Mystery of the Evil Digits: Impact of Reliable Communication Network on Womens Economic Participation in Pakistan *

Saher Asad †

January 15, 2018

Abstract: In the context of developing countries such as Pakistan, cultural constraints and high incidence of violence against women, restricts women to engage in economic opportunities with low returns and low mobility. Access to a safe and reliable communication network can allow women to communicate with their households while traveling. This can improve their mobility and allow them to engage in high return economic opportunities. Using data from a new survey module, that I designed, for the nationally representative Pakistan Social and Living Standards Measurement Survey(PSLM), I look at the impact of reliability of communication network on economic participation of women in Pakistan. For identification, I make use of a natural experiment, where a computerized numbering system in Pakistan randomly assigns numbers to different lines (destination codes). The variation in lines (destination codes) induces variation in network quality. The lines can be identified from 4th digit of the cell phone number and can be categorized as Good or Bad. Results show that having a bad number decreases the economic participation of women by 4-7 % for rural areas, 9-12 % for urban areas and 11 -13 % for major cities, all statistically significant. Analysis of mechanisms reveals that having a bad number has a negative and significant impact on probability of women switching towards sectors which require them to leave their homes. The estimates lie in the range of 28 to 33 % for women and are both statistically and economically significant. The effect on economic participation is also heterogeneous to the person being primary versus secondary household member as well as the age. I find that the effect is higher for secondary earners as compared to the primary earners.

Keywords: Cell Phones, Connectivity, Pakistan, Women's Empowerment, Economic Participation, ICTs and Development

*I gratefully acknowledge funding for this research from a five year William J. Fulbright Ph.D. Fellowship. I am indebted to my dissertation committee, Stephen Smith, James Foster and Ram Fishman for all their encouragement, advise and patience during the course of this project. This research greatly benefitted from discussions with Jenny Aker, Sarah Baird, Tony Castleman, William Jack, Remi Jedwab, Monica Singhal, David Weil and Chris Udry. I thank all participants at GWU Development Lunch and LUMS Seminar for comments and suggestions. I am grateful to Pakistan Bureau of Statistics for helping collect data for this paper by adding my questionnaire into the Pakistan Social and Living Standards Measurement Survey. All errors are my own.

†Assistant Professor of Economics, Lahore University of Management Sciences. Email: saher.asad@lums.edu.pk

1 Introduction

In 2011, a report by Thompson Reuter, named Pakistan as among the top 5 most dangerous places in the world to be a woman.[1] In such conditions, how can women in Pakistan engage in economic activities to support their households? Women in developing countries engage in low return economic activities as these do not require of them to leave their home. The primary cause of this is the high incidence of crime and violence against women. The lack of security makes going to work outside the home a high risk activity. In this setting, women can utilize a reliable communication network to interact with their household members if a problem or situation arises. This continuous interaction can reassure women as well as their household members. The reassurance may lead to the male members of the household to allow women to leave home for working. The existence of this mechanism has the potential to increase the mobility of women and thereby make them shift towards occupations that require them to leave their home, resulting in substantial income gains.

Cell Phones have played a role in creating an important network of communication. If communication is strong then women can benefit from this network by being able to call their household if a problem arises or just calling them to update them of their safety. The role of a safe and strong communication network is very important in shaping incentives for women to engage in economic activities. This paper looks at the impact of cell phone network quality on the mobility of women as well as their economic participation and occupation choice using micro-data from a new nationally representative household survey in Pakistan.

The data utilized in this paper comes from the Pakistan Social and Living Standards Measurement survey (PSLM) 2011-2012. PSLM is representative at rural, urban and big city levels. For the 2011-2012, I worked closely with the Pakistan Bureau of Statistics to introduce a module in the questionnaire related to the use of cell phones in Pakistan. This new module collected detailed individual level information on cell phone ownership,

[1] For details see “The World’s Most Dangerous Countries for Women 2011”

usage, purpose of usage, quality of service, network provider utilized as well as tariff package adopted. This level of detailed information on cell phone usage combined with the economic indicators data from the rest of the questionnaire allows me to test the impact of cell phones on economic decisions at a national level.

The identification strategy adopted to deal with endogenous network quality comes from the computerized assignment of cell phone number digits. In most countries, the quality assignment is determined by geographic location, which also determines the destination code for the number. In such cases network quality is highly correlated with geographical location. However, in Pakistan, a different numbering assignment procedure exists. The variation in call quality comes from a unique feature of cell phone numbering system procedure that is identical across all carriers in Pakistan. For every carrier there are different sub-lines also known as the NDCs(National Destination Codes). The NDC for each carrier can be identified by the fourth digit of their cell phone number. The differentiation in quality for each network comes due to differential infrastructures put in place by different contractors associated with each line. The digits assigned by a computerized algorithm determine the call quality of numbers. Based on percentage of calls that get dropped I assign a number to either being "Bad" or "Good".

The data is utilized to implement three different empirical strategies. The first strategy utilizes the natural experiment to look at the impact of being part of the bad cohort of cell phone digits. The second strategy uses the Instrumental Variable Approach, where being part of the bad cohort is used to instrument for percentage of phone calls dropped while in conversation. The first two strategies rely on the cross-sectional nature of data. The third strategy combines the natural experiment with a Difference in Difference Approach. All analysis is stratified by gender as well as urban, rural and big city level.

The results show that having a bad number decreases the economic participation of women by 4-7 % for rural areas, 9-12 % for urban areas and 11 -13 % for big cities, all statistically significant at 1 % level of significance. These results are statistically and economically insignificant for men. Analysis of data also reveals that having a bad number has a negative and significant impact on probability of women switching towards sectors which require them to leave their homes. The estimates lie in the range of 28 to 33 % for women and are both statistically and economically significant. The results are the strongest for the big city sample compared to the urban and rural samples.

Data shows that the key mechanism driving the impact on economic participation and sector choice is an improvement in the probability of being able to leave home. In addition, data reveals that women with less reliable networks are less likely to communicate with their household to be picked up or when they are late or faced with some problem. Another important finding is that women's access to a bad number also alters their male household members perception of their security while outside their home. The effect on economics participation is also heterogeneous to the person being primary versus secondary household member as well as the age. In case of women, the effect is higher for secondary earners as compared to the primary earners. For men, the effect is insignificant for primary earners and significant at 10 % for secondary earners. The impact on economic participation is strongest for women in the age range 30-35.

In addition to looking at the mechanisms, I also estimate the income loss that women experience. Results show that having a bad number can reduce income of women by 15 to 30% based on probit and D in D estimates. The results are strongest for the big city sample. There is no significant impact of reliable communication network on income of men in either of the three regions.

This paper makes several contributions to the literature. First, it looks at the impact of communication network on labor market outcomes for women. Second, this is the first paper to examine the different mechanisms or channels of phone usage that can empower women. Finally this paper utilizes a national level survey, with a national level natural experiment, which provides external validity to the estimates.

The rest of the paper is structured as follows. Section 2 presents the background information associated with this paper. Section 3 describes the data and measurement. Section 4 describes the identification strategy. Section 5 explains the empirical strategy and specifications. Section 6 describes estimation and results. Section 7 provides the policy implications and conclusion of the paper.

2 Background

Access to Information and Communication Technology can influence the decision making processes. Among these, one prominent decision is related to that of agriculture in rural areas in developing countries.[2]. Micro entrepreneurs can also be impacted by cell phones through an increase in their network [Donner & Escobari, 2010]. Cell Phones can also lead to an increase in consumption for rural households [Labonne & Chase, 2009].

Klonner & Nolen [2010] find that cell phone coverage causes women to shift away from agricultural occupations. It is also known that cell phones can ease the constraints related to migration. Aker et al. [2011] looks at the impact of a mobile phone based adult education program (Project ABC) in Niger on the likelihood of migration. Results from the paper suggest that access to this technology substantially influenced seasonal migration in Niger.

In Pakistan a major constraint on economic participation of women is related to their safety. Violence targeted towards women is very high; thereby making their households concerned about allowing women to travel to engage in high return economic opportunities. As a result, women are restricted to opportunities such as tutoring or working as domestic live-in maids.

[2]For complete review of studies on this topic see Aker [2010], Aker & Fafchamps [2013], Bayes [2001], Beuermann et al. [2011], Beuermann et al. [2012], Beuermann [2011], Camacho & Conover [2011], Chong et al. [2009], Cole & Fernando [2012], Curtois & Subervie [2014], Fafchamps & Minten [2012], Fu & Akter [2012], Futch & McIntosh [2009], Goyal [2010], Jensen [2007], Jensen [2010], Labonne & Chase [2009], Mitra et al. [2013], Mittal et al. [2010], Muto [2009], Nakasone [2013], Nyarko et al. [2013], Parker et al. [2013], Svensson & Yanagizawa [2009] and Wellenius [2002].

3 Data and Measurement

The data utilized in this paper comes from the Pakistan Social and Living Standards Measurement survey (PSLM) 2011-2012. PSLM is nationally representative as well as representative at rural, urban and big city level. This survey is conducted every year to measure Pakistan's progress towards meeting the Millennium Development Goals. The questionnaire for the survey is very similar to the standardized World Bank Living Standards Measurement Study (LSMS) surveys. For the 2011-2012 round, I worked closely with the Pakistan Bureau of Statistics to introduce a new module in the PSLM questionnaire. This new module collected data on detailed individual level information on cell phone ownership, usage, purpose of usage, security of women as perceived by the male members, quality of service, network provider utilized as well as tariff package adopted. This level of detailed information on cell phone usage combined with the detailed economic indicators data from the rest of the questionnaire allows to test the impact of cell phones on economic decisions at a national level.

The total number of households surveyed in PSLM 2011-2012 are 15,807. The survey used a two-stage stratified sampling design. Enumeration block for urban areas and villages for rural areas were selected in the first stage as the Primary Sampling Units (PSUs). In the second stage 16 households from every village and 12 households from every urban enumeration area were then selected randomly.

The main outcome variable in the analysis is the binary variable of whether women work or not. This is the measure of economic participation. The next important variable is obtained by dividing the sectors of employment into two categories based on the requirement for women having to leave home for work. In the data collection, women provided a brief description of their work in addition to categorization. The description provided was utilized to then construct the measure on occupation requiring leaving home. The definition was then constructed at a local level based on this description. Some of the occupations requiring to leave home include: teaching at a school, running a shop, working in factory and small scale mobile retailing in vegetables, bangles or clothes, house and baby-sitting and working in beauty salons. Occupations not requiring to leave home include: teaching Holy text to neighbor children, home tutoring, tailoring and domestic live-in maids.[3] To study the mechanisms, the paper looks at the impact of have a bad cell phone on the decision making related to women being able to travel. It is hypothesized that if women have access to a reliable communication network, they will be able to travel easily as they can call for help if there is a problem. The variables used to measure network quality include a proportion of phone calls dropped while the person was talking and as well as an assignment to a certain national destination code are also obtained from the survey. The importance of national destination code for the cell phone numbers is explained in the next section.

4 Identification from "Mystery Digits"

Cell Phone network quality can be highly endogenous due to location of households. For example people living in hilly areas may experience coverage different from those living in plains. In order to address these concerns,I rely on a natural experiment based on the computerized assignment of digits that determine the call quality. In most countries the quality assignment is determined by geographic location which also determines the destination code for the number. However, in Pakistan a different numbering assignment procedure exists. This identification comes from a special feature of the cell phone number assignment which is central to Pakistan only. The variation in call quality comes from a special structure of cell phone numbering system procedure that is identical across all carriers in Pakistan.

The cell phone numbers in Pakistan are not assigned based on geographical location but is based on a special numbering structure. The special structure of number assignment to

[3] It can be argued that in fact live-in maids live away from home to work. However it is in fact a change of living destination and once employed women live there. In addition in most cases women work as live-in maid in places where their mother, father, brother or uncle/aunt are already employed and hence have family living with them.

certain lines creates variation in quality of service. Each cell phone number consists of 11 digits “03cn-yyyyyyy”.

Every cell number starts with a 03 irrespective of carrier or line. The third digit “c” represents the company to which the cell phone number belongs. The customer has full control over choosing this part of the number as the customer is free to choose their carrier based on their own preference. The fourth digit “n” represents a special code, which also determines the line to which the number is assigned within a company. This is called the National Destination Code (NDC) for a cell phone number. A number is assigned to this line based on this digit. Customers do not have any control over this digit as it is pre-assigned by the company in a computerized number generator. It is important to note that customers assigned to a particular line have nothing in common other than the digit and can belong to any part of the country and can have any type of package. The introduction of multiple NDCs happened as the telecommunication authority started assigning companies into having these to meet growing demand. As reported by the Pakistan Telecommunication Authority themselves: "To meet the emerging demand for cell phone service, the Pakistan Telecommunication Authority (PTA) started issuing multiple NDCs to the different mobile operators. From the subscribers point of view, having multiple NDCs for a mobile company is not a good practice as it can create a large disparity in service quality across NDCs.”

Finally the last part of the number is the rest of the 7 digits yyyyyyy. These digits are also assigned by a computerized generator; however, they do not play any role in the process. Some part of this numbering is related to geographic location and also the package purchased by the customer e.g. pre-paid versus post-paid. There are 5 cell phone carriers operating in Pakistan. The number c runs from 0 to 4. Finally cn represents the carrier line combination. There are a total of 30 cn combinations out of which 17 can be classified as good numbers and 13 as bad. These categories were constructed using the data from the survey on the percentage of all phone calls that get dropped while in conversation. This variation in service quality between lines combined with the random assignment of customers to lines provides identification for variation in quality of service. Figure 1 shows the percentage of dropped calls by all providers. The difference between the two categories is in the neighborhood of 45%. This difference between the call quality of two types of NDCs is not driven by difference across carriers but is consistent across all carrier as shown by Figure 2 and 3.

Next step to establish the strength of the identification strategy is to study if a disproportionate percentage of population has access to the good number. Figure 3, shows the proportion of users with good number nationally as well as by carrier. As shown by the graph, the probability of any new user getting a new number is 0.53 and is consistent across all carriers. The final test to establish the credibility of this identification strategy is of the characteristics of users with the a good number. Results presented in table 1, show the difference between characteristics of people with a good number and a bad number. None of the individual level characteristics are significantly different across the two groups of people. Regardless of balance of observables it may be possible that the unobservable are causing the difference between the two categories. In addition, it could be the case that people keep on changing their phone numbers until and unless they are satisfied with the number they have. Based on the Pakistan Telecom Authority Regulations, it is very easy to purchase a SIM-card[4] for the first time, it is a much more complicated process to change your number. A person can only hold one SIM-card at a time. While a person can visit the local store to buy a SIM-card, the cancellation service is not available there. For cancellation, one needs to visit the head-quarter office as well as register again with the National Database and Regulation Authority. This process is much more complicated, cumbersome and difficult, making it unlikely that people changed their phones.[5] Despite the plausible reasons outlined for people not switching it is difficult to establish that without any data. To establish this,

[4]Subscriber Identity Module

[5]It is important to note that the same process does not hold for cases when one has their phone stolen. In those cases the person is re-issued a new SIM-card which has the same number as before.

I obtained 5 years record from 25 local stores located in the vicinity of Lahore, Islamabad and Rawalpindi. These stores were located in cities as well as the more remote villages. Due to the policy of the different service providers all local stores irrespective of their location have to maintain record of people who visit them for purchasing and then re-loading credit or paying bills for at least 5 years. Based on the customer data, 93% percent of customers who purchased a SIM-card return for adding credit on the same number at least once every month.[6][7] In addition to the tests and anecdotal evidence discussed above, I also provide Conley Bounds later in the paper, which show that the estimates are robust to some level of violation of exclusion restriction.

5 Empirical Strategy and Specification

This paper applies different estimation strategies. To utilize the natural experiment of random computerized assignment of numbers, equation 1 is utilized.

$$Y_i = \alpha_0 + \alpha_1 BadNumber_i + \alpha_2 X_j + \epsilon_j \tag{1}$$

Here Y_i represents, the outcome variable measuring economic participation for person i. $BadNumber_i$ is equal to 1 if person has a bad number or not. Controls include individual level variables such as education, parental education, household size, age, married, cell phone coverage as measured by total number of available bars on the phone, household land ownership, distance from market and district fixed effects as well as cell phone network fixed effects.

In addition to utilizing this natural experiment, an Instrumental Variable strategy based on using being assigned to bad number as an instrument for network quality is also applied.

[6]The customer data is identifiable as each customer can be recognized by their number as well as their NIC(National Identification Card) number

[7]This data does not have representativeness, however it helps me gauge the level of frequency with which the customers return to buy credit pay bills for the same number. The idea is that if the customers are revisiting to pay bill for the same number they must be still using it.

In this case the first stage of the IV regression becomes :

$$Drop_i = \alpha_0 + \alpha_1 BadNumber_i + \alpha_2 X_j + \epsilon_j \tag{2}$$

The second stage of the regression, then becomes:

$$Y_i = \alpha_0 + \alpha_1 Quality_i + \alpha_2 X_j + \epsilon_j \tag{3}$$

The utilization of natural experiment and the IV strategy are both based on cross-section nature of the data. In addition to collecting the 2011-2012 data, the survey also collected retrospective information on labor market, empowerment and cell phone variables in 2010, which was 2 years before the survey was conducted. This retrospective information was collected and can be utilized to implement a Difference in Difference with the natural experiment. To do this the sample is restricted to eliminate people who had a cell phone before 2010. This will allow to compare people who received a bad number after 2010 to those who received good number after 2010 overtime. The Difference in Difference (D in D) Strategy combined with the natural experiment can be written as:

$$Y_i t = \beta_0 + \beta_1 Post_t + \beta_2 BadNumber_i + \beta_3 (Post * BadNumber)_i t + \epsilon_i t \tag{4}$$

All specifications outlined are run separately for men and women in rural, urban and big city samples. This means there are a total of 6 groups. In all specifications the standard errors are clustered at the PSU level.

6 Estimation and Results

6.1 Impact on Economic Participation

The first part of the analysis involves looking at the impact of network quality on probability of economic participation. All three specifications are run, which include the probit, IV approach as well as the D in D approach combined with the natural experiment. The results in Table 2 show that having a bad number decreases the probability of women's' economic participation by 4-7 % for rural areas, 9-12 % for urban areas and 11 -13 % for big cities. It is important to note that these estimates have strong economic significance as well since the average participation level for women with a bad number is 17%. This means that having access to a reliable network doubles the economic participation of women. The IV estimate has a slightly different interpretation because the treatment variable in that case is a continuous measure of percentage of phone calls that get dropped while talking. The result from the IV estimate are consistent with PROBIT and D in D results.

While the results are statistically and economically significant for women, they are both statistically and economically insignificant for the case of men. This supports the original hypothesis that improvement in communication alleviates the constraints that women face. The men do not face these constraints, thereby having a reliable network does not impact them. Another plausible explanation for this result is that men already have a very high rate of economic participation. Moreover, men are the primary earners for households in Pakistan, therefore do not have sensitivity to reliability of network.

In addition to the gender difference, the results also show that there is some difference across the rural, urban and big city samples. It is possible to explore this type of heterogeneity as the survey sampled separately for each of the three categories of regions. The results are the strongest for the big city, followed by urban areas and then the rural areas. This can be attributed to the lower level of security in the big cities. Anecdotal evidence suggests that crime and violence against women is higher in the big cities.

6.2 Impact on Sector of Occupation

Another aspect of the analysis is to look at the impact of network quality on choice of occupation. It is hypothesized that access to a secured network will enhance women's ability to switch towards high return economic activities, which require them to leave home. The results from all three empirical strategies show that a bad number can have a negative and significant impact on probability of women switching towards such high return sectors. The estimates presented in Table 3 lie in the range of 28 to 33 % for women and are both statistically and economically significant. The results are the strongest for big city sample compared to urban and rural sample.

The gender difference in results is similar to that for economic participation. This again points to the fact that improved cell phone connectivity can alleviate the constraints on women. One of the plausible explanations for the greatest impact in the big city is because of the presence of complementary infrastructure. The results provide evidence that improvement in cell phone network quality can make women shift towards, high return sectors which require them to leave home.

6.3 Mechanisms

6.3.1 Is it Empowerment?

The change in economic participation and shift in sectors for women can be driven by change in women's ability to leave their home, which is a result of their ability to communicate with their household while they are outside. An example includes a situation where women are outside and face a problem. With a reliable network, they can call their household members for help or contact a reliable authority. This type of communication can result in an increase in women's ability to travel and therefore impacting their economic participation. To test these one can look at the impact on these aforementioned variables. First as shown in table 4, having access to a bad number leads to a decrease in women's ability to travel outside of their home. This result is negative and significant for women in rural areas, urban areas and also big cities. The coefficient size is the largest for the big city sample. The results are consistent with the previous results of impact on economic participation and sector change. Next, the use of cell phone by women is considered. Results show that having a bad number leads to a negative and significant impact on the probability of women contacting household when they are away. Table 5 then shows that this involves two types of uses, which include contacting household to asking a household member to come pick them up or to call and contact their household members when getting late or facing some problem. Results for both cases is significant across all three sample, being the strongest for the big city sample. Another important aspect of the hypothesis is related to the perception of men regarding the safety of women when they are outside. In all cases the question was asked from the father for unmarried women and husband for married women. The results in Table 6 show that in case where women have a bad phone number, the male household members feel that it is not safe for women to go outside. The coefficients for this variable are much higher for case of husband than for fathers. The study of mechanisms show that the main mechanism driving these results is that of being able to communicate with household resulting in improvement in mobility. Another plausible hypothesis is that there is a general increase in empowerment of women as measured by their ability to make decisions on education and marriage. The results in Table 7 show that in fact there is no overall increase in decision-making power. The only change that happens is through change in women's ability to travel and communicate as the male household members have experience a change in their perception of women's safety.

6.3.2 Primary Versus Secondary Earner?

All results presented in previous sections show having a bad number only impacts the economic participation for women. One explanation could be that since in Pakistan women are often not the primary earners, hence they maybe more sensitive to network connectivity compared to men who are the primary earners. To test for this explanation I divide all individuals by whether they are the primary household earners or not. The sample in all cases provides enough sample size to test whether the impact on economic participation only household for primary or secondary earners. Results in Tables 9 and 10 show that for the case of women, the effect is stronger for the case of secondary earners as compared to that of primary earners. In context of men, there is no significant impact on their economic participation if they are primary earners and there is a negative impact with 10% significance for case of secondary earners. This result can be explained by the fact that primary earners are much less sensitive to connectivity due to the lack of alternative. The secondary earners often have an alternative option of not working as the primary earner is already working. However with in the secondary earners, the effect on women is higher than that on men.

6.3.3 Heterogeneity by Age

Another aspect of heterogeneity could be that younger women are more sensitive to network connectivity as certain type of violence only effects young women. To test this hypothesis I run the economic participation results for the urban, rural and big city strata by age groups. To stratify the women by age, I split them into 5 groups which are: less than 25 years, 25 to 35 years, 35-45 years and above 45 years. Based on that I plot all the coefficients by age group. The results in Figure 4 reveal that while the results are significant for all age groups in all sample, the coefficient is highest for women in age range 30-35.

6.4 Income

The results in previous sections have shown that having a reliable cell phone connection can lead to an increase in economic participation of women and also make them shift towards high return economic activities. This change can lead to an increase in income of women. Table 8 presents the impact of having a reliable communication network on log of annual income. Results show that having a bad connection leads to a decrease in women's income by 15 to 30 % based on PROBIT and D in D estimates. These are based on the binary variable of having a good number. The IV estimates provide impact of network quality(a continuous variable) on income of women. This means that for women in rural areas, a 10% decrease in call drop rate is associated with a 3% increase in income of women. The estimate is much higher for women in urban areas and big cities. Similar analysis is conducted for men in the rural, urban and big city samples. The results show that the IV coefficient is negative and significant at a 10% level of significance of men in rural areas. The coefficients for men in urban areas and big cities are statistically insignificant. The analysis of income suggests that having reliable cell phone network can lead to substantial income gains for women in Pakistan.

6.5 Conley Bounds

All the results reported are based on the assumption that exclusion restriction holds which means there is no direct correlation between the instrument and outcome. However for additional robustness, I employ the recent bounds approach developed by Conley et al. [2012]. This approach relaxes the exclusion restriction by assuming that the coefficients on bad number in the main equation while controlling for call drop rate lies in an interval. The bounds are then estimated and reported for 95% confidence intervals.

The results in Table 11 for conley bounds show that the estimates do not vary significantly with the value of delta. The bounds provide evidence for a robust negative impact of having a poor connectivity on economic participation for women. The effect for men is also consistent with the earlier results. The IV estimates are robust to relaxing the exclusion restrictions imposed on the instruments. CI have no zero meaning that there is robust negative effect.

7 Policy Implications and Conclusion

This paper looks at the impact of cell phone network quality on mobility of women as well as their economic participation and occupation choice using micro-data from a new nationally representative household survey in Pakistan. Evidence provided from empirical analysis shows that access to a reliable communication network can increase the mobility of women and thereby make them shift towards high return occupations that require them to go outside home; resulting in substantial income gains.

Cell Phones have played a role in creating an important network of communication. If the communication is strong then women can benefit from this network by being able to call their household if a problem arises or just calling them to update them of their safety. In addition having a strong connection also assures the male household members that the women will be safer when outside home. If the network is weak then cell phones cannot impact women's ability to go out, if cell phone fails to connect or stops working when needed, then women cannot rely on this network. Role of a safe and strong communication network is very important in shaping incentives for women to engage in economic activities. The effect is strongest for 30-35 years.

This paper provides several policy implications. First, it shows that developing the communication networks and investing in their reliability can yield substantial returns in terms of improvement in economic participation as well as income. Second, the paper shows that reliable communication networks have a stronger impact when other types of infrastructure are well developed. This statement is supported by the stronger impact in big city and urban sample as compared to the rural sample.

References

Aker, J. (2010). Information from Markets Near and Far: Mobile Phones and Agricultural Markets in Niger. *American Economic Journal: Applied Economics*, *2 (3)*, 45-69.

Aker, J., Clemens, M., & Ksoll, C. (2011). Mobiles and Mobility: The Effect of Mobile Phones on Migration in Niger.

Aker, J., & Fafchamps, M. (2013). How does Mobile Phone Coverage Affect Farm-Gate Prices? Evidence from West Africa. *World Bank Economic Review*, *Forthcoming*.

Bayes, A. (2001). Infrastructure and Rural Development: Insights from a Grameen Bank Village Phone Initiative in Bangladesh. *Agricultural Economics*, *25(2-3)*, 261-272.

Beuermann, D. (2011). *Telecommunication Technologies, Agricultural Productivity, and Child Labor in Rural Peru.* University of Maryland, College Park, MD. Unpublished.

Beuermann, D., C, M., & Lopez, C. S. (2011). *The Effects of Mobile Phone Infrastructure: Evidence from Rural Peru.* Banco Central De Reserva Del Peru Working Paper 2012-012.

Beuermann, D., Mckelvey, C., & Vakis, R. (2012). Mobile Phones and Economic Development in Rural Peru. *Journal of Development Studies*, *48(11)*, 1-12.

Camacho, A., & Conover, E. (2011). *The Impact of Receiving Price and Climate Information in the Agricultural Sector.* IDB WOrking Paper Series IDB-WP-220.

Chong, A., Galdo, V., & Torero, M. (2009). Access to Telephone Service and Household Income in Poor Rural Areas using a Quasi Natural Experiment for Peru. *Economica*, *74(304)*, 623-648.

Cole, S., & Fernando, N. (2012). *The Value of Advice: Evidence from Mobile Phone-Based Agricultural Extension.* Harvard Business School Working Paper 13-047.

Conley, T., Hansen, C., & Rossi, P. (2012). Plausibly Exogenous. *Review of Economics and Statistics*, *94(1)*, 260-272.

Curtois, P., & Subervie, J. (2014). Farmer Bargaining Power and Market Information Services. *American Journal of Agricultural Economics*, *Published online: June 22, 2014*.

Donner, J., & Escobari, M. (2010). A Review of Evidence on Mobile Use by Micro and Small Enterprises in Developing Countries. *Journal of International Development*, *22(5)*, 641-658.

Fafchamps, M., & Minten, B. (2012). Impact of SMS-Based Agricultural Information on Indian Farmers. *World Bank Economic Review*, *28(1))*, 1-32.

Fu, X., & Akter, S. (2012). Impact of Mobile Telephone on the Quality and Speed of Agricultural Extension Services Delivery: Evidence from the Rural India. *paper presented at the International Association of Agricultural Economists annual conference, Foz do Iguacu, Brazil*.

Futch, M., & McIntosh, C. (2009). Tracking the Introduction of the Village Phone Product in Rwanda. *Information Technologies and International Development*, *5(3)*.

Goyal, A. (2010). Information, Direct Access to Farmers, and Rural Market Performance in Central India. *American Economic Journal: Applied Economics*, *2(3)*, 22-45.

Jensen, R. (2007). The Digital Provide: Information (Technology), Market Performance, and Welfare in the South Indian Fisheries Sector. *Quarterly Journal of Economics*, *122(3)*, 879-924.

Jensen, R. (2010). Information, Efficiency and Welfare in Agricultural Markets. *Agricultural Markets*, *41(S1)*, 203-216.

Klonner, S., & Nolen, P. (2010). *Cell Phones and Rural Labor Markets: Evidence from South Africa.* Proceedings of the German Development Economics Conference, Hanover, Germany, June 2425, 2010.

Labonne, J., & Chase, R. (2009). *The Power of Information: The Impact of Mobile Phones on Farmers' Welfare in Philippines.* World Bank Working Paper 4996.

Mitra, S., Mokherjee, D., Torero, M., & Visaria, S. (2013). *Asymmetric Information and Middleman Margins: An Experiment with West Bengal Potato Farmers.* Boston:Boston University.

Mittal, S., Gandhi, S., & Tripathi, G. (2010). Socio-Economic Impact of Mobile Phones on Indian Agriculture. *Indian Council for Research on International Economic Relations Working Paper 246*.

Muto, M. (2009). The Impact of Mobile Phone Coverage Expansion on Market Participation: Panel Data Evidence from Uganda. *World Development*, *37 (12)*, 1887-1896.

Nakasone, E. (2013). *The Role of Price Information in Agricultural Markets: Experimental Evidence from Rural Peru.* Washington, DC: International Food Policy Research Institute Unpublished.

Nyarko, Y., Hildebrandt, N., Romagnoli, G., & Soldani, E. (2013). Market Information Systems for Rural Farmers Evaluation of Esoko MISYear 1 Results. *New York: New York University*.

Parker, C., Ramdas, K., & Savva, N. (2013). *Is IT Enough? Evidence from a Natural Experiment in Indias Agriculture Markets.* London Business School Unpublished.

Svensson, J., & Yanagizawa, D. (2009). Getting Prices Right: The Impact of the Market Information Service in Uganda. *Journal of the European Economic Association*, *7(2-3)*, 435-445.

Wellenius, B. (2002). *Closing the Gap in Access to Rural Telecommunications: Chile 19952002.* World Bank Discussion Paper 430.

Table 1: Summary Statistics By Number Status

Variables	Good Connection	Bad Connection	Difference of Means
Characteristics			
Years of Schooling	6.23	6.35	-0.12
Mothers Years of Schooling	1.38	1.25	0.13
Fathers Years of Schooling	5.49	5.67	-0.18
Household Size	5.78	5.53	0.25
Age	36.32	36.22	-0.10
Land Ownership	1.13	1.39	-0.26
Marital Status	0.68	0.71	-0.02
Literacy	0.62	0.63	-0.01
Coverage in Boundary	2.35	2.39	-0.04
Coverage Outside Boundary	2.97	2.89	0.09
Bank Access	0.21	0.19	0.02
Involved in IT Sector	0.12	0.14	-0.02

$***p < 0.01, **p < 0.05, *p < 0.1$

The table shows individual level summary statistics for both outcome and control variables for individuals with access to a good versus a bad number. The results illustrate that individuals with access to a good number are not different from those with a bad number.

Table 2: Results for Economic Participation

	(Women)			(Men)		
	(Rural)	(Urban)	(Big City)	(Rural)	(Urban)	(Big City)
Probit	-0.07***	-0.12***	-0.13***	0.04*	0.07*	0.08
	(0.01)	(0.05)	(0.03)	(0.03)	(0.05)	(0.11)
IV	-0.03**	-0.06***	-0.07***	-0.01	-0.01	-0.02
	(0.005)	(0.02)	(0.003)	(0.15)	(0.17)	(0.15)
Under-Identification Test Satisfied	Y	Y	Y	Y	Y	Y
Weak Identification Test Satisfied	Y	Y	Y	Y	Y	Y
Diff-in Diff	-0.04**	-0.09***	-0.11**	-0.05	-0.04	-0.10
	(0.024)	(0.01)	(0.04)	(0.20)	(0.17)	(0.09)
District Fixed Effects	Y	Y	Y	Y	Y	Y
Clustering at PSU Level	Y	Y	Y	Y	Y	Y
Number of Observations	2703	1324	1114	6228	3008	2715

$***p < 0.01, **p < 0.05, *p < 0.1$

The average probability of economic participation for women is 0.18 and that for men is 0.82. Probit estimates are for the impact of having a bad number on economic participation. Negative values denote that having a bad network reduces the probability of economic participation. IV estimate uses proportion of dropped calls experienced by person as treatment varaiable. The type of network is then used to instrument for proportion of dropped calls.The rural area estimation uses all individuals in rural sample. The urban area estimation uses all individuals in urban areas sample which are not categorized as big cities. The big city sample uses all individuals in big city sample, where the big cities include Lahore, Faisalabad, Rawalpindi, Multan, Gujranwala, Sargodha, Sialkot, Bahawalpur, Islamabad, Karachi, Hyderabad, Sukkur, Peshawar and Quetta. Regressions are weighted using the pweights command in STATA.

Table 3: Results for Sectoral Change

	(Women)			(Men)		
	(Rural)	(Urban)	(Big City)	(Rural)	(Urban)	(Big City)
Probit	-0.33***	-0.38***	-0.42***	0.17*	0.12*	0.09
	(0.02)	(0.11)	(0.20)	(0.14)	(0.08)	(0.15)
IV	-0.11***	-0.13***	-0.16***	-0.13	-0.05	-0.04
	(0.03)	(0.05)	(0.06)	(0.14)	(0.11)	(0.06)
Under-Identification Test Satisfied	Y	Y	Y	Y	Y	Y
Weak Identification Test Satisfied	Y	Y	Y	Y	Y	Y
Diff-in Diff	-0.28**	-0.29***	-0.31**	0.06	0.03	0.05
	(0.024)	(0.01)	(0.04)	(0.20)	(0.17)	(0.09)
District Fixed Effects	Y	Y	Y	Y	Y	Y
Clustering at PSU Level	Y	Y	Y	Y	Y	Y

$***p < 0.01, **p < 0.05, *p < 0.1$

Note that the average probability of working in a sector requiring mobility sector for women is 0.20 and that for men is 0.85. The IV estimates pass the test of under identification as well as weak identification. The rural area estimation uses all individuals in rural sample. The urban area estimation uses all individuals in urban areas sample which are not categorized as big cities. The big city sample uses all individuals in big city sample, where the big cities include Lahore, Faisalabad, Rawalpindi, Multan, Gujranwala, Sargodha, Sialkot, Bahawalpur, Islamabad, Karachi, Hyderabad, Sukkur, Peshawar and Quetta. Regressions are weighted using the pweights command in STATA.

Table 4: Results for Womens Empowerment

	(Ability to Travel to Market)			(Women can Use Cell Phone to Contact Home)		
	(Rural)	(Urban)	(Big City)	(Rural)	(Urban)	(Big City)
Probit	-0.27***	-0.31**	-0.38***	-0.23***	-0.33***	0.42***
	(0.12)	(0.17)	(0.08)	(0.04)	(0.14)	(0.19)
IV	-0.05***	-0.06***	-0.08***	-0.05***	-0.07***	-0.10***
	(0.01)	(0.005)	(0.03)	(0.02)	(0.006)	(0.04)
Under-Identification Test Satisfied	Y	Y	Y	Y	Y	Y
Weak Identification Test Satisfied	Y	Y	Y	Y	Y	Y
Diff-in Diff	-0.25***	-0.27***	-0.35**	-0.26*	-0.34***	-0.38***
	(0.10)	(0.09)	(0.17)	(0.16)	(0.14)	(0.13)
District Fixed Effects	Y	Y	Y	Y	Y	Y
Clustering at PSU Level	Y	Y	Y	Y	Y	Y
Number of Observations	2703	1324	1114	2703	1324	1114

$***p < 0.01, **p < 0.05, *p < 0.1$

Note that the average probability of traveling to market for women is 0.17 and of using cell phone for calling home is 0.28. The IV estimates pass the test of under identification as well as weak identification. The rural area estimation uses all individuals in rural sample. The urban area estimation uses all individuals in urban areas sample which are not categorized as big cities. The big city sample uses all individuals in big city sample, where the big cities include Lahore, Faisalabad, Rawalpindi, Multan, Gujranwala, Sargodha, Sialkot, Bahawalpur, Islamabad, Karachi, Hyderabad, Sukkur, Peshawar and Quetta. Regressions are weighted using the pweights command in STATA.

Table 5: Results for Womens Type of Cell Phone Usage

	(Women Use Cell Phone to Call Home for Pick-up)			(Women use Cell Phone to Call Home when Late)		
	(Rural)	(Urban)	(Big City)	(Rural)	(Urban)	(Big City)
Probit	-0.24***	-0.33**	-0.45***	-0.18**	-0.28***	-0.37***
	(0.08)	(0.06)	(0.21)	(0.05)	(0.08)	(0.13)
IV	-0.03**	-0.08**	-0.12***	-0.03**	-0.06***	-0.13***
	(0.001)	(0.005)	(0.009)	(0.006)	(0.01)	(0.05)
Under-Identification Test Satisfied	Y	Y	Y	Y	Y	Y
Weak Identification Test Satisfied	Y	Y	Y	Y	Y	Y
Diff-in Diff	-0.18**	-0.28***	-0.38**	-0.15*	-0.26***	-0.33***
	(0.11)	(0.06)	(0.07)	(0.006)	(0.05)	(0.12)
District Fixed Effects	Y	Y	Y	Y	Y	Y
Clustering at PSU Level	Y	Y	Y	Y	Y	Y
Number of Observations	2703	1324	1114	2703	1324	1114

$***p < 0.01, **p < 0.05, *p < 0.1$

Note that the average for first variable is 0.31 and that for second is 0.43. The IV estimates pass the test of under identification as well as weak identification. The rural area estimation uses all individuals in rural sample. The urban area estimation uses all individuals in urban areas sample which are not categorized as big cities. The big city sample uses all individuals in big city sample, where the big cities include Lahore, Faisalabad, Rawalpindi, Multan, Gujranwala, Sargodha, Sialkot, Bahawalpur, Islamabad, Karachi, Hyderabad, Sukkur, Peshawar and Quetta. Regressions are weighted using the pweights command in STATA.

Table 6: Results for Male Household Members Security Perception for Mobility of Women

	(Father)			(Husband)		
	(Rural)	(Urban)	(Big City)	(Rural)	(Urban)	(Big City)
Probit	-0.17***	-0.25***	-0.31***	-0.10***	-0.29***	-0.41***
	(0.03)	(0.07)	(0.11)	(0.04)	(0.05)	(0.08)
IV	-0.02**	-0.05**	-0.09***	-0.01**	-0.07***	-0.11***
	(0.001)	(0.005)	(0.009)	(0.006)	(0.01)	(0.05)
Under-Identification Test Satisfied	Y	Y	Y	Y	Y	Y
Weak Identification Test Satisfied	Y	Y	Y	Y	Y	Y
Diff-in Diff	-0.09**	-0.29***	-0.36**	-0.11*	-0.34***	-0.39***
	(0.01)	(0.12)	(0.18)	(0.14)	(0.04)	(0.19)
District Fixed Effects	Y	Y	Y	Y	Y	Y
Clustering at PSU Level	Y	Y	Y	Y	Y	Y
Number of Observations	2703	1324	1114	2703	1324	1114

$***p < 0.01, **p < 0.05, *p < 0.1$

Note that the average for first variable is 0.18 and that for second is 0.20. The IV estimates pass the test of under identification as well as weak identification. The rural area estimation uses all individuals in rural sample. The urban area estimation uses all individuals in urban areas sample which are not categorized as big cities. The big city sample uses all individuals in big city sample, where the big cities include Lahore, Faisalabad, Rawalpindi, Multan, Gujranwala, Sargodha, Sialkot, Bahawalpur, Islamabad, Karachi, Hyderabad, Sukkur, Peshawar and Quetta. Regressions are weighted using the pweights command in STATA.

Table 7: Results for Womens Decision Making Power

	(Education Decision)			(Marriage Decisions)		
	(Rural)	(Urban)	(Big City)	(Rural)	(Urban)	(Big City)
Probit	-0.08	-0.15*	-0.09	-0.04	0.10	-0.08*
	(0.07)	(0.10)	(0.13)	(0.17)	(0.14)	(0.05)
IV	-0.03	-0.07	0.10	-0.03	-0.03	-0.02
	(0.91)	(0.15)	(0.09)	(0.06)	(0.13)	(0.15)
Under-Identification Test Satisfied	Y	Y	Y	Y	Y	Y
Weak Identification Test Satisfied	Y	Y	Y	Y	Y	Y
Diff-in Diff	-0.04	-0.11*	-0.04	0.06	-0.05	-0.07
	(0.037)	(0.08)	(0.09)	(0.05)	(0.13)	(0.21)
District Fixed Effects	Y	Y	Y	Y	Y	Y
Clustering at PSU Level	Y	Y	Y	Y	Y	Y
Number of Observations	2703	1324	1114	2703	1324	1114

$***p < 0.01, **p < 0.05, *p < 0.1$

Note that the average for first variable is 0.17 and that for second is 0.09. The IV estimates pass the test of under identification as well as weak identification. The rural area estimation uses all individuals in rural sample. The urban area estimation uses all individuals in urban areas sample which are not categorized as big cities. The big city sample uses all individuals in big city sample, where the big cities include Lahore, Faisalabad, Rawalpindi, Multan, Gujranwala, Sargodha, Sialkot, Bahawalpur, Islamabad, Karachi, Hyderabad, Sukkur, Peshawar and Quetta. Regressions are weighted using the pweights command in STATA.

Table 8: Results for Log of Annual Income

	(Women)			(Men)		
	(Rural)	(Urban)	(Big City)	(Rural)	(Urban)	(Big City)
Probit	-0.15***	-0.24***	-0.31***	0.06*	0.08	0.07
	(0.06)	(0.09)	(0.13)	(0.04)	(0.12)	(0.15)
IV	-0.04***	-0.08***	-0.07***	-0.03*	-0.05	0.01
	(0.01)	(0.03)	(0.03)	(0.02)	(0.16)	(0.19)
Under-Identification Test Satisfied	Y	Y	Y	Y	Y	Y
Weak Identification Test Satisfied	Y	Y	Y	Y	Y	Y
Diff-in Diff	-0.08***	-0.21***	-0.24***	-0.04	0.02	0.05
	(0.03)	(0.08)	(0.07)	(0.14)	(0.17)	(0.24)
District Fixed Effects	Y	Y	Y	Y	Y	Y
Clustering at PSU Level	Y	Y	Y	Y	Y	Y
Number of Observations	2703	1324	1114	6228	3008	2715

$***p < 0.01, **p < 0.05, *p < 0.1$

Probit estimates are for the impact of having a bad number on log of income. Negative values denote that having a bad network reduces the income. IV estimate uses proportion of dropped calls experienced by person as treatment varaiable. The type of network is then used to instrument for proportion of dropped calls.The rural area estimation uses all individuals in rural sample. The urban area estimation uses all individuals in urban areas sample which are not categorized as big cities. The big city sample uses all individuals in big city sample, where the big cities include Lahore, Faisalabad, Rawalpindi, Multan, Gujranwala, Sargodha, Sialkot, Bahawalpur, Islamabad, Karachi, Hyderabad, Sukkur, Peshawar and Quetta. Regressions are weighted using the pweights command in STATA.

Table 9: Economic Participation Results for Primary Earners Only

	(Women)			(Men)		
	(Rural)	(Urban)	(Big City)	(Rural)	(Urban)	(Big City)
Probit	-0.03***	-0.05***	-0.11***	0.01	0.01	0.02
	(0.01)	(0.009)	(0.03)	(0.04)	(0.03)	(0.13)
IV	-0.02***	-0.05***	-0.04***	0.001	0.01	0.02
	(0.01)	(0.01)	(0.02)	(0.09)	(0.10)	(0.07)
Under-Identification Test Satisfied	Y	Y	Y	Y	Y	Y
Weak Identification Test Satisfied	Y	Y	Y	Y	Y	Y
Diff-in Diff	-0.04***	-0.06***	-0.07***	0.03	-0.01	0.03
	(0.01)	(0.009)	(0.03)	(0.09)	(0.07)	(0.04)
District Fixed Effects	Y	Y	Y	Y	Y	Y
Clustering at PSU Level	Y	Y	Y	Y	Y	Y

$***p < 0.01, **p < 0.05, *p < 0.1$

Probit estimates are for the impact of having a bad number on economic participation. Negative values denote that having a bad network reduces the probability of economic participation. IV estimate uses proportion of dropped calls experienced by person as treatment varaiable. The type of network is then used to instrument for proportion of dropped calls. The rural area estimation uses all individuals in rural sample. The urban area estimation uses all individuals in urban areas sample which are not categorized as big cities. The big city sample uses all individuals in big city sample, where the big cities include Lahore, Faisalabad, Rawalpindi, Multan, Gujranwala, Sargodha, Sialkot, Bahawalpur, Islamabad, Karachi, Hyderabad, Sukkur, Peshawar and Quetta. Regressions are weighted using the pweights command in STATA.

Table 10: Economic Participation Results for Secondary Earners Only

	(Women)			(Men)		
	(Rural)	(Urban)	(Big City)	(Rural)	(Urban)	(Big City)
Probit	-0.13***	-0.18***	-0.21***	0.07*	0.08*	0.09*
	(0.04)	(0.12)	(0.11)	(0.04)	(0.05)	(0.07)
IV	-0.05***	-0.08***	-0.10***	-0.04	-0.07*	0.09*
	(0.01)	(0.02)	(0.05)	(0.10)	(0.04)	(0.05)
Under-Identification Test Satisfied	Y	Y	Y	Y	Y	Y
Weak Identification Test Satisfied	Y	Y	Y	Y	Y	Y
Diff-in Diff	-0.09***	-0.11***	-0.17***	-0.04	0.02	0.05
	(0.02)	(0.04)	(0.03)	(0.13)	(0.17)	(0.24)
District Fixed Effects	Y	Y	Y	Y	Y	Y
Clustering at PSU Level	Y	Y	Y	Y	Y	Y

$***p < 0.01, **p < 0.05, *p < 0.1$

Probit estimates are for the impact of having a bad number on economic participation. Negative values denote that having a bad network reduces the probability of economic participation. IV estimate uses proportion of dropped calls experienced by person as treatment varaiable. The type of network is then used to instrument for proportion of dropped calls.The rural area estimation uses all individuals in rural sample. The urban area estimation uses all individuals in urban areas sample which are not categorized as big cities. The big city sample uses all individuals in big city sample, where the big cities include Lahore, Faisalabad, Rawalpindi, Multan, Gujranwala, Sargodha, Sialkot, Bahawalpur, Islamabad, Karachi, Hyderabad, Sukkur, Peshawar and Quetta. Regressions are weighted using the pweights command in STATA.

Table 11: Conley Bounds for Economic Participation Results

	Urban Women		Rural Women		Big City Women	
	Lower CI	Upper CI	Lower CI	Upper CI	Lower CI	Upper CI
$\delta = [-0.001, +0.001]$	-0.04	-0.02	-0.09	-0.05	-0.13	-0.05
$\delta = [-0.005, +0.005]$	-0.06	-0.03	-0.11	-0.04	-0.11	-0.06
$\delta = [-0.01, +0.01]$	-0.05	-0.01	-0.08	-0.05	-0.13	-0.07
$\delta = [-0.05, +0.05]$	-0.04	-0.01	-0.09	-0.04	-0.16	-0.04
Number of Observations	1324		2703		1114	

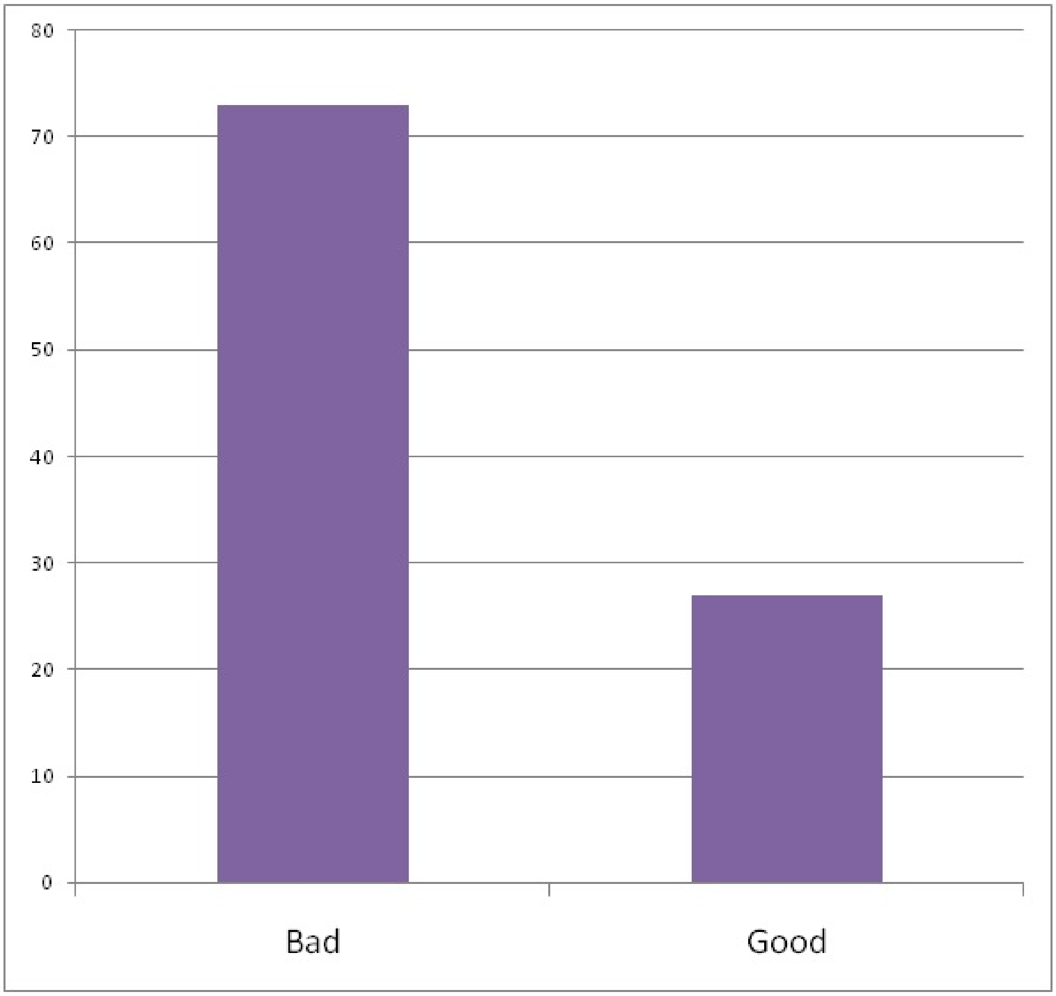

Figure 1: Percentage of Dropped Calls by Number Type for All Providers

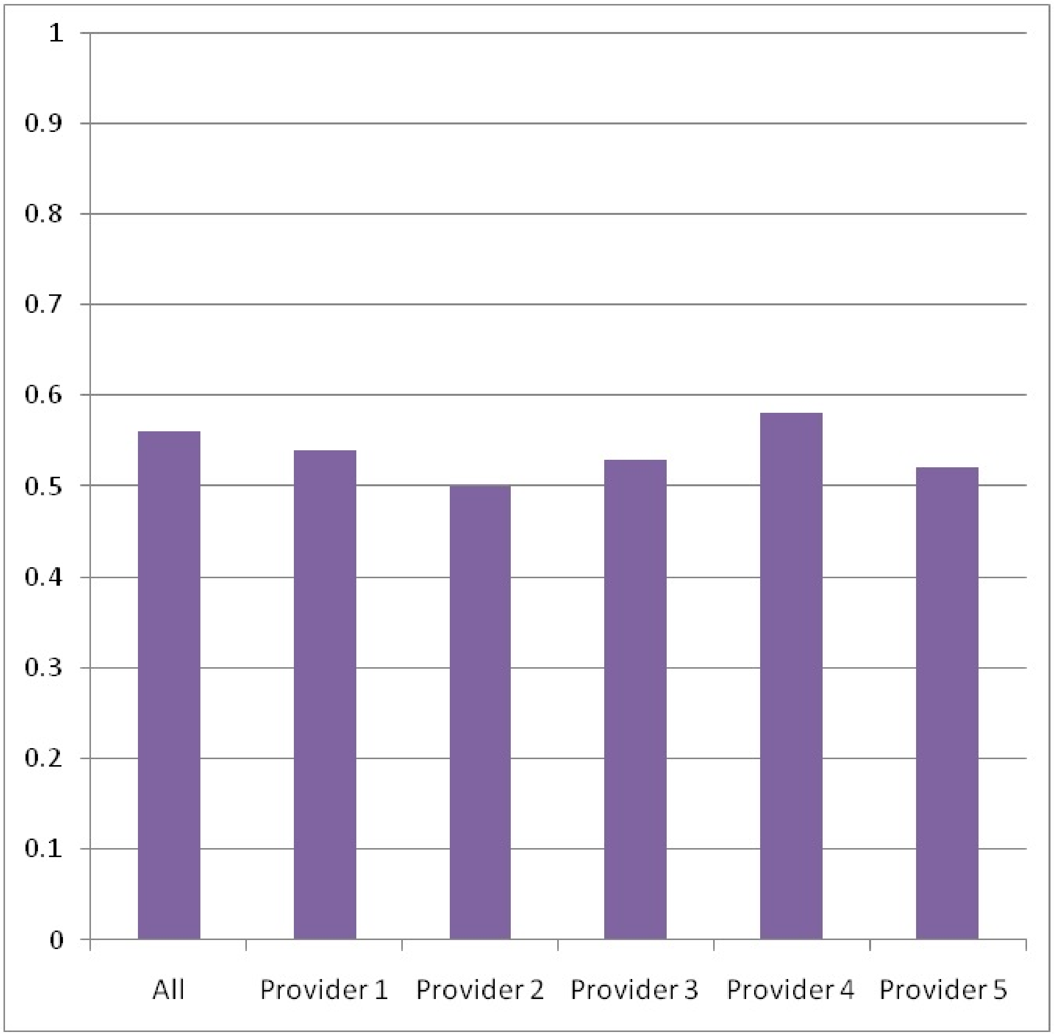

Figure 2: Proportion of Cell Phone Users with a Good Number by Provider

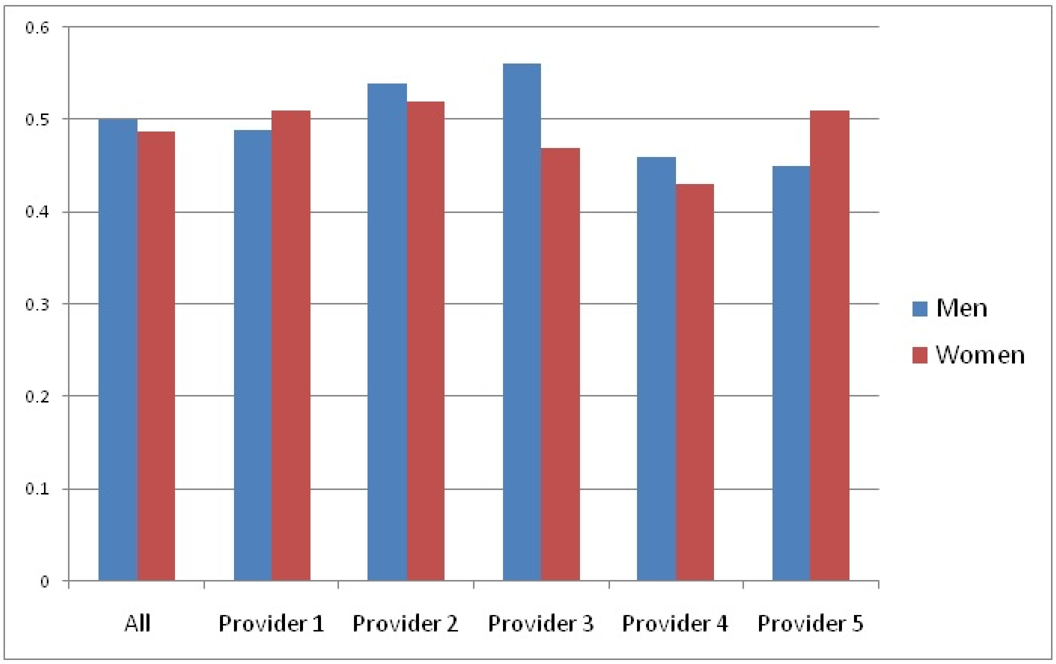

Figure 3: Proportion of Cell Phone Users with a Good Number by Provider and User Gender

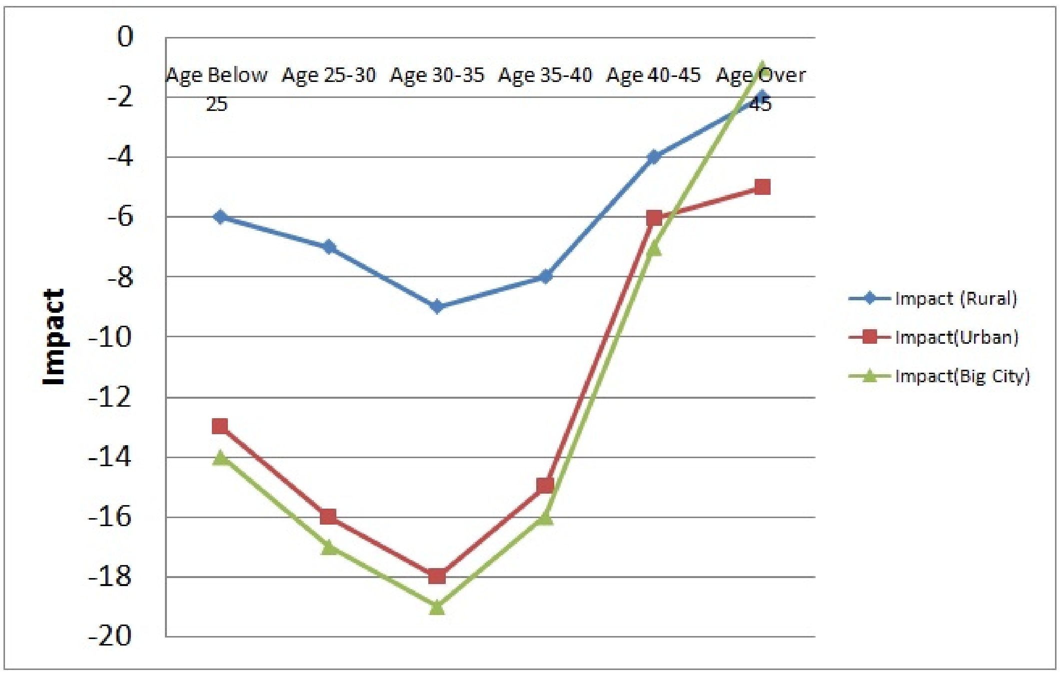

Figure 4: Impact of Bad Number on Economic Participation of Women Stratified by Age