mainly attributed to socio-cultural norms that prohibit women from taking

advantage of advances in technology. The constant term of the coefficient effect reveals that women from rural areas are the most disadvantaged group as they continue to face inequalities in ownership and use of digital technologies (mobile or smartphone), education, income, and wealth that limit their prospects to contribute to agricultural productivity, hence rural development. Moreover, considering low female labor force participation in Pakistan, we investigate the effect of mobile phone ownership on female labor force participation using 2SLS. In line with existing studies (using different digital tools), the results reveal that the ownership of a mobile phone is positively associated with labor market inclusion of females. We find a significant digital divide in mobile phone ownership between rural and urban women in Pakistan. The decomposition analysis of the rural–urban digital divide highlights those differences in observable characteristics, including income, education, literacy, labor force participation, household size, and household wealth index, explaining almost all of the differences between mobile phone ownership between rural and urban females. The result is consistent with the first decomposition results that affirm the marginalization of rural women, who play a key role in deriving agricultural productivity and rural development.

Our results show that a combination of individual, household, institutional, and socio-cultural factors explain the differences in mobile phone ownership between genders. Considering the importance of mobile phone ownership in facilitating female labor supply decisions, there is a need to expand employment opportunities for rural females through digitalization along with providing them with digital tools and upskilling them to bridge the gender digital divide. Interventions that provide digital training and upskilling programs for lower-income urban women and women from rural households may not only bridge the gender digital divide but also help them in uplifting their economic well-being through increased participation in the labor force. The results indicate that rural females continue to face limitations in their access to digital technologies, education, and finances that limit their potential to contribute to rural and agricultural development. Digitalization has a great potential to derive economic growth toward an inclusive future by stimulating greater productivity and sustainability of agricultural produce, as well as improved livelihood options (on- and off-farm employment) for women. Interventions that ensure that rural women have affordable and reliable mobile networks along with improvement in the provision of education and health facilities can serve as instruments for attaining gender equality, hence economic growth. More customized approaches, for example, agricultural advisory and market information about prices, information on weather conditions, and quality of inputs along with off-farm employment opportunities through interactive voice response (IVR) or short messages, can help women contribute to rural development.

The findings of the association of mobile phone ownership and women's participation in the labor force are subject to some limitations. First, the main variable of interest adds the ownership of mobile and smartphone devices, which may have a different impact on the female labor force participation. Second, due to the limitation of data on the lack of sufficient information about the purpose of using a mobile phone, we could not explore the channels through which mobile phones or smartphones can potentially facilitate the participation of women in the labor force. We believe that further research is needed to explore more information-rich data sets. Third, our conclusions are based on a cross-section of data that limits our analysis of the dynamic relationship between mobile phone ownership and women's labor market inclusion.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

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DATA AVAILABILITY STATEMENT

Availability of data and materials: The data used for the analysis is publicly available on the Pakistan Bureau of Statistics website (<https://www.pbs.gov.pk/content/pslm-district-level-survey-2019-20-microdata>). The cleaned data and stata codes used for the analysis are available from the corresponding author upon reasonable request.

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ENDNOTES

¹ According to the manual of instructions published by the Pakistan Bureau of Statistics, mobile phone (traditional) refers to a portable telephone subscribing to a public mobile telephone service using cellular technology. However, a smartphone is a multi-purpose mobile computing device distinguished from feature phones by their stronger hardware capabilities and extensive mobile operating systems.

² <https://data.worldbank.org/indicator/IT.CEL.SETS.P2?locations=PK>

³ Information on sampling design is available at: <https://www.pbs.gov.pk/content/pakistan-social-and-living-standards-measurement>

⁴ For the sake of brevity, we did not include results of robustness checks in the paper. However, the results are available from the author upon request.

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APPENDIX

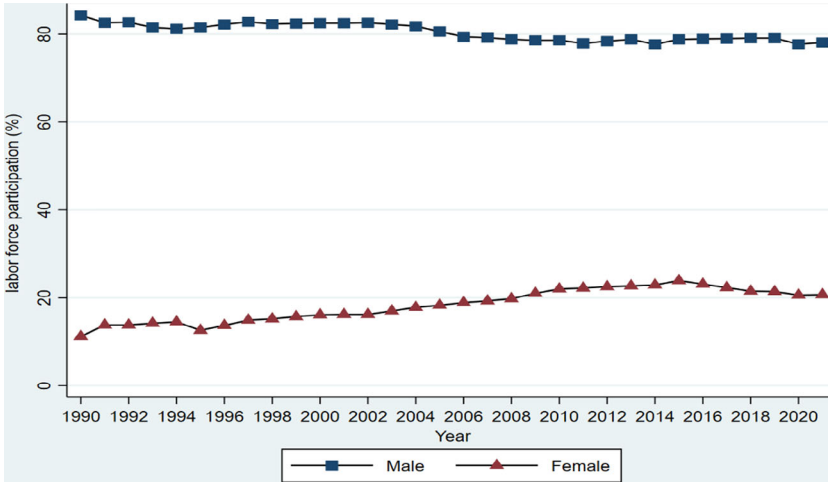


FIGURE A1 Labor force participation rate (%) of males and females (1990–2020). Source: World data bank (ILO modeled estimates). [Colour figure can be viewed at wileyonlinelibrary.com]

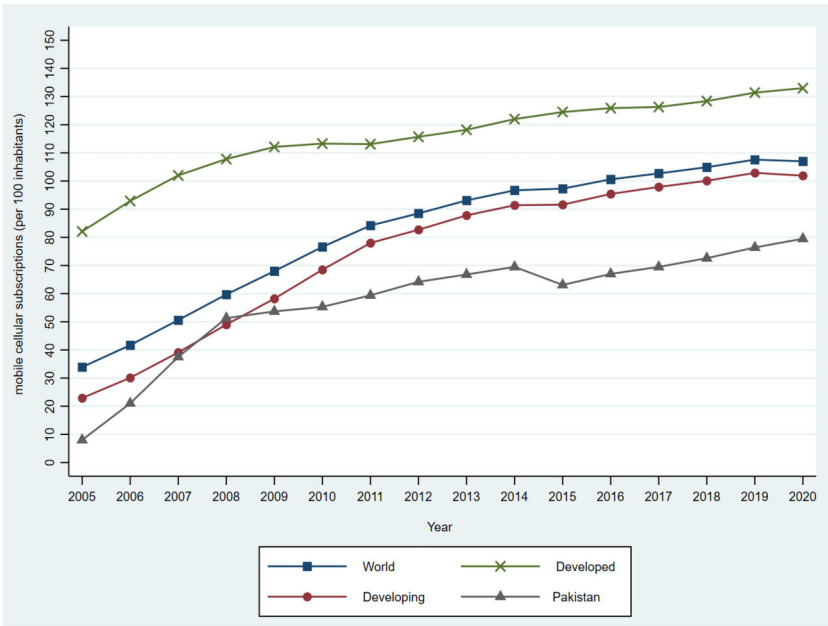


FIGURE A2 Mobile cellular subscriptions (2005–2020). Source: International Telecommunication Union and Pakistan Telecommunication Authority. [Colour figure can be viewed at wileyonlinelibrary.com]

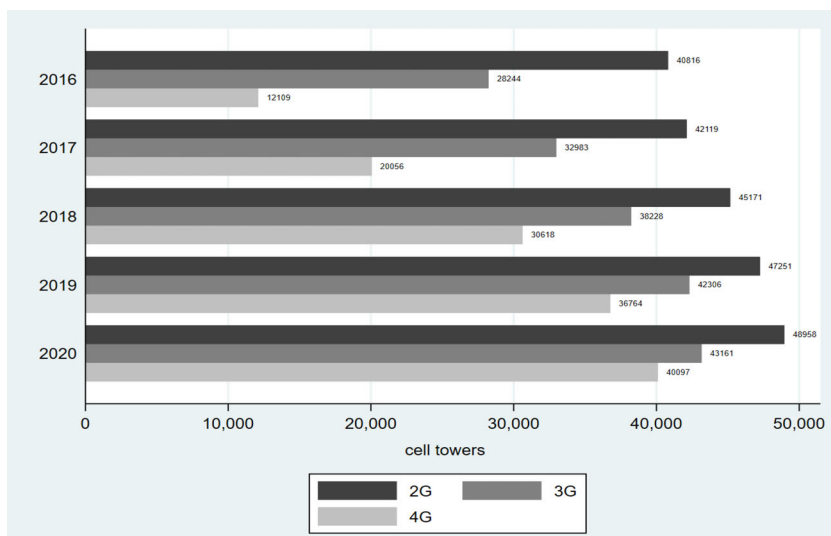


FIGURE A3 Cell towers (sites) all around Pakistan (2016–2020). *Source:* Pakistan Telecommunication Authority. [Colour figure can be viewed at wileyonlinelibrary.com]

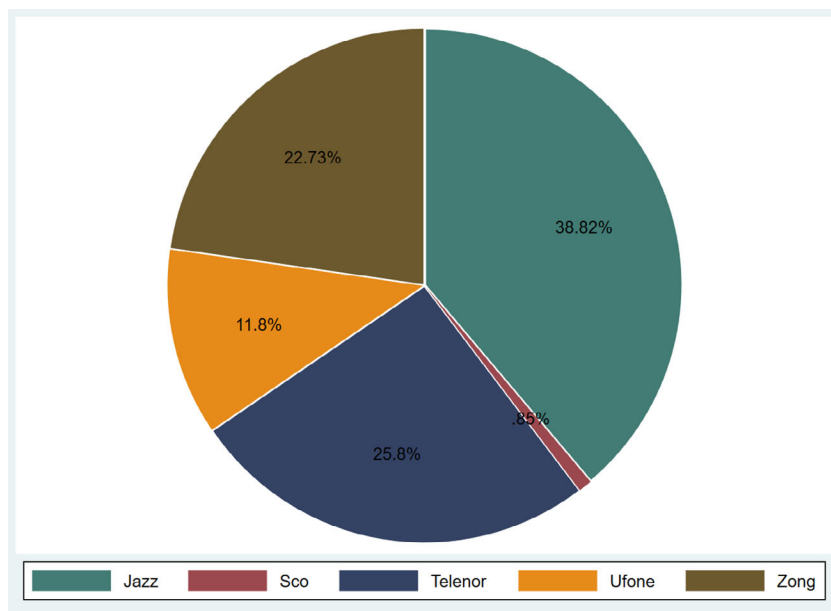


FIGURE A4 Mobile cellular providers in Pakistan. *Source:* Pakistan Telecommunication Authority (PTA). [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE A1 Number of observations (15–64).

| | No. of observations | Percent |
|--------|---------------------|---------|
| Male | 244,663 | 49.94 |
| Female | 245,254 | 50.06 |
| Total | 489,917 | 100.0 |

Source: Authors' own calculation from PSLM (2019–2020).

TABLE A2 Construction of control variables used in the study.

| Variable | Description |
|---------------------------|---|
| Age | In completed years |
| Age square | Square of age |
| Marital status | “1” if the individual is married and “0” otherwise |
| Female head | “1” if the household head is female and “0” otherwise |
| Education of head | Number of completed years of education |
| Literacy | “1” if the individual can read, write (simple statements), and solve simple math and “0” otherwise |
| No formal education | “1” if the individual does not have formal education and “0” otherwise |
| Primary education | “1” if the individual has a primary level of education and “0” otherwise |
| Secondary education | “1” if the individual has secondary level education and “0” otherwise |
| Tertiary education | “1” if the individual has a tertiary level of education and “0” otherwise |
| Log of annual income | Log of individual’s annual income in Pakistani Rupees |
| First income quintile | “1” if the household belongs to the first income quintile and “0” otherwise |
| Second income quintile | “1” if the household belongs to the second income quintile and “0” otherwise |
| Third income quintile | “1” if the household belongs to the third income quintile and “0” otherwise |
| Fourth income quintile | “1” if the household belongs to the fourth income quintile and “0” otherwise |
| Fifth income quintile | “1” if the household belongs to the fifth income quintile and “0” otherwise |
| Household size | The number of individuals living in a household |
| Nuclear family | “1” for the nuclear household and “0” otherwise |
| Household income security | Number of males paid employees in the household |
| Children (0–4) | Number of children between 0 and 4 years of age in the household |
| Location | “1” if individuals reside in an urban area and “0” otherwise |
| Agricultural land | “1” if the household possesses agricultural land and “0” otherwise |
| Nonagricultural land | “1” if the household possesses nonagricultural land and “0” otherwise |
| Own residence | “1” if the household possesses its own residence and “0” otherwise |
| Wealth index | Index of housing characteristics and durables in possession |
| Male employment rates | Employment rates of males in each district |
| Mobile network franchise | No. of mobile network franchises of all mobile network providers in each district (the data has been obtained from respective cellular provider’s websites) |

TABLE A3 Gender digital divide for labor force participation and different digital indicators (aged 15–64 years).

| (%) | Whole sample | Male | Female |
|--|--------------|------|--------|
| Labor force participation | 48 | 80 | 15 |
| Mobile phone ownership | 36 | 53 | 18 |
| Smartphone ownership | 18 | 26 | 10 |
| Internet use | 20 | 26 | 13 |
| Computer use | 7 | 10 | 5 |
| Mobile or smartphone ownership | 53 | 79 | 28 |
| Mobile or smartphone ownership and use | 52 | 77 | 27 |
| Mobile or smartphone use | 92 | 94 | 89 |

Source: Authors' own calculation from PSLM (2019–2020).

TABLE A4 Rural–urban divide for labor force participation and mobile or smartphone ownership and use (15–64).

| (%) | Male | | Female | |
|--------------------------------|-------|-------|--------|-------|
| | Rural | Urban | Rural | Urban |
| Labor force participation | 81 | 79 | 17 | 11 |
| Mobile or smartphone ownership | 76 | 83 | 21 | 43 |
| Mobile or smartphone use | 93 | 96 | 88 | 93 |

Source: Authors' own calculation from PSLM (2019–2020).

TABLE A5 Summary statistics of female sample disaggregated by MS ownership.

| | Does not own and use MS | Own and use MS | diff | Standard error |
|---------------------------|------------------------------------|-----------------------|-------------|-----------------------|
| | Mean | Mean | | |
| Labor force participation | 0.148 | 0.159 | -0.011*** | 0.002 |
| Age | 32.6 | 34.2 | -1.67*** | 0.059 |
| Age square | 1249.8 | 1289.5 | -39.7*** | 4.33 |
| Age of the head | 46.95 | 45.86 | 1.07*** | 0.06 |
| Marital status | 0.721 | 0.859 | -0.138*** | 0.002 |
| Female head of HH | 0.064 | 0.166 | -0.102*** | 0.002 |
| Education of HH head | 4.16 | 7.09 | -2.93*** | 0.023 |
| Literacy | 0.35 | 0.644 | -0.293*** | 0.002 |
| No formal education | 0.728 | 0.413 | 0.315*** | 0.002 |
| Primary education | 0.161 | 0.195 | -0.035*** | 0.002 |
| Secondary education | 0.092 | 0.246 | -0.154*** | 0.002 |
| Tertiary education | 0.018 | 0.144 | -0.126*** | 0.001 |
| First income quintile | 0.21 | 0.234 | -0.024*** | 0.002 |
| Second income quintile | 0.216 | 0.112 | 0.105*** | 0.002 |
| Third income quintile | 0.2 | 0.182 | 0.018*** | 0.002 |
| Fourth income quintile | 0.194 | 0.2 | -0.005*** | 0.002 |
| Fifth income quintile | 0.179 | 0.272 | -0.093*** | 0.002 |
| Household size | 6.66 | 5.61 | 1.048*** | 0.015 |
| Nuclear family | 0.6 | 0.655 | -0.056*** | 0.002 |
| Household income security | 0.707 | 0.589 | 0.118*** | 0.004 |
| Children (0-4) | 0.73 | 0.629 | 0.102*** | 0.005 |
| Location | 0.248 | 0.471 | -0.222*** | 0.002 |
| Own agricultural land | 0.28 | 0.203 | 0.076*** | 0.002 |
| Own nonagricultural land | 0.039 | 0.052 | -0.013*** | 0.001 |
| Own residence | 0.865 | 0.811 | 0.054*** | 0.002 |
| Wealth index | 69.9 | 96.8 | -26.9*** | 0.158 |
| Male employment rates | 0.759 | 0.738 | 0.021*** | 0.001 |
| Mobile network franchise | 17.7 | 32.1 | -14.3*** | 0.118 |
| Number of observations | 179,260 | 65,994 | | |

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

TABLE A6 Summary statistics rural–urban digital divide for the female sample.

| | <u>Rural</u> | <u>Urban</u> | | | <u>Average marginal effects (logit)</u> |
|-----------------------------------|--------------|--------------|-------------|-----------------------|---|
| | <u>Mean</u> | <u>Mean</u> | <u>diff</u> | <u>Standard error</u> | <u>Coefficient</u> |
| MS ownership and use | 0.205 | 0.411 | −0.205*** | 0.002 | Outcome variable |
| Labor force participation | 0.17 | 0.109 | 0.06*** | 0.002 | −0.02 (0.014) |
| Age | 32.9 | 33.2 | −0.271*** | 0.057 | 0.03*** (0.001) |
| Age square | 1255.9 | 1270.6 | −14.6*** | 4.16 | −0.004*** (0.000) |
| Marital status | 0.77 | 0.731 | 0.04*** | 0.002 | 0.133*** (0.009) |
| Literacy | 0.337 | 0.638 | −0.301*** | 0.002 | 0.151*** (0.009) |
| Primary level of education | 0.161 | 0.19 | −0.029*** | 0.002 | −0.050*** (0.008) |
| Secondary level of education | 0.09 | 0.231 | −0.141*** | 0.002 | 0.020** (0.008) |
| Tertiary level of education | 0.029 | 0.105 | −0.077*** | 0.001 | 0.160*** (0.011) |
| No formal education | 0.72 | 0.473 | 0.246*** | 0.002 | Ref. group |
| Log of income | 0.656 | 0.798 | −0.141*** | 0.012 | 0.010*** (0.001) |
| First income quintile | 0.25 | 0.142 | 0.108*** | 0.002 | Ref. group |
| Second income quintile | 0.216 | 0.123 | 0.093*** | 0.002 | −0.09*** (0.008) |
| Third income quintile | 0.192 | 0.203 | −0.01*** | 0.002 | −0.05*** (0.007) |
| Fourth income quintile | 0.179 | 0.233 | −0.053*** | 0.002 | −0.04*** (0.008) |
| Fifth income quintile | 0.162 | 0.3 | −0.138*** | 0.002 | −0.002 (0.010) |
| Household size | 6.56 | 5.97 | 0.593*** | 0.014 | −0.02*** |
| Children (0–4) | 0.764 | 0.566 | 0.198* | 0.004 | (0.001) |
| Ownership of agricultural land | 0.347 | 0.06 | 0.287*** | 0.002 | 0.001*** (0.002) |
| Ownership of nonagricultural land | 0.046 | 0.035 | 0.011*** | 0.001 | 0.03*** (0.009) |
| Own residence | 0.904 | 0.731 | 0.173*** | 0.002 | −0.005 (0.005) |
| Wealth index | 63.2 | 108.371 | −45.1*** | 0.132 | 0.002*** (0.000) |
| location | – | – | – | – | 0.014* (0.008) |
| Number of observations | 169,631 | 75,623 | | | 245,254 |

Note: Numbers in brackets represent standard errors.

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.