Narrowing the Gender Gap in Mobile Banking*

Jean N. Lee[†], Jonathan Morduch[‡], Saravana Ravindran[§] and Abu S. Shonchoy[¶]

February 1, 2021

Abstract

Mobile banking and related digital financial technologies can make financial services cheaper and more widely accessible in low-income economies, but gender gaps persist. We present evidence from two connected field experiments in Bangladesh designed to encourage the adoption and use of mobile banking by poor, illiterate households. We show that training can dramatically increase adoption and usage by women. At the same time, women on average persist in using mobile banking at a lower rate than men. The study focuses on migrants and their families in Bangladesh. Despite large differences between female and male migrants in income and education, the first experiment shows that a training program led to a similarly large, positive impact on mobile banking usage by female and male migrants, increasing usage rates for both by about 45 percentage points. That led to increases in remittances sent to rural areas, reduced rural poverty, and increased rural consumption. Both female and male migrants in the treatment group, however, reported worse physical and emotional health, adding to health challenges reported by women across treatment and control groups. A second experiment explores whether the way that the technology was introduced and explained made an additional difference in narrowing gender gaps. Despite the lack of statistical power to detect small treatment impacts, we find suggestive evidence that the treatment increased mobile banking adoption by female migrants.

JEL codes: R23, O33, O16.

Keywords: Gender, financial inclusion, digital money, migration, field experiment, Bangladesh.

*We are grateful to the Bill and Melinda Gates Foundation; the Institute for Money, Technology and Financial Inclusion; and the International Growth Centre for financial support. Ravindran is funded by a startup grant at the Lee Kuan Yew School of Public Policy, National University of Singapore. Shonchoy acknowledges fellowship support from IDE-JETRO. Morduch is grateful for support from the Mastercard Impact Fund in collaboration with the Mastercard Center for Inclusive Growth. We have benefited from comments from participants at the 2020 Annual Meeting of the Southern Economic Association. MOMODa Foundation and Gana Unayan Kendra were invaluable in the study's implementation, and Masudur Rahman, Sujan Uddin and Niamot Enayet provided excellent research assistance. This paper incorporates and updates results from a draft circulated as "Family Networks and the Digital Divide: Experimental Evidence on Mobile Banking in Bangladesh." The training experiment is registered in the AEA RCT Registry with the identifying number AEARCTR-0003149. The family network experiment is AEARCTR-0005722. All views and any errors are our own.

[†]World Bank, jlee20@worldbank.org.

[‡]Corresponding author: New York University Robert F. Wagner Graduate School of Public Service, 295 Lafayette St, New York, NY 10012, jonathan.morduch@nyu.edu.

[§]National University of Singapore, Lee Kuan Yew School of Public Policy, saravana@nus.edu.sg.

[¶]Florida International University, shonchoy@fiu.edu.

1 Introduction

Concern with gender has long been part of efforts to reduce inequalities in access to finance. The early promise of microcredit, especially, was based on the idea that, by gaining access to credit, poor women could grow their businesses, reduce dependence on their husbands, experience "empowerment", and help reduce their families' poverty (Rahman, 2000). But the strong focus on gender was diluted as microcredit gave way to the broader notion of "financial inclusion" and as efforts shifted toward technology-enabled finance such as mobile banking (Demirgüç-Kunt et al. 2013, Batista and Vicente 2020, Holloway et al. 2017). More men than women use digital finance today. Across low- and middle-income economies in 2017, for example, 40% of men had sent digital payments in the past year, but only 32% of women had (Demirgüç-Kunt et al. 2018).

Mobile banking and other digital financial services are often seen as a way to achieve the unmet promise of microcredit by making financial services cheaper and more accessible (Karlan et al. 2016). Efforts to narrow gender gaps in financial inclusion build from evidence on the impact of financial access for women. Researchers have found empowerment and other effects of access to financial products (Chiapa et al. 2016; Ashraf et al. 2010; Riley 2020), broad benefits from reduction in poverty and risk (Jack and Suri 2014; Suri and Jack 2016; Riley 2018), and differential impacts of access to and usage of financial products by gender (Dupas and Robinson 2013). So, why do gender gaps persist in mobile banking?

We present evidence from two connected field experiments in Bangladesh to examine gender gaps in the adoption and use of mobile banking, and we estimate their broader impacts. In 2017 in Bangladesh, which has one of the fastest growing mobile banking sectors, gender gaps were larger than the global averages above: 43% of men, but just 17% of women, had sent digital payments in the past year (Demirgüç-Kunt et al. 2018).

We show that gender gaps reflect systematic choices in how and where technologies are available and sold. The study focuses on migrants and their families, one of the main targets for mobile banking in Bangladesh. Members of the sample are mostly very poor and have limited education, however, and mobile banking providers had done little to encourage their adoption. Rates of adoption and usage had been low. Following Lee et al. (2021), we show that a training program customized for the sample had a large, positive impact on both female and male migrants, and below we examine outcomes by gender.

The study was carried out with two connected samples: The first included migrants in Dhaka who had left Bangladesh's northwest in search of jobs in the capital, and the second sample included the migrants' families (most often their parents and siblings) who remained in the rural northwest and were dependent on the migrants' remittances. The rural sample is particularly poor and historically vulnerable to periods of seasonal hunger.

Both migrants and their originating families were introduced to the bKash mobile banking technology under the assumption that network externalities would matter when making adoption decisions. We used an encouragment design in which households were randomly assigned to receive a short training session on how to enroll in and use bKash, as well as receiving basic assistance with the enrollment process. The interventions turned out to strongly increase take-up.

Despite large differences between female and male migrants in income and education, the first experiment shows that a training program had a similarly large, positive impact on mobile banking usage by female migrants and male migrants, in both cases increasing usage rates by about 45 percentage points. That led to increases in remittances to rural areas, reduced rural poverty, and increased rural consumption. Both female and male migrants in the treatment group, however, reported worse physical and emotional health, adding to health challenges reported by women across treatment and control groups. The results highlight the particular burdens felt by women—and an unintended negative consequence of a technology associated with autonomy and empowerment (Riley 2020).

A second experiment explores whether the way that the technology was introduced and explained made an additional difference in narrowing gender gaps. Like much digital technology, mobile banking is characterized by network externalities. It is most valuable when employers, shops, family, and friends are also part of the network. An early marketing campaign for M-Pesa, for example, highlighted the simple message, "Send money home," a reminder of M-Pesa's value for family members sending money to spatially-dispersed family networks.

The second experiment addresses the role of family networks directly. In one treatment, we randomly assign a sample of migrants to receive training and marketing about bKash before their originating families in the rural northwest were introduced to bKash. Another sample of migrants receive training and marketing after their originating families. When this second group of migrants made their choices, they had the possibility of knowing whether their families had also decided to adopt or not. We can thus measure whether migrants' adoption choices were influenced by variation in how exposed their broader families were to the technology.

In a related treatment, we randomly varied whether potential customers received a "pro-family" marketing message or an individualistic marketing message in order to explore the impact of increasing the salience of the family on adoption decisions. Random assignment to the second treatment was orthogonal to the first treatment.

As noted, the experiments took place against a backdrop of high take-up of bKash; the adoption rate for the sample that received training but neither of these two additional treatments was 68%. We show, however, that the two treatments increased adoption further. Receiving either treatment on average increased take-up by 5 percentage points, although the effect is measured imprecisely (coefficient = 0.051, standard error=0.050).

The interventions had very different impacts on male and female migrants. Women were on average less likely to use bKash than men, but the overall effect of exposure to the two family-related treatments erased the 15 percentage point gender gap in usage, though the estimate is imprecise. Thus, despite the lack of statistical power to detect small treatment impacts, we find suggestive evidence that paying attention to family networks can increase mobile banking adoption by female migrants, narrowing the gender gap.

The results reinforce optimism for the possibility to narrow gender gaps in technology use by adapting training and targeting to women. But the results also show the persistence of gender gaps in the impact of the technology. These gaps are consistent with the fact that women earn less on average. The findings suggest that democratizing access to finance is insufficient to equalize impacts when the economic playing field continues to be uneven.

2 Background and Experimental Design

2.1 Experimental Context and Sampling

Mobile technologies have rapidly expanded in the developing world (Aker and Mbiti 2010; Aker 2010; Jensen 2007), and phones are serving as broad-distribution platforms for financial services and products. These financial technologies—also known as mobile money, digital money, or mobile banking—are penetrating markets that banks had avoided due to the costs of building and maintaining brick-and-mortar bank branches. The popular M-Pesa product in Kenya, for example, allows customers, even those in remote regions, to use their phones to transfer, deposit, and withdraw funds to and from electronic accounts or "mobile wallets" based on the digital network (Jack and Suri 2014).

Bangladesh has long been a center for financial innovation designed to address poverty, especially through microcredit and, more recently, through "graduation programs" (Rahman 2000, Banerjee et al. 2015, Bandiera et al. 2017). The approaches have mainly focused on women, with recognition that poor women have been particularly disadvantaged in financial markets (Armendáriz and Morduch 2010).

In recent years, Bangladesh has also been home to several large, innovative providers of mobile banking services. We partnered with bKash, one of the leading providers of mobile money in Bangladesh, a subsidiary of BRAC Bank which during our experiment held 17 million of the 23 million open mobile banking accounts in the country (*Wall Street Journal*, 2015). Established in 2011, the service provides a mobile wallet and person-to-person transfer services and is compatible with most mobile carriers in Bangladesh. To use the service, individuals deposit and withdraw money through bKash's extensive agent network, which includes local retailers as well as dedicated agents. The service enjoys good brand recognition and high general interest in our study context. It provides basic banking services (mobile banking) without physical bank branches.

bKash is a commercial company and does not make poverty reduction nor gender equity specific goals. Its customers tend not to be poor. At the beginning of our study, adoption of the service was low in our rural sample (which had a poverty rate of 75% as measured by the local poverty line), and by the endline only 20% of the control group had adopted. A starting question for the study was whether it was possible to substantially raise the adoption rate, for poor, illiterate women and men.

The experiment involved two sites, and individuals were paired across the sites. The first site is Gaibandha, a district in rural northwest Bangladesh which is a net provider of migrant workers who move to Dhaka for jobs in the garment sector or other unskilled vocations. Gaibandha is in Rangpur, one of the poorest regions of Bangladesh, with vulnerability to seasonal famine in September through November (*monga*) and substantially lower rates of food consumption per capita than other regions in the country (Bryan et al. 2014).

In order to reduce extreme poverty in Rangpur, the United Kingdom Department for International Development (DfID) had included it in the set of eligible populations for its set of SHIREE projects. Through our partner organization, the non-governmental organization Gana Unnayan Kendra (GUK), DfID implemented a program to train young people to work in garment factories in the Dhaka region. The SHIREE program, run through GUK, consisted of six to eight weeks of training in a fully equipped training facility located at the GUK headquarters. Trainees were then assisted in finding jobs in the garment sector in Dhaka. These jobs are competitive and although salaries are low relative to developed country salaries for comparable jobs, they pay well relative to daily agricultural labor. The base salary for most factory work was 3500 Taka (approximately 47 dollars) per month at the time of the experiment. Workers were offered more generous rates for overtime work, and typically earned between 6000 and 8000 taka (80 and 107 dollars) per month in total. The SHIREE training was targeted to "ultra-poor" households (poor even relative to poor families in Rangpur), a population also targeted by Bandiera et al. (2017).

In the first site, in rural Gaibandha, the sample population was formed from the the families of the trainees, which often included their parents and siblings. Since the trainees later migrated, these families were their originating households.

The second site was Dhaka, the capital of Bangladesh, and the sample population was the pool of approximately 1100 individuals trained for garment work by GUK under the DfID-funded SHIREE program. We targeted these trainees for enrollment in the mobile money service, along with their families in Gaibandha.

Starting with this universe of SHIREE trainees and originating families, we recruited 341 household and migrant pairs to participate in the study. In order to expand the sample, we then engaged in snowball sampling by asking to be referred to friends and acquaintances of the original sample in Gaibandha, conditional on their having household members who had migrated to Dhaka for work. This yielded a sample of 815 household-migrant pairs. Of the 815 pairs, 413 household-migrant pairs were randomly assigned to a treatment group that was introduced to bKash and form the sample for this study. The balance was randomly assigned to the control group.

In the "training treatment," we analyze both rural and urban samples. In the "family-network treatment," our focus is on the migrant part of the household-migrant pairs in the treatment group. We investigate how variation in the treatment affected their adoption decisions and subsequent use of the technology. Of the migrants, 29% of the treatment group and 31% of the control group were women, and we are interested in the impact of mobile banking on these women and their families.

2.2 Experimental Design

The two experiments were part of a field trial designed to examine aspects of the economics of mobile money. Lee et al. (2021) provide results on impacts of the training experiment described below, in which impacts were aggregated across men and women. Here, we extend those findings by disaggregating by gender and presenting results from the family-network experiment designed to further encourage adoption.

2.2.1 Training Experiment

After being recruited and consented, and after a baseline survey, a randomly-assigned sample of urban migrants and rural households was approached between early April and early May 2015 with the offer of training and assistance with enrollment in bKash. The assistance included a 30- to 45-minute training session on how to use bKash and guidance through the enrollment process.

The training covered the enrollment process and how to activate the account, cash in, cash out, and transfer funds. All received information with a script that highlighted bKash use cases, security, and flexibility. The uses included the ability to safely deposit salary, send money to others for emergencies, hold savings in the mobile wallet, avoid loss by not holding cash, and earn interest on savings. Participants were given a small sum (200 taka per individual or household, or approximately US$3) to cover their time, which was conditional on the successful completion of mock transfers to and from the field agent, ensuring that subjects had demonstrable knowledge of how to use the service by the time the training was completed, but payment was not conditional on adoption.

There was no gender-specific element of the training. Male and female migrants and their families were treated identically. A first question here is whether the identical treatments led to important differences in outcomes by gender.

2.2.2 Family-Network Experiment

Participants in the training were randomly assigned to receive different marketing messages and differently-timed trainings. We describe this as the "family-network treatment" because the treatments highlight the participants' relationships with their families. In the first treatment arm, we randomized whether migrants in Dhaka were trained and received marketing about bKash before their families in Gaibandha ("migrant first"), or whether they were treated after their families ("family first"). We did not explicitly tell migrants whether or not their families had also received training, but they could discuss the intervention via mobile phone. Thus, migrants in the family-first sample could know that their rural-based family had already signed up for bKash before they were asked to make their own adoption decision. The migrant-first sample could not since their family had not yet received training.

In the second treatment arm, migrants received marketing and information about using bKash. In addition to the training and marketing described above, a randomly-assigned sub-sample received an additional message that highlighted that their rural-based family had shown a general interest in opening a bKash account: "We talked with your rural household and they showed their interest in opening a Bkash account." This statement was based on an initial conversation at the time when households were recruited into the sample and the study's focus on bKash was described. Unlike the first treatment arm, the rural household had not necessarily learned about the specifics of bKash nor actually signed up; the aim was to increase the salience of the family at the time of the migrants' considering bKash adoption.

The two treatment arms were orthogonal to each other, so roughly one quarter of the treated sample did not receive either of the family-network treatment variants; they were assigned to the migrant-first treatment and did not receive the pro-family message. Roughly another quarter was exposed to both family-network variants, being assigned to the family-first training intervention and also receiving the pro-family marketing message. The balance of the treated group was split between households receiving the family-first training intervention only or the pro-family marketing only.

The treatment arms are similar in their purpose, and to preserve power we analyze both treatment arms together in comparison to the part of the migrant sample that was exposed to neither. Power calculations are presented in Appendix D. We are able to detect treatment effect sizes of at least 14 percentage points with 80% power. We are able to detect treatment effect sizes of at least 26 percentage points with 80% power when analyzing the differential impact of any family-network treatments for female migrants. Given the lack of power to detect effect sizes of a smaller magnitude, we treat the results on family networks as exploratory.

3 Data and Empirical Methods

3.1 Descriptive Statistics and Randomization Balance

The sample is very poor, and was designated by our partner GUK as being "ultra-poor" in the sense of Bandiera et al. (2017). Although nearly everyone (99% of individuals in the sample) had access to a mobile phone, financial inclusion was low, as reflected by the 9-12% rate of bank accounts at baseline (Table 2). Most migrants in the sample had moved to Dhaka not long before our study, with the average migrant living fewer than three years in Dhaka and working fewer than 2 years at their current job. Fewer than half of migrants (47%) completed primary schooling. Most migrants were employed in the formal sector (90-93%), about 30% were female, and the average age was 24. At baseline migrants earned on average 7830 taka (105 dollars) per month and sent a large portion of these earnings home as remittances. Average monthly remittances sent by migrants at baseline were 2479 Taka (17356/7), which is almost one third of average monthly migrant income (2479/7830 = 32%).

3.1.1 Training Experiment

Following the min-max t-stat re-randomization procedure described in Bruhn and McKenzie 2009, we randomized which migrants received the training intervention. The baseline survey was run from December 2014 to March 2015 and the endline survey was conducted one year later (February 2016 to June 2016). The surveys collected data on household demographics and financial behavior including remittances-sending and savings. The interventions took place in April and May 2015. In addition to the baseline and endline surveys, we obtained account-specific transaction-level administrative data from bKash directly for the user accounts in the sample. These data allow us to study active use of accounts.

Attrition was very low. For the rural sample, we lost 2 of 815 households, an attrition rate of 0.2 percent. For the urban sample, we lost 6 of 815 migrants, an attrition rate of 0.7 percent. The final samples for training experiment analysis thus include 813 rural households and 809 migrants.

3.1.2 Family-Network Experiment

Following again the min-max t-stat re-randomization procedure described in Bruhn and McKenzie 2009, we cross-randomized which migrants received the family-first training intervention and which received the pro-family marketing intervention. Randomization was done such that the treatments were orthogonal to each other. Table 2 shows baseline summary statistics by treatment status, showing balance on observables for assignment to the pro-family marketing treatment in Panel A and balance on observables for assignment to the family-first training intervention in Panel B. Treatment status for both interventions is balanced on key observables, including ownership of a mobile phone, having a bank account, whether the migrant has a formal job, and the urban migrant's gender. The p-value for difference in migrant's daily per capita expenditure is 0.065 for the pro-family marketing treatment assignment, with migrants in the pro-family marketing treatment group being slightly poorer (116 Taka verus 125 Taka per capita daily expenditures). The p-value for difference in migrant's age is 0.033 for the family-first' treatment assignment, with migrants visited after their paired households being slightly younger (23.5 versus 24.6 years). To take into account these differences, we control for migrant's daily per capita expenditure and migrant's age at baseline. These correlations with treatment status are not more frequent than would be expected at random, and in absolute terms, the mean differences across treatment groups are small. The p-value of the F-tests for joint orthogonality (0.424 and 0.868, respectively) show overall balance for the two interventions. In Appendix A, we present the treatment-control balance for the interventions within female and male migrants and note that all F-tests for joint orthogonality are not statistically significant at conventional levels, suggesting balance within gender in our sample.

As above, attrition was very low. In the urban sample, only 1 of 413 migrants attrited (0.2%). The final sample for the family-network experiment thus includes 412 migrants.

3.2 Empirical Methods

3.2.1 Training Experiment

We combine the survey data with administrative data from bKash to estimate impacts. For most outcomes, we estimate intention-to-treat (ITT) effects using an Analysis of Covariance (ANCOVA) specification:

$$\begin{aligned} Y_{i,t+1} &= \beta_0 + \beta_1 Treatment_i + \beta_2 FemaleMigrant_i \\ &\quad + \beta_3 Treatment_i * FemaleMigrant_i + \beta_4 Y_{i,t} + \mathbf{X}_{i,t} + \varepsilon_{i,t+1} \end{aligned} \tag{1}$$

where β_3 is the coefficient of interest that captures the differential impact of the training experiment for household-migrant pairs where the migrant was a female. $\mathbf{X}_{i,t}$ is a vector of baseline controls: gender, age, and primary school completion of household head or migrant, as well as household size. Periods t and $t+1$ refer to the baseline and endline, respectively. The regressions are run separately for the rural household and urban migrant sample. Since randomization took place at the household level, we do not cluster standard errors.

The surveys include questions on a range of outcome indicators, and we address multiple inference by creating broad "families" of outcomes such as consumption, education, and health. Outcome variables are transformed into z-scores (relative to the baseline distribution) and then aggregated to form a standardized average across each outcome in the family (i.e., an index). We test the overall effect of the treatment on the index (see Kling et al. 2007).

For remittances, we collected monthly data for the current month and the previous 6 months. To exploit the temporal variation in these variables within migrants, we estimate equation (2) on the stacked baseline and endline migrant-month level data:

$$
\begin{aligned}
Y_{i,t} = {} & \beta_1 Endline_t + \beta_2 Treatment_i * Endline_t \\
& + \beta_3 Endline_t * FemaleMigrant_i \\
& + \beta_4 Treatment_i * Endline_t * FemaleMigrant_i \\
& + \sum_{t=1}^{7} \beta_{5,t} Month_t + \beta_{6,i} + \varepsilon_{i,t}
\end{aligned} \tag{2}
$$

Here, $\beta_{5,t}$ captures month fixed effects and $\beta_{6,i}$ refers to migrant fixed effects. The variable $Endline_t$ is an indicator for an endline observation. The coefficient of interest is β_4, the coefficient on the interaction between $Treatment_i$, $Endline_t$, and $FemaleMigrant_i$. The coefficient captures the differential impact for female migrants in the dependent variable at endline between migrants in the treatment group and migrants in the control group after controlling for differences between baseline and endline, migrant fixed effects, and month fixed effects. Standard errors for regressions run using equation (2) are clustered at the migrant level.

3.2.2 Family-Network Experiment

Since the bKash mobile banking service offers two key features – a money transfer service to remit money and a mobile wallet with which to save – we choose to study the impact of the family-network interventions on four key outcomes of interest for migrants: (i) adoption, (ii) active use of accounts, (iii) remittances sent, and (iv) savings. *Adopted bKash* is an indicator equal to 1 if the migrant signed up for bKash. *Active bKash account* is an indicator that takes the value 1 if the migrant performed any type of bKash transaction over the 13 month period from June 2015 - June 2016. These transactions include (but are not limited to) deposits, withdrawals, remittances, and airtime top-ups. This variable is constructed using administrative data from bKash that details every transaction recorded in accounts of the study population. We collected monthly data (for the current month and the previous six) on remittances and total remittances refer to the sum of remittances sent over this 7 month-period. For savings, we use the inverse hyperbolic sine transformation.

To study the impact of either of the family-network treatments on mobile money adoption, we estimate ITT impacts using the following specification:

$$Y_{i,t} = \beta_0 + \beta_1 AnyFamilyNetworkTreatment_i + \mathbf{X}_{i,t} + \varepsilon_{i,t} \tag{3}$$

where $\mathbf{X}_{i,t}$ is a vector of the following baseline controls: gender, age, and primary school completion of the migrant, household size, and daily per capita expenditure of the migrant. $AnyFamilyNetworkTreatment_i$ is an indicator variable that takes the value 1 if the migrant was approached after the household ("family-first") or if mobile money service was marketed with the "pro-family" treatment.

To explore heterogeneous treatment impacts by gender, we estimate treatment effects using an interaction term with any family-network treatments as follows:

$$\begin{aligned} Y_{i,t+1} = \beta_0 &+ \beta_1 AnyFamilyNetworkTreatment_i \\ &+ \beta_2 AnyFamilyNetworkTreatment_i * FemaleMigrant_i + \beta_3 Y_{i,t} + \mathbf{X}_{i,t} + \varepsilon_{i,t+1} \end{aligned} \tag{4}$$

where β_2 is the coefficient of interest that captures the differential treatment impact of the family-network interventions for female migrants.

4 Results

The context for the results can be seen in Table 1, which provides summary statistics for migrants by gender. Table 1 shows that by the endline female and male migrants had adopted bKash at a very similar rate (71% and 72% respectively), despite the gender gaps in digital financial inclusion in Bangladesh (Shrader 2015). The estimates below allow us to examine gaps in active usage. Second, the baseline monthly income of female migrants is 31% lower on average than their male counterparts (5.95 thousand taka versus 8.61 thousand taka). All else the same, the lower disposable income of women means that they have less money to remit home—and Table 1 confirms that women, on average, remit 42% less than men. The estimates allow us to trace the implications for poverty and well-being.

4.1 Training Experiment

While adoption rates are similar for women and men, Table 1 shows that active use of bKash is lower for female migrants than for male (61% versus 71% respectively). Table 3 shows this more clearly with treatment effects on the percentage of the migrant sample (n=809) that adopted and actively used bKash during the study period. Active use is calculated at the endline from bKash administrative data during the prior year.

The first column of Table 3 shows that exposure to the training, averaged across men and women, sharply increased the use of bKash accounts. While 21% of the control group used bKash at the endline, the treatment group's rate of bKash use was triple that level (47.5 percentage points higher). Across treatment and controls, however, women used bKash less on average: column (2) shows a decrease of 12.3 percentage points. Netting that out, column (3)—without controls—and column (4)—with controls—show that the training raised usage rates roughly equally for men and women. (The interaction between being a female migrant and receiving the training indicates a 13% boost in the treatment impact for women, but the coefficient is measured very imprecisely; coefficient = 0.06 with s.e.= 0.07.) The increase in bKash usage by similar amounts for men and women suggests that the relatively low rates of technology use by women can be countered by effective interventions. At the same time, women tend to use the technology less overall, and that reduces its overall development impact.

Lee et al. (2021) showed that using mobile banking increased remittances from urban migrants to their families in Northwest Bangladesh villages. Broader development impacts in the villages were consistent with the relative increase in money flowing in from the capital. The Lee et al. (2021) evidence on remittances is reproduced in columns (1), (3), and (5) of Table 4. The first column shows that remittances (sent via bKash or via other methods) were 328 taka lower overall at the endline compared to the baseline (2582 taka on average). The second row of column (1), however, shows that active users of bKash effectively erased the decline in remittances. The second row in Column (3) shows that the positive impact on remittances was largely due to bKash specifically, and column (5) shows that the pattern is echoed when looking at income shares devoted to remittances.

The remaining columns—(2), (4), and (6)—disaggregate the results by gender. The fourth row gives the treatment effect for female migrants; the negative results are consistent with women earning less and thus remitting less than men who use bKash. In column (6), the main treatment effect is measured noisily (a 3 percentage point increase in the income share devoted to remittances) and the treatment effect for women is effectively identical as that for men. While the training experiment increased bKash adoption and use, impacts on levels of remittances were smaller for female than male migrants, consistent with lower earnings by female migrants.

The results on broader outcomes for female migrants are consistent with the results on remittances. Table 5 provides evidence on poverty rates, the probability of working in a garment factor, saving, and a health index. The second row shows that female migrants, as a group, tend to be poorer than male migrants, are more likely to work in garment factories, have saved less, and report worth health. The third row gives the differential impact for female migrants in the training treatment. Here, consistent with the mixed results above, estimates are imprecise and relatively small. Table 6 provides similar results for the components of the health index, including physical and emotional health. Females report worse outcomes on every measure (row 2), as do migrants exposed to treatment (row 1). But the differential treatment effects for female migrants (row 3) are again mixed and imprecisely measured. The table shows that exposure to the treatment reduced self-reported health; for female migrants that reduction reinforced self-reported health difficulties that were common across female migrants. The perceived burdens were thus greater for women than men.

Using bKash makes remitting easier, potentially helping the receivers, i.e., families at home in rural Gaibandha. The final results from the training experiment are for impacts in the villages. The outcomes in Table 7 include rural poverty, extreme poverty (proxied by the squared poverty gap), and indices for consumption, education, and health. The first row echoes Lee et al. (2021), showing no impact on the poverty headcount but a decrease in extreme poverty; increases in consumption and education measures; and no discernible impact on the health index. The impacts are contributed by both male and female migrants. The third row shows (again) that the differential treatment effects for female migrants are mixed and imprecisely measured.

In sum, the training treatment increased the adoption and use of mobile banking by migrants, with increases by women of similar magnitude to those by men. While the adoption of the technology led to increases in remittances sent by migrants, a reduction in poverty and increase in consumption for rural households, there were no notable treatment differences in these broader development impacts by gender, neither for the migrants themselves, nor for their families in the Northwest.

4.2 Family-Network Experiment

To respond to the gender gap in the use of digital financial services, we varied the nature and timing of the training pitch to determine if it could affect adoption rates. We implemented two approaches that increased the salience of the migrants' families at the time of the bKash adoption decision. Sending money home is the main use case for mobile money, and both treatments highlighted the family network. We analyze the treatment arms in combination to maximize power.

Figure 1 summarizes the impacts of the two family-network interventions on bKash adoption rates. Adoption rates were generally high: 68% of migrants adopted when exposed to neither family-network treatment. The figures show, however, show that both treatments increased average bKash adoption further. The right panel of Figure 1 highlights that exposure to any family-network treatment had a large impact on bKash adoption (by 15 percentage points) for female migrants, while treatment impacts for male migrants were very close to zero. We explore these differences in Tables 8 and 9.

Table 8 presents the impact of being in either of the family-network treatment arms, focusing on adoption, active use of accounts, remittances, and savings. Migrants in any family-network treatment arm were 5 percentage points more likely to adopt bKash in comparison to migrants in the comparison group, although the point estimate is imprecisely estimated (coefficient = 0.051, s.e. = 0.050). Overall, measured impacts on active account use, remittances, and savings are relatively small and imprecise.

Table 9 presents heterogeneity in treatment impacts by gender of the migrant. The digital gender gap in adoption of mobile banking is clear: female migrants in the control group that did not receive either the pro-family marketing or family-first training interventions were 13 percentage points less likely to adopt bKash than male migrants in the control group (mean adoption rate for control group = 68%). The interventions helped to close this gender divide to different degrees. Panel A shows that female migrants in any family-network treatment group were 15 percentage points more likely than men in any family-network treatment group to take up bKash, although this is noisily measured with a large standard error (coefficient = 0.145, s.e. = 0.108). Female migrants exposed to any family-network treatment were 15 percentage points more likely to adopt bKash, thereby closing the digital gender gap, and the overall impact for female migrants is statistically significant at the 10% level.[1]

5 Conclusion

The experiments show the differences between men and women in mobile money adoption in Bangladesh. The urban migrants at the center of the study originally came from from some of the poorest villages in one of the poorest regions. The results show that appropriately-designed interventions can dramatically increase technology adoption by women, leading to similar-sized treatment effects across genders. This is especially notable in a poor population with limited education that has historically been among the most "financially excluded."

Both the training experiment and the family network experiment had positive impacts on women, suggesting the possibility of greatly narrowing, if not fully erasing, gender gaps in technology usage. Still, we found that women sent home a substantially lower value of remittances, consistent with their lower average earnings in Dhaka. Technology can facilitate sending remittances, but it does not equalize wages. The gender gaps on which we focus accompany wider gender gaps that may be harder to close.

We also found that both women and men in the training experiment reported worsened self-reported health (physical and mental). For women, those challenges added to a broader set of health challenges reported by women across the sample, in treatment and control groups. These unintended consequences of technology adoption also reflect a wider set of gender gaps that deserve attention.

The results we report are specific to the context. The migrants tend to be young and

[1]In Appendix B, we explore heterogeneity of treatment impacts for female migrants along dimensions of education and age, two proxies for women empowerment. However, we do not find evidence of heterogeneity along these dimensions. This suggests that other factors, including norms governing women's roles in the family, play a stronger role in the differential impact by gender.

open to new technology, and reliably sending remittances back to their rural-based families is a key obligation. The population is of particular concern for efforts to increase financial inclusion. The migrant population is often also relatively isolated in the city, separated from their extended families and working long hours in difficult conditions. The study shows possibilities for improving access to a potentially helpful financial technology, but the evidence also shows that the technology is embedded within a broader set of social and economic constraints and possibilities that are attached to wider inequalities.

Table 1: Migrant Summary Statistics by Gender (Baseline)

	Female Mean	Female SD	Male Mean	Male SD	Difference p-value
Any bank account	0.09	0.29	0.12	0.32	0.472
Formal employee	0.95	0.22	0.90	0.30	0.087***
Average monthly income (‘000 Taka)	5.95	2.15	8.61	2.34	0.000***
Age	24.27	5.50	23.98	5.17	0.611
Completed primary school	0.36	0.48	0.52	0.50	0.002***
Tenure at current job	1.55	1.45	1.75	1.63	0.258
Tenure in Dhaka	1.82	1.29	2.68	1.98	0.000***
Daily per capita expenditure	103.61	45.95	127.20	42.97	0.000***
Total Remittances sent, past 7 months (‘000 Taka)	11.43	9.59	19.78	11.91	0.000***
bKash Remittances sent, past 7 months (‘000 Taka)	6.86	8.32	10.19	9.90	0.001***
Total Savings (‘000 Taka)	1.10	3.23	0.98	2.97	0.718
Adopted bKash (post-intervention)	0.71	0.46	0.72	0.45	0.810
Active bKash Account (endline)	0.61	0.49	0.71	0.45	0.032**

Notes: Summary statistics are presented for the 413 migrants surveyed at baseline. 120 migrants were female while 293 migrants were male. P-values are given for tests of differences in means by gender.

Table 2: Migrant Summary Statistics by Treatment Assignment (Baseline)

Panel A: Pro-family versus Individual Marketing	Pro-family Marketing Mean	Pro-family Marketing SD	Individual Marketing Mean	Individual Marketing SD	Group Differences p-value
Any bank account	0.12	0.33	0.09	0.29	0.274
Formal employee	0.93	0.26	0.90	0.30	0.324
Average monthly income (‘000 Taka)	7.80	2.52	7.86	2.66	0.813
Female	0.29	0.46	0.29	0.45	0.959
Age	24.00	5.17	24.13	5.39	0.793
Completed primary school	0.48	0.50	0.47	0.50	0.923
Tenure at current job	1.75	1.64	1.63	1.51	0.426
Tenure in Dhaka	2.45	2.06	2.40	1.59	0.792
Remittances sent, past 7 months (‘000 Taka)	17.61	12.36	17.08	11.39	0.649
Daily per capita expenditure	116.43	37.17	124.63	52.18	0.065*
p-value of F-test for joint orthogonality = 0.424.					

Panel B: Migrant Trained After (Family First) or Before Household (Migrant First)	Family First Mean	Family First SD	Migrant First Mean	Migrant First SD	Group Differences p-value
Any bank account	0.10	0.30	0.12	0.32	0.644
Formal employee	0.91	0.28	0.91	0.28	0.952
Average monthly income, (‘000 Taka)	7.77	2.28	7.89	2.84	0.657
Female	0.30	0.46	0.28	0.45	0.703
Age	23.48	4.89	24.59	5.55	0.033**
Completed primary school	0.50	0.50	0.45	0.50	0.375
Tenure at current job	1.72	1.76	1.66	1.39	0.709
Tenure in Dhaka	2.45	2.07	2.40	1.63	0.788
Remittances sent, past 7 months (‘000 Taka)	17.49	12.03	17.23	11.80	0.821
Daily per capita expenditure	119.38	47.50	121.23	42.87	0.678
p-value of F-test for joint orthogonality = 0.868.					

Notes: Summary statistics are presented for the 413 migrants surveyed at baseline. For the first treatment in Panel A, 216 migrants were randomized into the pro-family marketing group, while 197 migrants were randomized into the individual marketing group. For the second treatment in Panel B, 197 migrants were visited after their paired household, while 216 migrants were visited before their paired household. P-values are given for tests of differences in means by treatment status. F-tests for joint orthogonality include rural household variables in Tables 1 and 2 of Appendix A.

Table 3: Active Account Use by Gender

	(1) Active bKash Account	(2) Active bKash Account	(3) Active bKash Account	(4) Active bKash Account
Treatment	0.475***	0.472***	0.455***	0.454***
	(0.031)	(0.030)	(0.036)	(0.036)
Female Migrant		-0.123***	-0.168***	-0.153***
		(0.035)	(0.047)	(0.048)
Treatment ∗ Female Migrant			0.060	0.059
			(0.067)	(0.067)
Treatment + Treatment ∗ Female Migrant			0.515	0.514
			[0.000]	[0.000]
R^2	0.228	0.252	0.245	0.253
Baseline Controls	No	Yes	No	Yes
Endline Control Group Mean	0.207	0.207	0.207	0.207
Observations	809	809	809	809

Standard errors in parentheses and F-test p-values in square brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. "Active account use" takes the value 1 if the migrant performed any type of bKash transaction over the 13-month period from June 2015 - June 2016 (including deposits, withdrawals, remittances, and airtime top-ups), constructed using administrative data from bKash.

Table 4: Remittances Sent by Gender

	(1) Total, taka	(2) Total, taka	(3) bKash, taka	(4) bKash, taka	(5) Total, share	(6) Total, share
Endline	-327.8***	-310.7**	-119.0	-126.0	-0.030***	-0.027*
	(121.7)	(157.0)	(96.8)	(122.7)	(0.12)	(0.014)
Treatment ∗ Endline	316.1*	353.1*	385.9***	520.4***	0.030*	0.030
	(163.0)	(212.3)	(130.1)	(167.6)	(0.16)	(0.020)
Endline ∗ Female Migrant		-57.9		19.7		-0.010
		(216.7)		(179.0)		(0.024)
Treatment ∗ Endline ∗ Female Migrant		-135.3		-473.3*		-0.004
		(303.8)		(246.1)		(0.035)
R^2	0.29	0.29	0.44	0.44	0.24	0.24
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Household Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Baseline Mean	2,582	2,582	1,364	1,364	0.28	0.28
Observations	10,526	10,526	10,526	10,526	10,526	10,526

Standard errors in parentheses, clustered by household. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable in column 1 is total remittances (sent through any means) sent in the prior seven months as self-reported by urban migrants. The dependent variable in column 2 is remittances sent through bKash. The dependent variable in column 3 is total remittances as a share of migrant income.

Table 5: Migrant Poverty, Occupation, Saving, and Health by Gender

	(1) Poverty head count	(2) Garment worker?	(3) Any saving?	(4) Value of saving	(5) Health index
Treatment	-0.04	0.06	0.16***	0.57*	-0.17
	(0.03)	(0.04)	(0.03)	(0.32)	(0.11)
Female Migrant	0.09**	0.14***	-0.06	-0.48	-0.36**
	(0.04)	(0.05)	(0.04)	(0.42)	(0.14)
Treatment ∗ Female Migrant	-0.05	-0.04	0.05	-0.36	-0.00
	(0.06)	(0.08)	(0.05)	(0.58)	(0.19)
R^2	0.139	0.030	0.091	0.039	0.094
Baseline Mean	0.208	0.549	0.379	2.84	0
Observations	809	809	809	809	809

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Column 1 is an indicator of poverty status judged by the 2016 urban poverty line in Bangladesh. Column 2 is a binary indicator for working in a garment factory. Column 3 is a binary indicator for holding any financial saving. The dependent variable in column 4 is the inverse hyperbolic sine of savings. Column 5 is an index based on a set of variables transformed as z-scores, standardized relative to their baseline distributions. All regressions are estimated with baseline control variables and the baseline dependent variable.

Table 6: Migrant Health by Gender

	(1) Better overall health	(2) Fewer physical health problems	(3) Fewer difficulties with daily work	(4) Less bodily pain	(5) Higher energy	(6) Fewer social activities	(7) Fewer emotional problems	(8) Fewer severe emotional problems
Treatment	-0.215	-0.184	-0.313**	-0.284*	-0.103	-0.378**	-0.304**	-0.413***
	(0.153)	(0.155)	(0.157)	(0.155)	(0.156)	(0.156)	(0.155)	(0.157)
Female Migrant	-0.708***	-0.410**	-0.496**	-0.631***	-0.646***	-0.321	-0.467**	-0.599***
	(0.203)	(0.205)	(0.206)	(0.202)	(0.206)	(0.207)	(0.204)	(0.204)
Treatment *	0.175	-0.170	-0.045	0.187	-0.048	0.085	0.013	0.161
Female Migrant	(0.276)	(0.281)	(0.281)	(0.278)	(0.285)	(0.282)	(0.283)	(0.282)
R^2	0.02	0.03	0.02	0.02	0.03	0.04	0.02	0.02
Baseline Mean	3.01	4.08	4.84	4.52	4.16	3.72	4.25	4.39
Observations	809	809	808	809	806	808	808	806

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are run as ordered logit regressions. All variables are self-reported and ordered on a scale of 1–5 with a reference frame of the past four weeks. The regressions are estimated with baseline control variables and the baseline dependent variable.

Table 7: Rural Consumption, Poverty, Education, and Health by Migrant Gender

	(1) Poverty head count	(2) Squared poverty gap	(3) Consumption index	(4) Education index	(5) Health index
Treatment	0.007	-0.018*	0.129**	0.160**	-0.019
	(0.019)	(0.010)	(0.056)	(0.081)	(0.031)
Female Migrant	-0.003	0.020	0.025	-0.046	-0.069*
	(0.025)	(0.014)	(0.073)	(0.102)	(0.040)
Treatment * Female Migrant	-0.005	-0.007	-0.021	-0.201	0.080
	(0.035)	(0.019)	(0.103)	(0.138)	(0.056)
R^2	0.044	0.180	0.428	0.155	0.028
Baseline Mean	0.751	0.091	0	0	0
Observations	807	807	807	395	807

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Column 1 is an indicator of poverty status. Column 2 is the squared poverty gap calculated for each household. Columns 3, 4, and 5 are indices based on a set of variables transformed as z-scores, standardized relative to their baseline distributions. All regressions are estimated with baseline control variables and the baseline dependent variable.

Table 8: Adoption, Active Use, Remittances, and Savings

	(1) Adopted bKash	(2) Active bKash Account	(3) Total Remittances Sent (Taka)	(4) bKash Remittances Sent (Taka)	(5) IHS (Savings)
Any Family-Network Treatment	0.051	-0.003	1152.4	-93.0	0.475
	(0.050)	(0.053)	(1481.6)	(1237.6)	(0.395)
R^2	0.084	0.020	0.161	0.254	0.062
Baseline Controls	Yes	Yes	Yes	Yes	Yes
Baseline Dep. Var. Control	No	No	Yes	Yes	Yes
Dep. Variable Mean	0.716	0.682	14,719	9,228	6.69
Dep. Variable Mean for Individual Marketing / Migrant-First Training	0.683	0.683	13,397	8,636	6.41
Observations	412	412	412	412	412

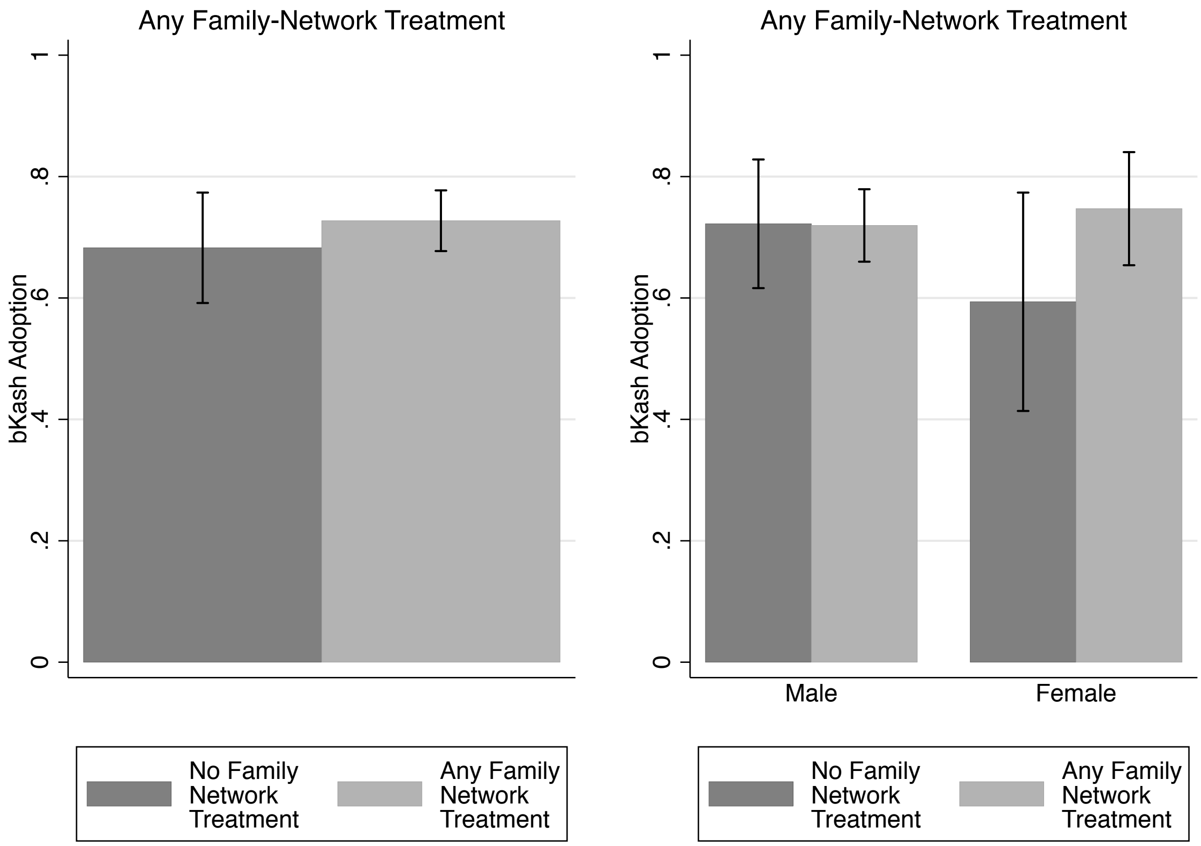
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. The dependent variable in column (1) takes the value 1 if the migrant signed up for bKash following the intervention. The dependent variable in column (2) takes the value 1 if the household performed any type of bKash transaction over the 13 month period from June 2015 - June 2016 (including deposits, withdrawals, remittances, and airtime top-ups), constructed using administrative data from bKash. The dependent variables in columns (3) and (4) are total and bKash remittances (sent through any means) sent in the prior 7 months as self-reported by urban migrants, respectively. Column (5) dependent variable is the inverse hyperbolic sine of total savings value. The unit of observation is the migrant for all regressions.

Table 9: Adoption, Active Use, Remittances, and Savings by Gender

	(1) Adopted bKash	(2) Active bKash Account	(3) Total Remittances Sent (Taka)	(4) bKash Remittances Sent (Taka)	(5) IHS (Savings)
Female Migrant	-0.126	-0.019	-5453.1*	-4314.1*	-1.251*
	(0.095)	(0.101)	(2879.0)	(2377.9)	(0.751)
Any Family-Network Treatment	0.008	0.029	1382.6	-214.9	0.402
	(0.059)	(0.063)	(1765.2)	(1475.1)	(0.471)
Any Family-Network Treatment	0.145	-0.109	-778.4	411.7	0.247
∗ Female Migrant	(0.108)	(0.116)	(3236.0)	(2702.5)	(0.858)
Any Family-Network Treatment +	0.154*	-0.080	604.2	196.8	0.648
Any Family-Network Treatment	[0.091]	[0.412]	[0.824]	[0.931]	[0.369]
∗ Female Migrant					
R^2	0.088	0.023	0.161	0.254	0.062
Baseline Controls	Yes	Yes	Yes	Yes	Yes
Baseline Dep. Var. Control	No	No	Yes	Yes	Yes
Dep. Variable Mean	0.716	0.682	14,719	9,228	6.69
Dep. Variable Mean for Individual					
Marketing / Migrant-First Training	0.683	0.683	13,397	8,636	6.41
Observations	412	412	412	412	412

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses and F-test p-values in square brackets. The dependent variable in column (1) takes the value 1 if the migrant signed up for bKash following the intervention. The dependent variable in column (2) takes the value 1 if the household performed any type of bKash transaction over the 13 month period from June 2015 - June 2016 (including deposits, withdrawals, remittances, and airtime top-ups), constructed using administrative data from bKash. The dependent variables in columns (3) and (4) are total and bKash remittances (sent through any means) sent in the prior 7 months as self-reported by urban migrants, respectively. Column (5) dependent variable is the inverse hyperbolic sine of total savings value. The unit of observation is the migrant for all regressions.

Figure 1: bKash Adoption Rates by Any Family-Network Treatment and Gender



Notes: "bKash Adoption" is an indicator variable that takes the value 1 if the migrant signed up for bKash following the intervention. The solid lines represent 95% standard error bars corresponding to each group.

References

Aker, J. (2010): "Information from Markets Near and Far: Mobile Phones and Agricultural Markets in Niger," *American Economic Journal: Applied Economics*, 2, 46–59.

Aker, J. C. and I. M. Mbiti (2010): "Mobile Phones and Economic Development in Africa," *Journal of Economic Perspectives*, 24, 207–232.

Armendáriz, B. and J. Morduch (2010): *The Economics of Microfinance, 2nd edition*, Cambridge, MA: MIT Press.

Ashraf, N., D. Karlan, and W. Yin (2010): "Female Empowerment: Further Evidence From a Commitment Savings Product in the Philippines," *World Development*, 38, 333–344.

Bandiera, O., R. Burgess, N. C. Das, S. Gulesci, I. Rasul, and M. Sulaiman (2017): "Labor Markets and Poverty in Village Economies," *The Quarterly Journal of Economics*, 132, 811–870.

Banerjee, A., E. Duflo, N. Goldberg, D. Karlan, R. Osei, W. Parienté, J. Shapiro, B. Thuysbaert, and C. Udry (2015): "A multifaceted program causes lasting progress for the very poor: Evidence from six countries," *Science*, 348.

Batista, C. and P. Vicente (2020): "Adopting Mobile Money: Evidence from an Experiment in Rural Africa," *AEA Papers and Proceedings*, 110, 594–98.

Bruhn, M. and D. McKenzie (2009): "In Pursuit of Balance: Randomization in Practice in Development Field Experiments," *American Economic Journal: Applied Economics*, 1, 200–232.

Bryan, G., S. Chowdhury, and A. M. Mobarak (2014): "Underinvestment in a Profitable Technology: The Case of Seasonal Migration in Bangladesh," *Econometrica*, 82, 1671–1758.

Chiapa, C., A. Parker, and S. Prina (2016): "The Effects of Financial Inclusion on Children's Schooling, Parental Aspirations and Expectations," *Journal of International Development*, 28, 683–696.

Demirgüç-Kunt, A., L. Klapper, and D. Singer (2013): "Financial Inclusion and Legal Discrimination Against Women: Evidence from Developing Countries," *World Bank Policy Research Working Paper Series*, 6416.

Demirgüç-Kunt, A., L. Klapper, D. Singer, S. Ansar, and J. Hess (2018): *The Global Findex Database 2017: Measuring Financial Inclusion and the Fintech Revolution*, Washington, DC: World Bank.

Dupas, P. and J. Robinson (2013): "Savings Constraints and Microenterprise Development: Evidence from a Field Experiment," *American Economic Journal: Applied Economics*, 5, 163–92.

Holloway, K., Z. Niazi, and R. Rouse (2017): "Women's Economic Empowerment Through Financial Inclusion: A Review of Existing Evidence and Remaining Knowledge Gaps," Report, Innovations for Poverty Action.

Jack, W. and T. Suri (2014): "Risk Sharing and Transactions Costs: Evidence from Kenya's Mobile Money Revolution," *American Economic Review*, 104, 183–223.

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

Karlan, D., J. Kendall, R. Mann, R. Pande, T. Suri, and J. Zinman (2016): "Research and Impacts of Digital Financial Services," *NBER Working Paper*, 22633.

Kling, J. R., J. B. Liebman, and L. F. Katz (2007): "Experimental Analysis of Neighborhood Effects," *Econometrica*, 75, 83–119.

Lee, J., J. Morduch, S. Ravindran, A. Shonchoy, and H. Zaman (2021): "Poverty and Migration in the Digital Age: Experimental Evidence on Mobile Banking in Bangladesh," *American Economic Journal: Applied Economics*, 13, 38–71.

Rahman, A. (2000): *Women And Microcredit In Rural Bangladesh: An Anthropological Study Of Grameen Bank Lending*, Routledge.

Riley, E. (2018): "Mobile Money and Risk Sharing Against Village Shocks," *Journal of Development Economics*, 135, 43 – 58.

——— (2020): "Resisting Social Pressure in the Household Using Mobile Money: Experimental Evidence on Microenterprise Investment in Uganda," *Working paper, Oxford University.*

Shrader, L. (2015): "Digital Finance in Bangladesh: Where are all the Women?" *Consultative Group to Assist the Poor.*

Suri, T. and W. Jack (2016): "The long-run poverty and gender impacts of mobile money," *Science*, 354, 1288–1292.