Narrowing the Gender Gap in Mobile Banking*

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

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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. The study focuses on migrants who live in Dhaka and send money back to their extended families. Despite large differences between female and male migrants in income and education, the first experiment shows that a training program led to similarly large, positive impacts on mobile banking use by female migrants (a 51 percentage point increase) and male migrants (46 percentage point increase), substantially narrowing the gender gap. However, the increases in adoption did not lead to similar patterns in usage: men increased digital remittances by 11 times as much as women. A second experiment tests whether introducing the technology in the context of family networks made an additional difference to gender gaps. The evidence suggests an 11 percentage point increase in adoption by women and just a 1 percentage point increase by men, although statistical power is low for this comparison and estimates are imprecise.

JEL codes: R23, O33, O16.

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†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 was based on the idea that poor women could grow their businesses by gaining access to credit, reduce dependence on their husbands, experience "empowerment", and help reduce their families' poverty (Rahman, 2000). This 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). Still, mobile banking and other digital financial services are seen as ways 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 digital financial inclusion build from evidence on the broader impact of financial access for women. Researchers have found empowerment and other effects of access to financial products (Garz et al. 2020, 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).

A challenge is that women use digital finance at lower rates than men. 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). In 2017 in Bangladesh, which has one of the fastest growing mobile banking sectors, gender gaps were larger than these global averages: 43% of men, but just 17% of women, had sent digital payments in the past year (Demirgüç-Kunt et al. 2018).

We present evidence from two connected field experiments in Bangladesh designed to increase the adoption and use of mobile banking, and we estimate their broader impacts on gender gaps. The study extends the analysis of Lee et al. (2021) which focuses on impacts pooled for men and women. Here, we show critical differences for male and female participants, and we report on a family-network experiment that was part of the initial study but not analyzed by Lee et al. (2021).

We show that gender gaps reflect systematic choices in how and where technologies are available and sold. The study was carried out with two connected samples: The first includes migrants in Dhaka who had left Bangladesh's northwest in search of jobs in the capital, and the second sample includes 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. 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.

At the start of the study, mobile banking providers had done little to encourage adoption by this population, and rates of adoption and usage were low. Lee et al. (2021), however, show that a training program had a large, positive impact on adoption and active use of mobile banking. The increase in active use led to large increases in urban-to-rural digital remittances. Here, when disaggregating by gender, we find increases in active use by both female migrants (by 51 percentage points) and male migrants (by 46 percentage points), narrowing the gender gap in usage. By the endline, the female-to-male ratio of active users in the treatment group was 85%, compared to 35% in the control group. However, the increases in adoption did not lead to similar patterns of usage by gender: Men increased digital remittances by 11 times as much as women, creating stronger downstream benefits for rural families of male migrants versus female.

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 Kenya's 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, which was implemented with participants in the training program, addresses the role of family networks directly. In one treatment arm, a randomly-assigned 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. In a cross-randomized treatment arm, we 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. One group received neither of these two family-network treatments, and we compare this group to the pooled sample that received either (or both) of the two treatment arms.

The family-network experiments were carried out only with those migrants who were introduced to bKash through the training program, so the sample is relatively small (n=412) and it took place against a backdrop of generally high take-up of bKash. (The adoption rate for the sample that received training but neither family-network treatments was 68%.) We use simulations to show reasonable statistical power when estimating pooled treatment effects (pooling male and female migrants) but low statistical power to detect effects when disaggregating by gender. The evidence suggests a modest increase in adoption for female migrants, although statistical power is low and estimates are noisy.

Taken as a whole, the results show the possibility to narrow gender gaps in technology use through targeted interventions, but the results also show the persistence of gender gaps in the broader impacts of the technology. These gaps are consistent with the facts that female migrants earn less than men on average, face cultural barriers, and are less likely to live independently. The findings suggest that democratizing access to finance will not necessarily equalize broader impacts when the economic and social playing field is highly 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 who offer basic banking services (mobile banking) without physical bank branches. We partnered with bKash, the leading provider 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.

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 21% of the control group had adopted. An aim of the study was to test possibilities to raise the adoption rate, for poor, illiterate women and men.

The study involved two sites, and individuals were paired across the sites.[1] 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

[1] See Lee et al. (2021) for the original study and further details on the site and benchmark experiment.

families in Rangpur), a population also targeted by Bandiera et al. (2017).

In rural Gaibandha, the sample population was formed from 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. As described in Lee et al. (2021), 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, 341 household and migrant pairs were recruited to participate in the study. In order to expand the sample, snowball sampling was employed 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, leaving 412 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.

2.2 Experimental Design

Lee et al. (2021) provide results on impacts of the experiment described above, 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]

Of the migrants, 29% of the treatment group and 31% of the control group were women. The initial experimental design did not involve stratification by gender, but in sections 3.1.1

[2]The study was implemented before pre-analysis plans were common in the experimental literature. We investigate the key outcomes analyzed by Lee et al. (2021) following the original survey instruments.

and 3.1.2 we show that, with a few exceptions that we control for in the estimation, the samples are balanced on key variables separately by gender.

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.

The study's dual-site design meant that we could follow both the remitters (urban migrants) and remittees (rural families). Once we completed the initial sampling and subsequent snowball sampling of migrants, we collected information and consent from migrants to communicate with their families located in Gaibandha district. This enabled us to locate the remittance-receiving families in rural areas to conduct the baseline survey and execute the intervention and follow-ups. Similarly, knowing the rural families helped us track migrants (in case of location or phone number change), greatly reducing sample attrition.

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.

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 gender-neutral treatment reinforced existing gender biases, narrowed them, or left them the same.

2.2.2 Family-Network Experiment

All participants in the "family-network" experiment were part of the training experiment described above in section 2.2.1. As part of the training, participants 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, in addition to the training and marketing described in section 2.2.1, 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 one quarter of the treated sample did not receive either of the family-network treatment variants (i.e., they were assigned to the migrant-first treatment and did not receive the pro-family message). The treatment arms are similar in their purpose, and to preserve power we pool both treatment arms together (n=309) and compare them to the quarter of the migrant sample that was exposed to neither (n=104). Power calculations are presented in Section 3.2.3 and the algorithm used is described in Appendix E.

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 every household (99% of respondents in the sample; Tables 1 and 2) had access to a mobile phone, financial inclusion was low, as reflected by the 9% (for females) and 12% (for males) rate of bank accounts at baseline (Table 1).

Most migrants in the sample had moved to Dhaka not long before the study started, with the average migrant living fewer than three years in Dhaka and working fewer than two years at their current job. Most worked in the formal sector (90-95%), and their average age was 24. Just over half of male migrants (52%) and a third of female migrants (36%) had completed primary schooling.

Pooling males and females, at baseline migrants earned on average 7830 taka (105 dollars) per month and sent a large portion of these earnings home as remittances. Women, however, earned on average just 69% as much as men (5.95/8.61 thousand taka; Table 1). 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%). Men in the training treatment group remitted 33% (2826/8610) of average monthly income and women remitted 27% (1633/5950). In absolute terms, women thus remitted 58% as much as men at baseline (11.43/19.78 thousand taka in the past 7 months; Table 1).

About 30% of the migrants in the sample were female (120/413). We do not know marital status for migrants who do not live with their spouses, but Table 1 shows that about half (49%) of female migrants lived with their spouses versus just about one quarter (24%) of male migrants. This difference in co-residence patterns, together with lower incomes, is consistent with the lower level of remittances sent by women versus men.

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. Table 1 shows baseline summary statistics by training treatment status for female migrants in Panel A and male migrants in Panel B. The F-tests for joint orthogonality (p=0.52 for the female sample and p=0.99 for the male sample) show that training treatment status is balanced on key observables. The cell sizes are smaller for the female sample (n=120) than the male (n=293), and the differences in some variables are notable although not statistically significant. These include agricultural land-holdings by rural families. The families of female migrants in the treatment group hold 2.28 decimals of agricultural land on average (a decimal is a hundredth of an acre, or 436 square feet), while families of female migrants in the control group hold

5.24 decimals on average. The standard deviations are large, however: 13.35 and 16.46, respectively. Comparing Panel A and Panel B shows that the families of male migrants on average hold more agricultural land (12.33 and 13.28 decimals for the treatment and control group respectively) compared to the holdings for the families of female migrants, again with large standard deviations.

In sum, we see differences between genders, but generally we have balance across treatment and control groups.

3.1.2 Family-Network Experiment

Again following the min-max t-stat re-randomization procedure described in Bruhn and McKenzie 2009, we cross-randomized which migrants received the family-first treatment arm and which received the pro-family treatment arm. Randomization was done such that the treatments were orthogonal to each other, and, as described in Section 2.2.2, we pooled migrants in both arms to compare them to the quarter of the sample in neither arm. Table 2 shows baseline summary statistics disaggregated by gender, showing balance on observables for female migrants in Panel A and male migrants in Panel B. Tables 1-3 of Appendix A present balance tables for the family-first training intervention and pro-family marketing intervention separately.

The F-tests for joint orthogonality (p=0.23 for the female sample and p=0.87 for the male sample) show that family-network treatment status is balanced on key observables. Four variables individually show differences in the female migrant sample: female migrants in the treatment group are more likely to have a formal job (98% in the treatment versus 88% in control), earn a higher monthly income (6,300 Taka versus 4,970 Taka), have completed primary school (41% versus 22%) and have sent more remittances in the past 7 months (12,610 Taka versus 8,200 Taka). To take into account these differences, we control for the four variables in the analysis.

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:

$$Y_{i,t+1} = \beta_0 + \beta_1 Treatment_i + \beta_2 Y_{i,t} + \mathbf{X}_{i,t} + \varepsilon_{i,t+1} \tag{1}$$

$$\begin{aligned} Y_{i,t+1} = {} & \beta_0 + \beta_1 Treatment_i + \beta_2 FemaleMigrant_i \\ & + \beta_3 Treatment_i * FemaleMigrant_i + \beta_4 Y_{i,t} + \mathbf{X}_{i,t} + \varepsilon_{i,t+1} \end{aligned} \tag{2}$$

where β_3 of Equation (2) 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. (We assess robustness to clustering of standard errors for the key results on active account use and remittances; in the estimates in Appendix C, standard errors are clustered by 275 rural villages, and changes in the results are very small.)

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). Within the family of eight migrant health outcomes considered, we also adjust p-values for multiple hypothesis testing via the free step-down resampling methodology of Westfall and Young (1993), using the implementation by Jones et al. (2019).

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 (3) on the stacked baseline and endline migrant-month level data:

$$
\begin{aligned}
Y_{i,t} = \beta_1 Endline_t &+ \beta_2 Treatment_i * Endline_t \\
&+ \beta_3 Endline_t * FemaleMigrant_i \\
&+ \beta_4 Treatment_i * Endline_t * FemaleMigrant_i \\
&+ \sum_{t=1}^{7} \beta_{5,t} Month_t + \beta_{6,i} + \varepsilon_{i,t}
\end{aligned} \tag{3}
$$

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 (3) 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 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:

$$Y_{i,t} = \beta_0 + \beta_1 AnyFamilyNetworkTreatment_i + \mathbf{X}_{i,t} + \varepsilon_{i,t} \tag{4}$$

where $\mathbf{X}_{i,t}$ is a vector of baseline controls that includes all variables that are show individual differences between the any family-network treatment and control group in Table 2: gender, age, and primary school completion of the migrant, household size, daily per capita expenditure of the migrant, an indicator for whether the migrant was employed in the formal sector, average monthly income of the migrant, and total remittances sent in the past 7 months. $AnyFamilyNetworkTreatment_i$ 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:

$$Y_{i,t+1} = \beta_0 + \beta_1 AnyFamilyNetworkTreatment_i + \beta_2 AnyFamilyNetworkTreatment_i * FemaleMigrant_i + \beta_3 Y_{i,t} + \mathbf{X}_{i,t} + \varepsilon_{i,t+1} \tag{5}$$

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

3.2.3 Power Calculations

We use simulations to calculate power for the key empirical specifications in the "Training Treatment" and "Any Family Network Treatment" regressions. The ex-post power calculations use the true proportion of bKash adoption in the control group and the full set of control variables. See Appendix E for more detail on the algorithm.

Figure 1 gives plots of power against the minimum detectable effect (MDE) for the training treatment corresponding to Equation (1), which pools the treatment effects for males and females. We are able to detect treatment effect sizes of at least 7 percentage points with 80% power ($\alpha = 0.1$). Figure 2 presents plots of power against MDE for Equation (2), which disaggregates treatment effects by gender. Treatment effects are reported relative to estimates of β_3, i.e. with respect to the variable $Treatment_i * FemaleMigrant_i$, and for MDE values between 0.1 and 0.2. We are able to detect female-specific treatment effect sizes of at least 15 percentage points with 80% power ($\alpha = 0.1$).

Plots of power against MDE for the "Any Family Network Treatment" corresponding to Equation (4) are presented in Figure 3. Power is considerably lower for gender comparisons in this experiment since the sample is limited to the treatment group for the training experiment (n=412). We can detect pooled (males and females together) treatment effect sizes of at least 14 percentage points with 80% power ($\alpha = 0.1$). Figure 4 shows plots of power against MDE for Equation (5). Treatment effects are reported relative to estimates of β_2, i.e. with respect to the variable $AnyFamilyNetworkTreatment_i * FemaleMigrant_i$, and for MDE values between 0.25 and 0.35. When disaggregating by gender, we are able to detect treatment effect sizes of at least 35 percentage points with 80% power ($\alpha = 0.1$). Given the lack of power to detect smaller effect sizes by gender, we treat the comparisons in the family-network experiment as exploratory.

4 Results

Using both experiments, we show intention-to-treat estimates pooled for males and females (replicating Lee et al. (2021)) and disaggregated by gender. The disaggregation shows important differences by gender in the training experiment.

4.1 Training Experiment

Table 3 shows 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. (See section 3.2.2 for the variable definition.)

The first column of Table 3, corresponding to equation (1), 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), replicating a result in Lee et al. (2021).

Disaggregating by gender shows how this increase narrowed the gender gap in usage. At endline, 26% of control group male migrants and 9% of female migrants were actively using bKash, an absolute difference of 17 percentage points. The ratio of female-to-male usage was 35%. In the treatment group, in contrast, usage had increased sharply and the gender gap had substantially narrowed. By the endline, males in the treatment group had increased bKash use to 71% and females to 61%. The absolute gender gap was 11 percentage points and the female-to-male usage ratio was 85%.

These patterns are seen in the treatment effects in the even-numbered columns of Table 3. Column (2) shows that women are 12.3 percentage points less likely to adopt bKash overall, but 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 6 percentage point boost in the treatment impact for women, but the coefficient is measured imprecisely; coefficient = 0.06 with s.e.= 0.07.) The combined coefficients on treatment + [treatment * (Female migrant)] show a 51 percentage point increase (p=0.00) for women. The increase for men is 45 percentage points (s.e.=0.04). By creating similar-sized increases in absolute terms, the training intervention narrowed the gender gap in relative terms.

Lee et al. (2021) showed that using mobile banking increased remittances from urban migrants to their families in Northwest Bangladesh villages, bringing broader development impacts in the villages. 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), but the second row of column (1) shows that the treatment effectively erased the decline in remittances (coefficient = 316 taka). 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 of Table 4—(2), (4), and (6)—disaggregate the results by gender, and the fourth row gives the treatment effect for female migrants. Below that, we calculate the combined treatment effect for women.

The disaggregation by gender shows that the results on remittances in Lee et al. (2021) are driven by male migrants. Table 3 showed that the treatment increased active bKash use for women and men by similar amounts, but column (2) shows that women in the treatment group remit less than men. The treatment effect for female migrants is -135.3 taka (s.e.=303.8), and the combined treatment effect for females is 217.9 taka (p-value of the F-test of the combined effect=0.317). The combined treatment effect shows an increase in taka sent as remittances for women, but it is smaller than for men (353.1 taka) and measured imprecisely.

The results for remittances sent through bKash specifically show much larger differences for male and female migrants. Column (4) shows that women in the treatment group remit 473.3 taka less than men through bKash. The combined treatment effect for females is just 47.1 taka. This combined effect is small in both relative and absolute terms. The treatment effect for male migrants is 11 times the combined treatment effect for females. On average, bKash is not an important way that female migrants send money home (p-value of the F-test of the combined treatment effect=0.79).

In column (6), the main treatment effect on the share of income remitted is measured noisily (a 3 percentage point increase in the income share devoted to remittances) and the treatment effect for women (-0.4 percentage points, s.e. = 3.5 percentage points) is not statistically different from that for men.

The results on remittances are consistent with the lower earnings of female migrants and their higher rate of co-residing with spouses, as shown in Table 1. We describe these and other possible explanations in Section 5.

The results on broader outcomes for female migrants are consistent with these modest results on remittances. Table 5 provides evidence on poverty rates for migrants, 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 worse health. The third row gives the differential impact for female migrants in the training treatment. Consistent with the results above, estimates are imprecise and relatively small, although column (3) shows a precisely-measured increase by 22 percentage points in the probability that female migrants have any saving. The combined effect in column (4) shows a roughly 21 percent increase in the value of saving held by female migrants (measured imprecisely; p-value of the F-test in column 4 = 0.66).

Table 6 provides parallel results for the components of the health index, including physical and emotional health. Given the large number of variables considered for migrant health (8), we adjust p-values for multiple hypothesis testing via the free step-down resampling methodology of Westfall and Young (1993). The table shows that across the treatment and control groups, females report worse outcomes on every measure (row 2). Lee et al. (2021) show that health worsens for members of the treatment group. Here, we find negative combined treatment effects for female migrants, but all have large p-values. The results show more pronounced health challenges for male migrants in the treatment group; they are less likely to have social activities and more likely to report severe emotional problems.

The outcomes in Table 7 pertain to the migrants' extended families. Using the rural sample, the outcomes 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 combined effect for female migrants is not statistically different from zero for any outcome, although combined effects for the squared poverty gap and for the consumption index are large relative to the baseline means.

In sum, the training treatment substantially increased the adoption and use of mobile banking by all migrants (male and female), reducing the gender gap in usage. However, men, but not women, were far more likely to use bKash to send remittances back to rural families, and men increased overall remittances by larger amounts than women. The downstream impact on rural families reflects these patterns.

4.2 Family-Network Experiment

We varied the nature and timing of the training process to determine if the nature of the introduction would affect adoption rates. This was cross-randomized with the training intervention described above. 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. The two treatment arms are pooled to maximize statistical power, and they are compared to part of the sample that was exposed to the training intervention but to neither of these family-network treatments. The experiment has power to detect a 14 percentage point pooled treatment effect with 80% power ($\alpha = 0.1$) and a 35 percentage point treatment effect when disaggregated by gender, as described in Section 3.2.3. The results are thus exploratory.

Figure 5 summarizes the impacts of the two family-network interventions on bKash adoption rates. Adoption rates were generally high: when pooling males and females, 68% of migrants adopted when exposed to only the training experiment and neither family-network treatment. The left panel of the figure 5 shows that exposure to a family-network treatment led to only a small positive increase in bKash adoption. This is replicated in column (1) of Table 8: on average, migrants exposed to a family-network treatment were 4.3 percentage points more likely to adopt bKash in comparison to migrants in the comparison group, but the point estimate is imprecisely estimated (coefficient = 0.043, s.e. = 0.050). Columns (2) through (5) show that, similarly, measured impacts on active account use, remittances, and savings are relatively small and imprecise. When pooled across male and female migrants, the results suggest that the family-network experiment had little impact above and beyond the training intervention.

Disaggregating by gender, however, suggests a possible impact for female migrants, although statistical power for this comparison is low. The right panel of Figure 5 shows that exposure to the family-network treatments made a relatively large difference in bKash adoption (by 15 percentage points) for female migrants (with wide confidence intervals), while treatment impacts for male migrants were close to zero. Similarly, the combined treatment effect in Table 9 shows that female migrants exposed to a family-network treatment were 11 percentage points more likely to adopt bKash relative to female migrants in the control group (coefficient = 0.114, p-value = 0.214). For male migrants, the treatment effect on adoption is just over 1 percentage point (coefficient = 0.014, s.e. = 0.059). Again, however, we note the concerns with power and that these estimates are not statistically significant; the remaining columns in the table yield noisy estimates.[3]

5 Discussion

In section 4.1, the results show (1) large increases in active usage of bKash by female migrants, but (2) very small increases in digital remittances (in contrast to large increases for men).

The first finding is surprising. There are many reasons to expect that women might instead have been reluctant to adopt the new technology (e.g., Barboni et al. (2018)). Akter et al. (2016), for example, find that women, when faced with limited resources, vulnerable social positions, and high levels of household responsibility, may have heightened aversion to risk and greater reluctance to invest in new technologies. Similarly, Rea and Nelms (2017) point to the ways that technology is embedded in existing cultural norms and social practices that are often gendered; see also Morvant-Roux et al. (2017), Archambault (2017), and Barboni et al. (2018). Although mobile money and related digital financial technologies have lower costs than formal service delivery, they may still be perceived as more expensive than cash. Spencer et al. (2018) find that women often need to have significant trust in digital financial services before they adopt.

Experts had hoped that women would benefit from the privacy of the mobile platform

[3] 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.

to secure their own savings, thereby increasing financial independence, but evidence from Kenya found that women were much more likely to use mobile money for replicating cash transfer obligations—often to their husbands—while mobile wallets intended for use as savings instruments were dormant (Stuart, 2011). Women may face expectations and demands to distribute their savings, and some may therefore choose not to save on the mobile phone (Rea and Nelms, 2017).

Phone ownership and official government-issued identification may also create barriers to opening a mobile money account (Klapper, 2019). Women in Bangladesh are less likely than men to have the required identification, especially government IDs and birth certificates (Shrader, 2015). The gender gap in phone ownership is about 17 percentage points in Bangladesh, and most low-income households have only one phone per household, often held by husbands or older children. Women are more likely to be secondary sharers of a mobile phone with less immediate access and lower daily mobile usage (Handforth, 2019). Clear and easy-to-understand product terms may be especially important for low-income women, given their relatively limited financial experience and capability (Klapper, 2019).

Using mobile money requires engaging with local agents to "cash in" and "cash out". In Bangladesh, few mobile money agents are women, and women tend to have cultural barriers around going "out" to agents located in male-dominated markets (Shrader, 2015). Women face gendered barriers to digital services beyond their household, and report being harassed or turned away by mobile money agents (Financial Inclusion Insights, 2018).

Despite these concerns, the present study finds that women in the treatment group adopted mobile banking at a high rate. We cannot determine which constraints were most binding for the control group, but introducing both rural families and urban migrants (in the treatment group) to the technology likely made an important difference in the treatment group.

A second puzzle concerns remittances. Why, despite actively using bKash, do most female migrants in the treatment group not use it to send money home? One direct explanation is that, in general, female migrants remit less home than males. As section 3.1 described, female migrants remitted 58% as much as men at baseline (Table 1). The baseline monthly income of female migrants in the treatment group is 31% lower on average than their male counterparts (5.95 thousand taka versus 8.61 thousand taka), and, all else the same, the lower disposable income of women means that they have less extra money to remit home.

Another factor is that women in the treatment group are twice as likely to co-reside with spouses in Dhaka (49% of women versus 24% of men). The higher rate of co-residence with spouses decreases the motivation to remit since spouses are less likely to be left behind in rural areas. Men, in contrast, are more likely to send money home, potentially to wives and children who remained in the village. (With more data, we would be able to explore this explicitly.)

An additional possibility is that females remit less because they make more frequent visits back to the rural areas. To the extent that is true, sending remittances through mobile money might be done in emergencies, but in general female migrant workers would bring money home physically, carrying cash with them while visiting the family (Stuart, 2020). Again, our data do not permit us to test the hypothesis, but it could be part of the overall explanation.

Anthropologists illuminate the complex gendered dynamics of digital finance and its networked characteristics. Johnson (2017) argues that the original M-Pesa marketing push reflected these gendered dynamics: it was, she writes, a "story of men – in this case probably well-educated, young, urban, employed men – sending funds to their rurally based mothers." Her study describes mobile money as a network technology that connected people and fits into a pattern of gender relations in which urban-based men earn and remit to rural-based women. The networked nature of mobile money in the context of remittances gets women included, unlike formal financial services that are not networked. As Kusimba et al. (2017) illustrates for western Kenya, women, especially mothers, are central to the social networks around mobile money.

Over time, these social networks—and the cultural links that run through them—may shift, and, when they do, digital financial technology may open different obligations and possibilities for both men and women. In the current context, digital remittances appear to be a largely male-dominated activity.

6 Conclusion

The study revisits and extends the experiment in Lee et al. (2021), bringing an explicit gender lens. The analysis shows the importance of disaggregating by gender in understanding technology adoption and use (Klapper 2019, Barboni et al. 2018). The urban migrants at the center of the study originally came from from one of the poorest regions in Bangladesh. The results show that appropriately-designed interventions can dramatically increase technology adoption by women, leading to similar-sized treatment effects for men and women. This is especially notable in a poor population with limited education that has historically been among the most "financially excluded." Female migrants in the treatment group actively used bKash at the end of the study at a rate that was 85% that of men, versus 35% in the control group.

Both the training experiment and the family network experiment had positive impacts on choices by women, suggesting the possibility of narrowing, if not fully erasing, gender gaps in technology adoption and active usage. Still, the data show that, unlike males, female migrants sent home a substantially lower value of remittances, consistent with their lower average earnings relative to men and higher likelihood of living with spouses. Digital remittances to extended family members jumped for male migrants, but they barely moved for female migrants.

The results are specific to the context. The migrants tend to be young and open to new technology, and reliably sending remittances back to their rural-based families is a key obligation, especially for men, most of whom do not live with spouses in Dhaka. 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, for women especially, 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 gender inequalities.

Table 1: Summary Statistics by Training Treatment Assignment (Baseline)

Panel A: Female Migrants		Treatment Mean	Treatment SD	Treatment N	Control Mean	Control SD	Control N	Group Differences p-value
Urban	Any bank account	0.09	0.29	120	0.11	0.31	123	0.715
	Formal employee	0.95	0.22	120	0.89	0.31	123	0.107
	Average monthly income, (‘000 Taka)	5.95	2.15	120	6.20	1.94	123	0.347
	Age	24.27	5.50	120	24.32	5.34	123	0.942
	Completed primary school	0.36	0.48	120	0.29	0.46	123	0.277
	Tenure at current job	1.55	1.45	120	1.45	1.37	123	0.575
	Tenure in Dhaka	1.82	1.29	120	1.86	1.15	123	0.773
	Remittances sent, past 7 months (‘000 Taka)	11.43	9.59	120	13.32	9.55	123	0.125
	Spouse co-resides in Dhaka	0.49	0.50	120	0.40	0.49	123	0.145
	Daily per capita expenditure (Taka)	103.61	45.95	120	102.42	35.38	123	0.821
Rural	Any mobile	0.98	0.13	120	0.97	0.18	123	0.428
	Household size	3.62	1.46	120	3.77	1.53	123	0.444
	Number of children	1.33	1.04	120	1.46	1.13	123	0.352
	Household head age	45.93	12.38	120	46.30	12.80	123	0.820
	Household head female	0.17	0.38	120	0.17	0.38	123	0.930
	Household head educated	0.15	0.36	120	0.09	0.29	123	0.147
	Decimal of owned agricultural land	2.28	13.35	120	5.24	16.46	123	0.125
	Number of rooms of dwelling	1.60	0.68	120	1.60	0.66	123	0.985
	Dwelling owned	0.93	0.25	120	0.91	0.29	123	0.511
	Daily per capita expenditure (Taka)	63.15	34.55	120	59.78	26.19	123	0.392
	Poverty rate (national threshold)	0.76	0.43	120	0.80	0.40	123	0.473
	Poverty rate (global $1.90 threshold)	0.46	0.50	120	0.53	0.50	123	0.276
	Gaibandha subdistrict	0.42	0.50	120	0.46	0.50	123	0.465
p-value of F-test for joint orthogonality = 0.524.								

Panel B: Male Migrants		Treatment Mean	Treatment SD	Treatment N	Control Mean	Control SD	Control N	Group Differences p-value
Urban	Any bank account	0.12	0.32	293	0.11	0.32	279	0.960
	Formal employee	0.90	0.30	293	0.88	0.33	279	0.461
	Average monthly income, (‘000 Taka)	8.61	2.34	293	8.46	2.32	279	0.451
	Age	23.98	5.17	293	23.94	5.02	279	0.931
	Completed primary school	0.52	0.50	293	0.51	0.50	279	0.818
	Tenure at current job	1.75	1.63	293	1.75	1.50	279	0.957
	Tenure in Dhaka	2.68	1.98	293	2.78	1.88	279	0.528
	Remittances sent, past 7 months (‘000 Taka)	19.78	11.91	293	20.43	13.09	279	0.538
	Spouse co-resides in Dhaka	0.24	0.43	293	0.23	0.42	279	0.863
	Daily per capita expenditure (Taka)	127.20	42.97	293	128.79	40.32	279	0.648
Rural	Any mobile	0.99	0.08	293	0.99	0.10	279	0.615
	Household size	3.83	1.71	293	3.86	1.63	279	0.786
	Number of children	1.09	1.00	293	1.12	1.02	279	0.725
	Household head age	47.89	13.26	293	46.22	13.62	279	0.137
	Household head female	0.10	0.30	293	0.11	0.31	279	0.637
	Household head educated	0.21	0.41	293	0.19	0.39	279	0.586
	Decimal of owned agricultural land	12.33	32.40	293	13.28	35.02	279	0.737
	Number of rooms of dwelling	1.91	0.73	293	1.92	0.78	279	0.921
	Dwelling owned	0.95	0.23	293	0.95	0.22	279	0.813
	Daily per capita expenditure (Taka)	63.75	35.50	293	61.45	34.11	279	0.432
	Poverty rate (national threshold)	0.72	0.45	293	0.76	0.43	279	0.280
	Poverty rate (global $1.90 threshold)	0.51	0.50	293	0.53	0.50	279	0.661
	Gaibandha subdistrict	0.54	0.50	293	0.56	0.50	279	0.637
p-value of F-test for joint orthogonality = 0.993.								

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Summary statistics are presented for the 815 migrants surveyed at baseline. P-values are given for tests of differences in means by treatment status. F-tests for joint orthogonality include urban migrant and rural household variables in each panel.

Table 2: Summary Statistics by Any Family-Network Treatment Assignment (Baseline)

Panel A: Female Migrants		Treatment Mean	Treatment SD	Treatment N	Control Mean	Control SD	Control N	Group Differences p-value
Urban	Any bank account	0.09	0.29	88	0.09	0.30	32	0.962
	Formal employee	0.98	0.15	88	0.88	0.34	32	0.023**
	Average monthly income, (‘000 Taka)	6.30	1.94	88	4.97	2.41	32	0.002***
	Age	23.89	5.01	88	25.31	6.66	32	0.211
	Completed primary school	0.41	0.49	88	0.22	0.42	32	0.055*
	Tenure at current job	1.61	1.53	88	1.41	1.20	32	0.520
	Tenure in Dhaka	1.88	1.38	88	1.66	1.00	32	0.414
	Remittances sent, past 7 months (‘000 Taka)	12.61	10.46	88	8.20	5.62	32	0.025**
	Spouse co-resides in Dhaka	0.49	0.50	88	0.50	0.51	32	0.913
	Daily per capita expenditure (Taka)	101.70	36.78	88	108.87	65.33	32	0.452
Rural	Any mobile	0.98	0.15	88	1.00	0.00	32	0.394
	Household size	3.60	1.48	88	3.69	1.42	32	0.779
	Number of children	1.35	1.05	88	1.28	1.02	32	0.742
	Household head age	46.55	12.56	88	44.25	11.91	32	0.371
	Household head female	0.16	0.37	88	0.22	0.42	32	0.451
	Household head educated	0.14	0.35	88	0.19	0.40	32	0.492
	Decimal of owned agricultural land	3.11	15.53	88	0.00	0.00	32	0.260
	Number of rooms of dwelling	1.61	0.70	88	1.56	0.62	32	0.717
	Dwelling owned	0.92	0.27	88	0.97	0.18	32	0.352
	Daily per capita expenditure (Taka)	64.94	38.70	88	58.21	18.52	32	0.347
	Poverty rate (national threshold)	0.74	0.44	88	0.81	0.40	32	0.408
	Poverty rate (global $1.90 threshold)	0.44	0.50	88	0.50	0.51	32	0.584
	Gaibandha subdistrict	0.41	0.49	88	0.44	0.50	32	0.782
p-value of F-test for joint orthogonality = 0.234.								

Panel B: Male Migrants		Treatment Mean	Treatment SD	Treatment N	Control Mean	Control SD	Control N	Group Differences p-value
Urban	Any bank account	0.13	0.33	221	0.08	0.28	72	0.320
	Formal employee	0.89	0.32	221	0.93	0.26	72	0.290
	Average monthly income, (‘000 Taka)	8.54	2.39	221	8.80	2.17	72	0.411
	Age	23.84	5.21	221	24.40	5.07	72	0.421
	Completed primary school	0.52	0.50	221	0.54	0.50	72	0.704
	Tenure at current job	1.73	1.63	221	1.78	1.64	72	0.822
	Tenure in Dhaka	2.66	2.08	221	2.74	1.64	72	0.767
	Remittances sent, past 7 months (‘000 Taka)	19.77	11.97	221	19.82	11.79	72	0.979
	Spouse co-resides in Dhaka	0.22	0.41	221	0.29	0.46	72	0.197
	Daily per capita expenditure (Taka)	126.15	45.88	221	130.43	32.51	72	0.463
Rural	Any mobile	1.00	0.07	221	0.99	0.12	72	0.404
	Household size	3.82	1.72	221	3.85	1.68	72	0.903
	Number of children	1.09	1.00	221	1.10	1.01	72	0.960
	Household head age	47.80	13.16	221	48.19	13.68	72	0.825
	Household head female	0.09	0.29	221	0.12	0.33	72	0.396
	Household head educated	0.21	0.41	221	0.21	0.41	72	0.997
	Decimal of owned agricultural land	12.95	35.02	221	10.46	22.69	72	0.572
	Number of rooms of dwelling	1.93	0.73	221	1.86	0.72	72	0.503
	Dwelling owned	0.94	0.24	221	0.96	0.20	72	0.579
	Daily per capita expenditure (Taka)	63.80	35.94	221	63.57	34.38	72	0.962
	Poverty rate (national threshold)	0.71	0.45	221	0.75	0.44	72	0.517
	Poverty rate (global $1.90 threshold)	0.52	0.50	221	0.46	0.50	72	0.328
	Gaibandha subdistrict	0.54	0.50	221	0.53	0.50	72	0.875
p-value of F-test for joint orthogonality = 0.874.								

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Summary statistics are presented for the 413 migrants surveyed at baseline. P-values are given for tests of differences in means by treatment status. F-tests for joint orthogonality include urban migrant and rural household variables in each panel.

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

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses and p-values for F-tests of the combined coefficients in square brackets. "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)	(0.012)	(0.014)
Treatment ∗ Endline	316.1*	353.1*	385.9***	520.4***	0.030*	0.030
	(163.0)	(212.3)	(130.1)	(167.6)	(0.016)	(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)
Treatment ∗ Endline +		217.9		47.1		0.027
Treatment ∗ Endline ∗ Female Migrant		[0.317]		[0.794]		[0.347]
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

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses, clustered by household, and p-values for F-tests of the combined coefficients in square brackets. Data are for migrant-months following equation (3). The dependent variable in column 1 is total remittances (sent through any means) sent in the prior month as self-reported by urban migrants. The dependent variable in column 2 is remittances sent through bKash in the prior month. The dependent variable in column 3 is total remittances as a share of migrant income in the prior month.

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)
Treatment +	-0.08*	0.02	0.22***	0.21	-0.17
Treatment ∗ Female Migrant	[0.09]	[0.70]	[0.00]	[0.66]	[0.30]
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: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses and p-values for F-tests of the combined coefficients in square brackets. 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)
	{0.320}	{0.360}	{0.160}	{0.180}	{0.517}	{0.070}	{0.161}	{0.045}
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)
	{0.003}	{0.081}	{0.044}	{0.009}	{0.009}	{0.126}	{0.052}	{0.014}
Treatment ∗ Female Migrant	0.175	-0.170	-0.045	0.187	-0.048	0.085	0.013	0.161
	(0.276)	(0.281)	(0.281)	(0.278)	(0.285)	(0.282)	(0.283)	(0.282)
	{0.939}	{0.939}	{0.995}	{0.939}	{0.995}	{0.989}	{0.995}	{0.939}
Treatment +	-0.040	-0.354	-0.358	-0.097	-0.150	-0.293	-0.291	-0.252
Treatment ∗ Female Migrant	[0.860]	[0.133]	[0.126]	[0.676]	[0.530]	[0.214]	[0.221]	[0.285]
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: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses and p-values adjusted for multiple hypothesis testing via the free step-down resampling methodology of Westfall and Young (1993) in {curly brackets}. P-values for chi-squared tests of the combined coefficients in square brackets. 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)
Treatment +	0.002	-0.025	0.108	-0.042	0.061
Treatment ∗ Female Migrant	[0.950]	[0.122]	[0.210]	[0.710]	[0.193]
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: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses and p-values for F-tests of the combined coefficients in square brackets. 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	0.043	-0.004	1041.3	-163.4	0.424
	(0.050)	(0.053)	(1452.3)	(1218.2)	(0.397)
R^2	0.100	0.027	0.202	0.285	0.068
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

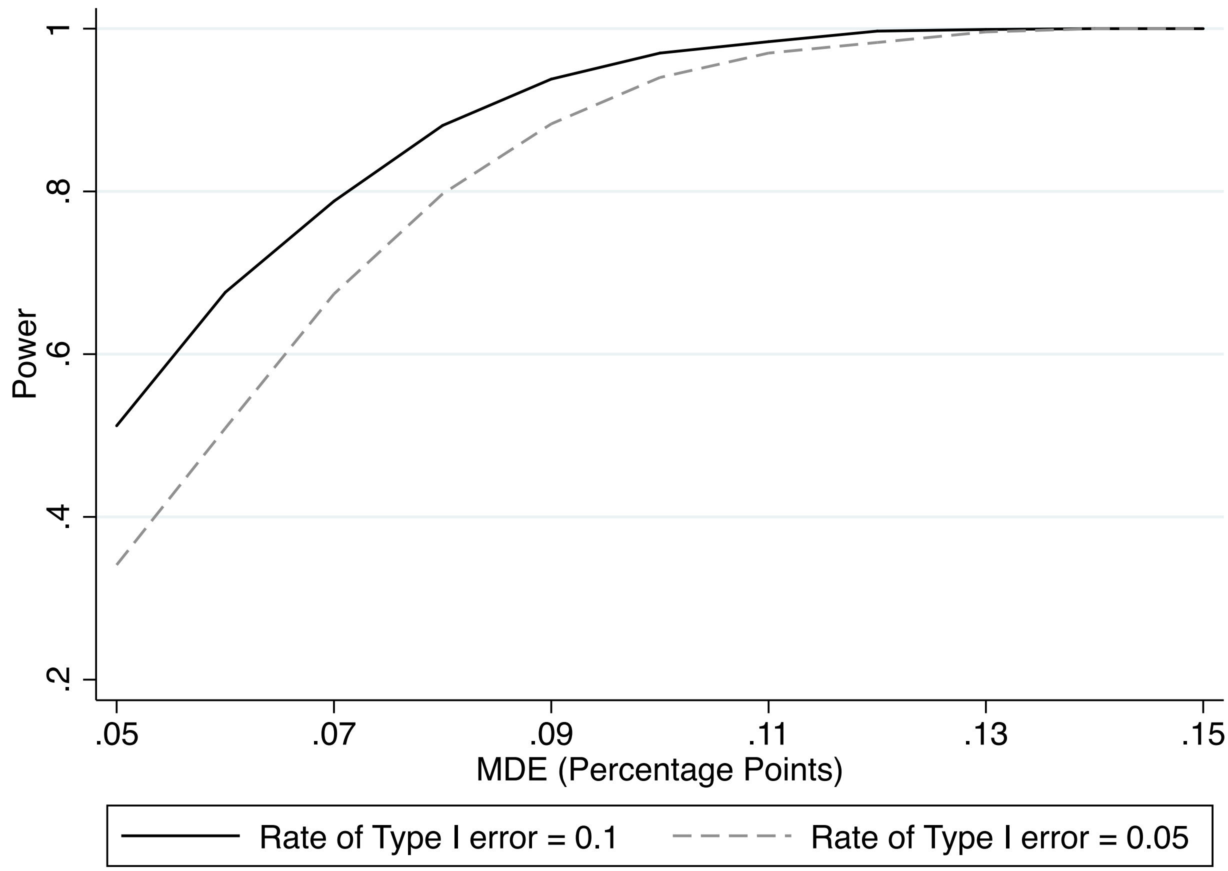
Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. The dependent variable in column (1) takes the value 1 if the migrant signed up for bKash following the intervention. The dependent variable in column (2) takes the value 1 if the household performed any type of bKash 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)
Any Family-Network Treatment	0.014	0.031	1231.2	-382.9	0.390
	(0.059)	(0.063)	(1733.7)	(1451.4)	(0.472)
Female Migrant	-0.059	0.015	-3617.4	-3086.2	-0.901
	(0.101)	(0.108)	(2951.4)	(2474.5)	(0.802)
Any Family-Network Treatment	0.101	-0.119	-647.2	751.0	0.116
∗ Female Migrant	(0.109)	(0.117)	(3218.9)	(2691.7)	(0.872)
Any Family-Network Treatment +	0.114	-0.089	584.0	368.1	0.507
Any Family-Network Treatment	[0.214]	[0.370]	[0.829]	[0.871]	[0.490]
∗ Female Migrant					
R^2	0.102	0.030	0.202	0.286	0.068
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

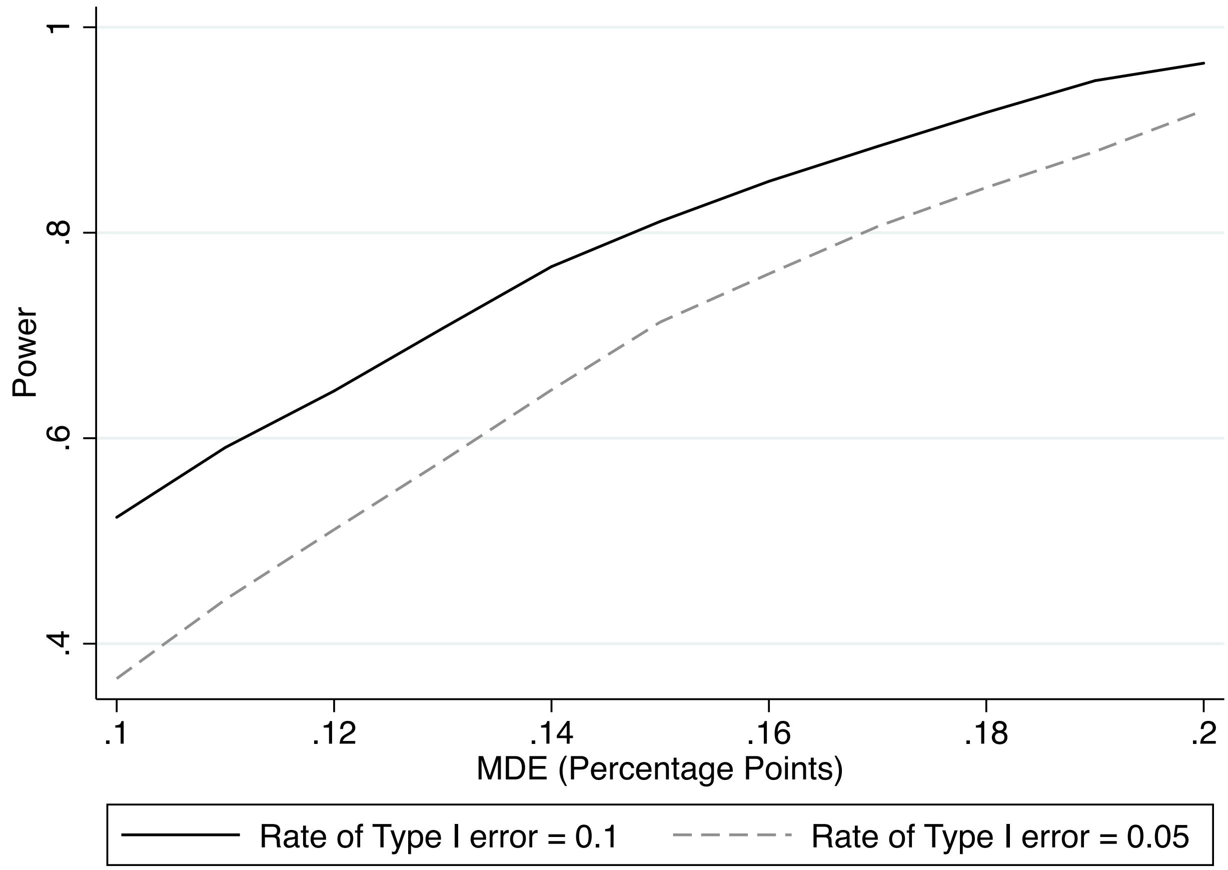
Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses and F-test p-values in square brackets. The dependent variable in column (1) takes the value 1 if the migrant signed up for bKash following the intervention. The dependent variable in column (2) takes the value 1 if the 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: Power Calculations: Training Treatment



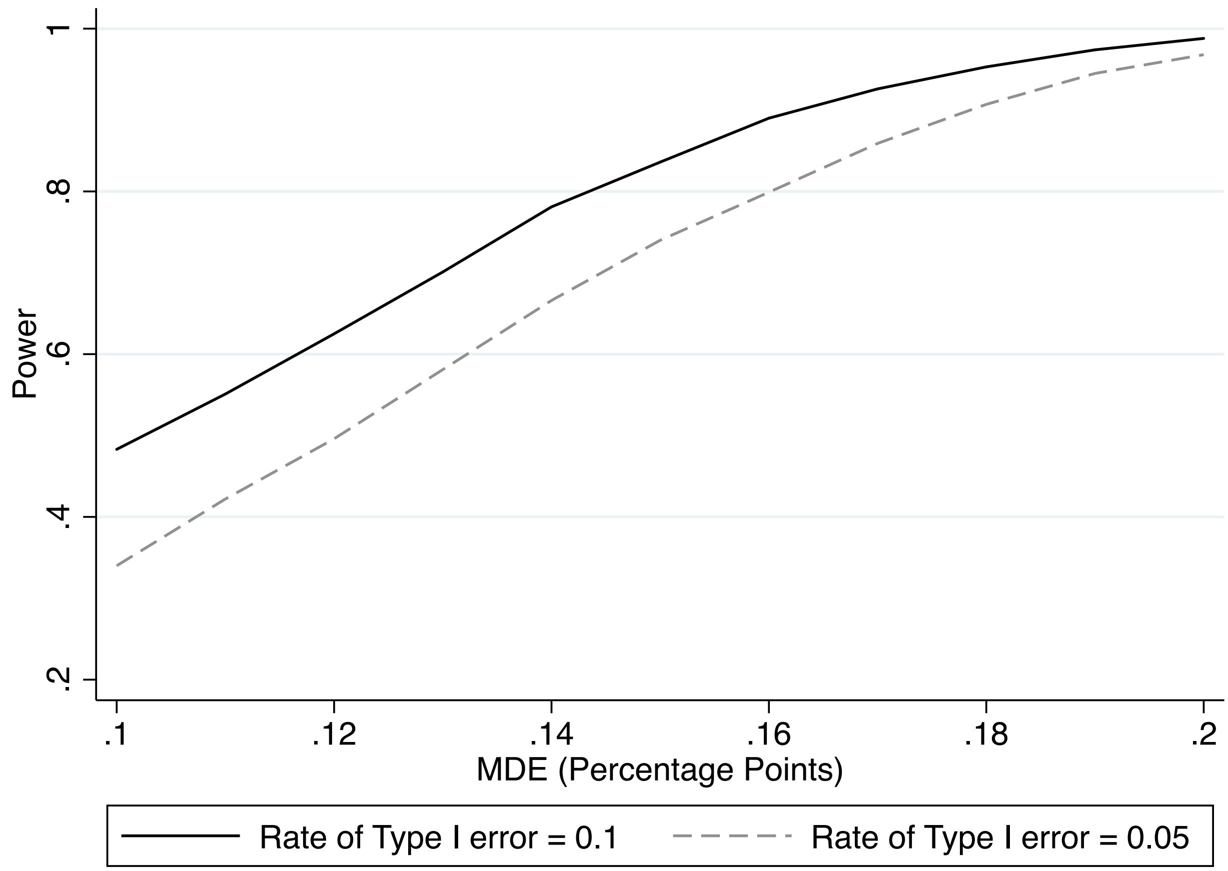
Notes: Minimum Detectable Effects (MDEs) reported in percentage points (not standard deviation units) due to the binary nature of the bKash adoption variable. The solid black line plots power when α, the rate of Type I error, is equal to 0.1 and the dashed gray line plots power when $\alpha = 0.05$. Power calculations are shown for Equation (1) with bKash adoption as the dependent variable. MDEs are with respect to the variable $Treatment_i$. Power is computed using 1,000 simulations for each level of MDE at intervals of 0.01 between 0.05 and 0.15.

Figure 2: Power Calculations: Training Treatment by Gender



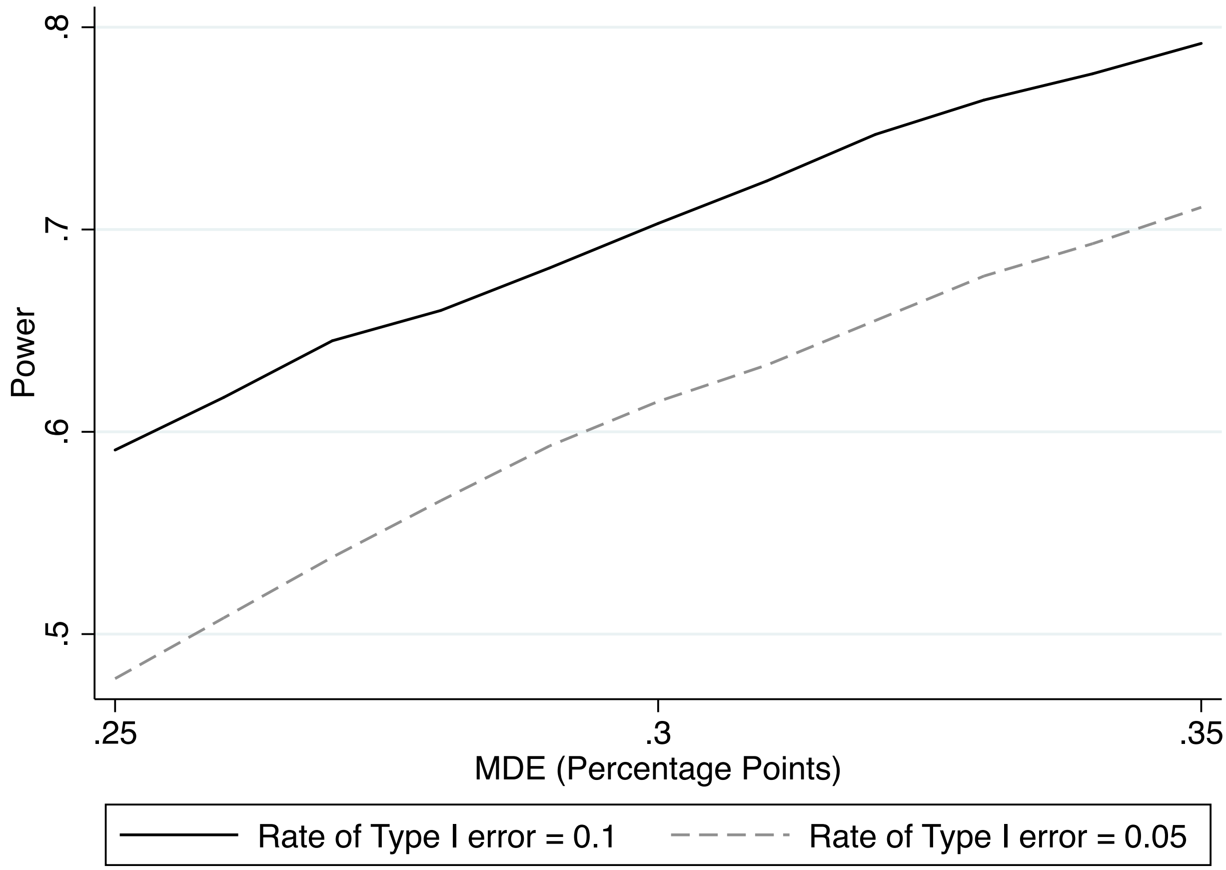
Notes: Minimum Detectable Effects (MDEs) reported in percentage points (not standard deviation units) due to the binary nature of the bKash adoption variable. The solid black line plots power when α, the rate of Type I error, is equal to 0.1 and the dashed gray line plots power when $\alpha = 0.05$. Power calculations are shown for Equation (2) with bKash adoption as the dependent variable. MDEs are with respect to the variable $Treatment_i * FemaleMigrant_i$. Power is computed using 1,000 simulations for each level of MDE at intervals of 0.01 between 0.1 and 0.2.

Figure 3: Power Calculations: Any Family-Network Treatment



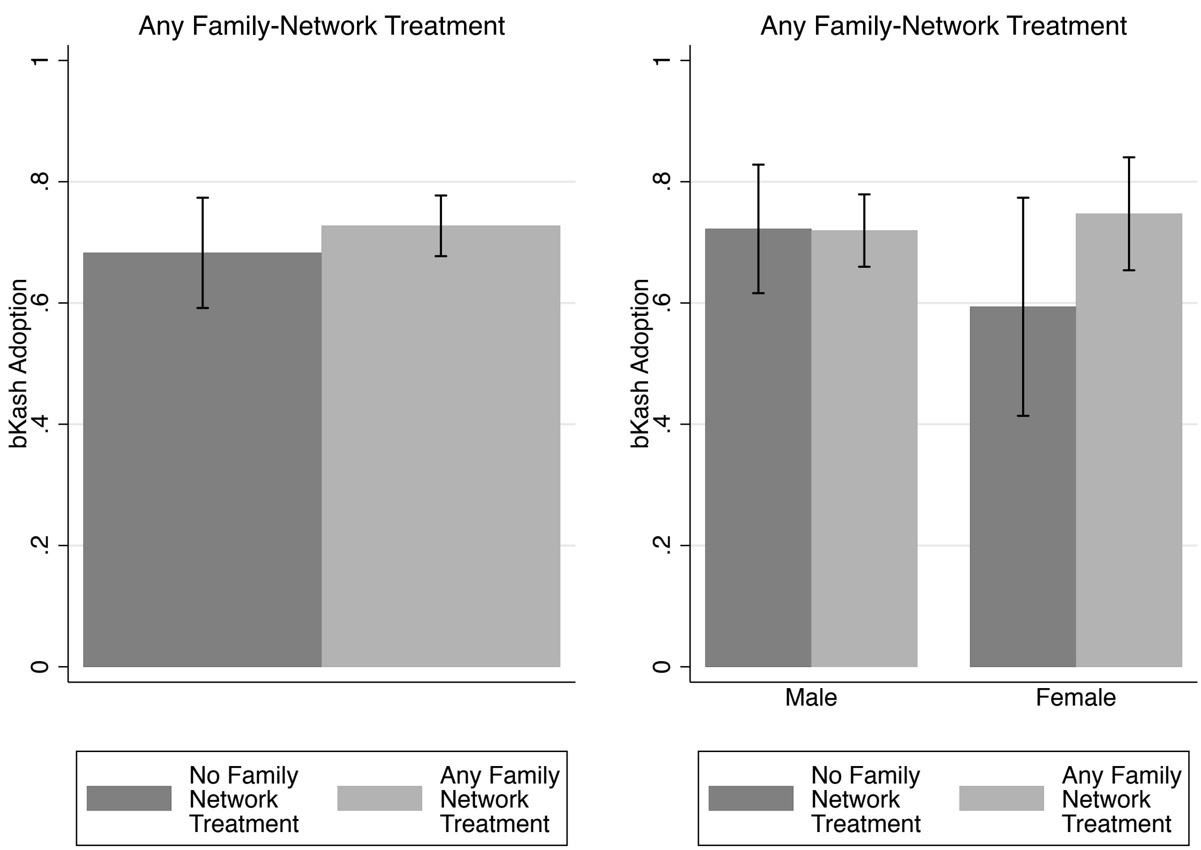
Notes: Minimum Detectable Effects (MDEs) reported in percentage points (not standard deviation units) due to the binary nature of the bKash adoption variable. The solid black line plots power when α, the rate of Type I error, is equal to 0.1 and the dashed gray line plots power when $\alpha = 0.05$. Power calculations are shown for Equation (4) with bKash adoption as the dependent variable. MDEs are with respect to the variable $AnyFamilyNetworkTreatment_i$. Power is computed using 1,000 simulations for each level of MDE at intervals of 0.01 between 0.1 and 0.2.

Figure 4: Power Calculations: Any Family-Network Treatment by Gender



Notes: Minimum Detectable Effects (MDEs) reported in percentage points (not standard deviation units) due to the binary nature of the bKash adoption variable. The solid black line plots power when α, the rate of Type I error, is equal to 0.1 and the dashed gray line plots power when $\alpha = 0.05$. Power calculations are shown for Equation (5) with bKash adoption as the dependent variable. MDEs are with respect to the variable $AnyFamilyNetworkTreatment_i * FemaleMigrant_i$. Power is computed using 1,000 simulations for each level of MDE at intervals of 0.01 between 0.25 and 0.35.

Figure 5: 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.

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