Poverty and Migration in the Digital Age: Experimental Evidence on Mobile Banking in Bangladesh*

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Abstract

Rapid urbanization is reshaping economies and intensifying spatial inequalities. In Bangladesh, we experimentally introduced mobile banking to very poor rural households and family members who had migrated to the city, testing whether mobile technology can reduce inequality by modernizing traditional ways to transfer money. One year later, for active mobile banking users, urban-to-rural remittances increased by 26% of the baseline mean. Rural consumption increased by 7.5% and extreme poverty fell. Rural households borrowed less, saved more, sent additional migrants, and consumed more in the lean season. Urban migrants experienced less poverty and saved more, but bore costs, reporting worse health.
JEL Codes: R23, O16, I32, O33

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1 Introduction

Early theories of modernization and economic growth defined progress as the movement of workers from subsistence sectors to modern, industrial sectors through rural-to-urban migration (e.g., Lewis 1954). By the 1970s, however, surveys showed that too many poor people in developing economies were being left behind, especially in rural areas (Chenery et al 1974). Concern with rural poverty turned attention back to programs to raise rural incomes through direct interventions like farm mechanization, improved agricultural marketing, and credit schemes (Bardhan 1984).

Today, rapid urbanization, coupled with new money transfer technologies, opens the possibility to reduce rural poverty by promoting the rural-to-urban movement of people coupled with the efficient urban-to-rural movement of money back to relatives remaining in home villages (Ellis and Roberts 2016, Suri and Jack 2016). Mobile money technologies make sending money quick and relatively cheap (Gates Foundation 2013), but their social and economic impacts have been hard to evaluate since, especially in early stages, adoption is highly self-selected.

To assess the migration/remittance mechanism and address self-selection, we provided a randomly-assigned treatment group in Bangladesh with training on mobile financial services and facilitated account set-up. Referred to as "mobile banking" or as "mobile money," these services have penetrated markets previously unreached by traditional banks due to the relatively high costs of expanding brick-and-mortar bank branches, particularly in rural areas (Aker and Mbiti, 2010; Aker, 2010; Jensen, 2007). Mobile money allows individuals to deposit, transfer, and withdraw funds to and from electronic accounts or "mobile wallets" based on the mobile phone network, cashing in or cashing out with the help of designated agents. Kenya's M-Pesa mobile money service, for example, started in 2007 and grew by promoting its use to simply "send money home." M-Pesa is used by at least one person in 96% of Kenyan households, and has helped lift 2% of Kenyan households from poverty (Suri and Jack 2016).

Our study builds on the evidence from Kenya (Jack and Suri 2014, Suri and Jack 2016) to connect migration, remittances via mobile banking, and poverty reduction in a sample characterized by extreme poverty and vulnerability to seasonal deprivation. We follow both senders (urban migrants) and receivers (rural families) in Bangladesh, allowing measurement of impacts on both sides of transactions. The rural site is in northwest Bangladesh, about 8 hours from the capital by bus (12-14 hours with stops and traffic). It is one of the poorest regions of Bangladesh and historically vulnerable to seasonal food insecurity during the *monga* season (Khandker 2012, Bryan et al 2014).

The intervention, which cost less than $12 per family, led to a large increase in use of mobile banking accounts. Bryan et al (2014) note that in 2005 data only 5% of households in vulnerable districts in northwest Bangladesh received domestic remittances, consistent with the limited development of migration-remittance mechanisms prior to the introduction of mobile money. By our endline, 70% of the rural treatment group had an actively-used mobile banking account relative to 22% of the control group.

Migrants actively using mobile banking accounts increased remittances sent by 26% of the baseline mean in value one year after the intervention, relative to the control group. For rural recipients of remittances, daily per capita consumption among active users increased by 7.5% and extreme poverty fell, although overall rural poverty rates were unchanged. Rural households borrowed less, were more likely to save, and fared better in the lean season. Investment increased as seen in a rising rate of self-employment and increased out-migration for work. The rate of child labor fell relative to the trend in the control group, and we find evidence that hours of study improved. Rural health indicators were unchanged. Migrants in the treated group had lower poverty and higher savings, but lower self-reported health status. Exploratory work shows an increase in labor supply for migrants in the garments sector, especially for women. Poverty rates among migrants declined 11 percent among active users (significant at the 10 percent level), while savings increased 38 percent (significant at the 5 percent level).

The rural results show how technology can facilitate income redistribution, overcoming constraints in money-transfer mechanisms, facilitating access to resources at key times, and broadening the gains from economic development. The results for migrants to Dhaka, however, show tradeoffs of these rural gains. Migrant workers reported declines in physical and emotional health, consistent with pressures to work longer hours and increase remittances enabled by the new technology.

2 Context and Related Literature

Global income inequality has been driven in part by growing economic gaps between cities and rural areas (Young 2013). In 1970, most of the world's population lived in rural areas, with just 37 percent in cities. By 2016, however, 55 percent lived in urban areas (United Nations 2016). Migration has taken people, especially the young, from the periphery into the center (Lopez-Acevedo and Robertson 2016). The population of Bangladesh's capital city, Dhaka, for example, grew by 3.6% per year between 2000 and 2016, growing in size from 10.3 million people to 18.3 million. By 2030, Dhaka is projected to be home to 27 million people (United Nations 2016), and demographers estimate that Bangladesh's rural population has now started declining in absolute numbers. A pressing economic question is how to connect rural populations to urban economic opportunities.

Bryan et al (2014) evaluate urban-rural links using a randomized experiment in a rural sample in northwest Bangladesh (near the population we study). Their focus is on inducements to migrate to the city temporarily during the lean agricultural season (and then return for the remainder of the year). The $8.50 incentive studied by Bryan et al (2014) was enough to buy a bus ticket to Dhaka, and the payment led 22% of their sample to out-migrate seasonally. Migrating increased consumption by about a third in households in origin villages. As in our study, the mechanism studied by Bryan et al (2014) involves taking advantage of urban job opportunities while maintaining strong ties to rural villages.

Our rural sample includes households that had been identified as "ultra-poor."[1] As extreme poverty falls globally, the households that remain poor are increasingly those facing the greatest social and economic challenges (Banerjee et al 2015). NGOs have responded with "ultra-poor" programs that provide a bundle of assets, training, and social support to facilitate income growth through rural self-employment – a goal similar to microfinance (Armendáriz and Morduch 2010). Results have been encouraging in Bangladesh (Bandiera et al 2017) and other countries (Banerjee et al 2015).[2] Our intervention involves a complementary approach closer to efforts to "just give money to the poor" through cash transfers from donors or governments (Hanlon et al 2010, Haushofer and Shapiro 2016). Here, the mechanism works by increasing the efficiency of making domestic transfers within families rather than by distributing external funds.

The mobile banking mechanism builds from the growth of mobile money services. By the end of 2016, 33 million registered clients used mobile financial services in Bangladesh, an increase of 31 percent from 2015 (Bilkis and Khan 2016); this growth is attributed to the spread of mobile financial services in "far-flung" areas like the rural northwest where we worked (Bhuiyan 2017). An advertisement for the bKash service highlights the appeal of easing urban-to-rural remittances, featuring a young female worker in an urban garment factory with the words, "Factory, overtime, household chores...and the added hassle of sending money home? Now I send money through bKash. It's safe and convenient, and money reaches home instantly!"

The Global Findex Survey shows that 7% of adults (age 15 and above) reported making or receiving a digital payment in 2014 in Bangladesh. With the spread of mobile banking services like bKash, the share rose to 34% in 2017 (Demirguç-Kunt et al 2018). Usage is widest among better-off Bangladeshis: 39% of the top three income quintiles reported digital payments in 2017 versus 26% of the bottom 2 income quintiles. Just 14% of adults with primary schooling (or less)—a group overlapping most of our rural sample—had mobile money accounts. Still, Bangladesh is a global leader overall: just 5% of adults in developing economies had mobile banking accounts in 2017 (Demirguç-Kunt et al 2018).

The relatively low diffusion rates (globally) contrast with the potential value of the technology for the poorest households. Urban-to-rural remittances from family members share advantages of information-

1. Bryan et al (2014) also focus on districts in northwest Bangladesh, and, like us, they focus on households with limited land-holding and vulnerability to seasonal hunger.

2. Bauchet et al 2015 report on an "ultra-poor" program akin to those studied by Bandiera et al (2017) and Banerjee et al (2015). In South India, participants faced high opportunity costs such that many in the program eventually abandoned it in order to participate in the (increasingly tight) local wage labor market, showing that self-employment was not preferred when viable jobs were available.

intensive informal transfer networks together with the ability to mobilize relatively large sums from outside local economies. But Table 1 shows that traditional mechanisms for urban-rural remittances can be costly. (The table reports on the cost of sending 4000 taka, or about $48, gathered from interviews with eight focus groups in July 2018; mechanisms are listed from most costly to least costly.) A common mechanism, traveling between Dhaka and the northwest to deliver money, for example, takes at least a day and can require absence from work. Other mechanisms are not always available when needed (e.g., asking a friend to carry money) or are insecure. In contrast, the final row shows that the cost is 79 taka ($0.94) to send a 4000 taka transfer ($48) via mobile banking and transmission is instantaneous.

The spread of mobile banking has potential economic impacts for families receiving remittances through four main channels: (1) direct impacts on consumption; (2) increases in liquidity in the face of adverse shocks; (3) impacts on investment, in part by overcoming financing constraints; and (4) general equilibrium effects and spillovers to non-users.

Direct consumption impacts. The most direct way that remittances help receiving households is by providing money to spend on basic needs. Suri and Jack (2016) use plausibly exogenous variation in expansions in access to mobile money in Kenya between 2008 and 2014 to estimate the long-term impacts of mobile money on households, finding that access to mobile money increased consumption and lifted 194,000 (or 2% of) Kenyan households out of poverty. The impacts were more pronounced for female-headed households (the impact on consumption for female-headed households was more than twice the average impact). Batista and Vicente (2017), in a field experiment in rural Mozambique, show that access to a mobile money savings account increased savings and increased use of agricultural inputs and also expenditures, particularly on goods that are purchased relatively infrequently. They suggest that this reflects decreased pressure in the treatment arm to share resources with friends and family. Munyegera and Matsumoto (2016) investigate mobile money in rural Uganda with a difference-in-difference estimator, propensity score matching, and IV using the log of the distance to the nearest mobile money agents as an instrument for mobile money adoption. Under the identifying assumption that distance is exogenous, the adoption of mobile money services led to a 13% increase in household per capita consumption and an increase in food consumption. Spending on non-food basic expenditures, education and health services, and social contributions increased. Similar to our findings below, they find that in households with at least one mobile money subscriber, the total annual value of remittances is 33% higher than in non-user households.

Shocks and liquidity. Mobile money may help receiving households by providing resources that can be saved for later or that can facilitate borrowing (or substitute for credit). Remittances can have particularly large impacts when local, rural financial markets are imperfect and incomplete (Rapoport and Docquier 2006). Mbiti and Weil (2016), for example, find that M-Pesa users send more transfers

Table 1: Cost Comparison of Alternative Methods of Sending Money

Method	Direct and indirect financial cost (Taka)	Time for transfer	Other Costs and Considerations
Family members	990	2 days	Requires family member capable of traveling to Dhaka, potential theft in transit.
Self-travel	780	1 day	Loss of income while traveling, potential loss of employment.
Post Office	340	3-7 days	Low penetration of post offices in rural areas, fixed office hours excluding weekends.
Bank Account	233	1 day	Low penetration of banks in rural areas, extensive documentation required to open bank accounts, fixed office hours exclude weekends.
Bus Driver	200	1 day	Few bus stops outside district cities, potential theft, requires familiarity with bus driver.
Friends/Colleagues	200	1 day	Popular but may need to wait to find friend/colleague traveling to required destination, potential theft in transit.
Agent-assisted mobile banking	80	Instant	Neither sender nor receiver needs a phone or mobile banking account. Requires receiver to also be in physical presence of an agent at time of transfer. Direct agent-to-agent transfer not legal.
Mobile banking (personal account)	79	Instant	Need account and PIN. Can take advantage of other features like mobile wallet to hold savings. Transfers do not require coordination.

Notes: Financial cost includes the total cost to both the sender and receiver, including transport costs and the opportunity cost of time, required to send 4,000 Taka from Dhaka to northwest Bangladesh. Rural time valued at 70 taka per day. Urban time valued at 190 taka per day. Evidence from eight focus groups held in Gaibandha, Rangpur in July 2018.

and switch from informal savings mechanisms to storing funds in their M-Pesa accounts (with a drop in the propensity to use informal savings mechanisms such as ROSCAS by 15 percentage points). Blumenstock et al (2015) run an RCT, focusing on the impact of paying salaries via mobile money rather than cash in Afghanistan. Employers found immediate and significant cost savings. Workers, however, saw no impacts as measured by individual wealth; small sums were accumulated but total savings did not increase as users substituted savings in mobile money accounts for alternative savings mechanisms.

In the absence of adequate saving by rural households, the ability to instantly send and receive money also means that remittances can function as an insurance substitute, helping to protect consumption in the face of negative shocks. Jack and Suri (2014) show that, in the face of a negative shock, households that used Kenya's M-pesa mobile money service were more likely to receive remittances and to do so from a wider network of sources. As a result, the households were able to maintain consumption levels in the face of shocks, while non-users of mobile money experienced consumptions dips averaging 7%. The effects were strongest for the bottom three quintiles of the income distribution.

Batista and Vicente (2019) use an RCT to show increases in remittances received by rural households in Mozambique particularly in the presence of adverse shocks. With that, rural households in the treatment group were less vulnerable to adverse shocks, particularly for episodes of hunger. No impact was found on savings, assets, or overall consumption, although there were improvements in measures of access to food, clean water, medicines and school supplies, and there was evidence of reduced investment in agriculture and business and greater outmigration.

Investment and liquidity. Remittances can provide investible funds for capital-constrained households. Angelucci (2015), for example, shows that remittances from Mexican migrants help fund migration by other family members previously constrained by lack of capital. Suri and Jack (2016), in their long-run study in Kenya, find that poverty reduction was driven by changes in financial behavior and labor market outcomes; individuals in areas which gained mobile money access more likely to choose non-farm employment. The impacts were strongest for women: Suri and Jack estimate that the spread of mobile money helped induce 185,000 women to switch into business or retail as their main occupation. In contrast, they see little effect on migration.

Wider impacts. By facilitating cash flows from outside of a local economy, mobile money can generate general equilibrium effects that affect users and non-users. Riley (2018) uses a difference-in-difference approach in Tanzania to investigate consumption smoothing in communities served by mobile banking. She considers the impacts of large aggregate shocks like droughts and floods, focusing on both users and non-users of mobile banking. While it is plausible that non-users would benefit from the increased liquidity introduced into communities during times of covariate difficulty, she does not find evidence to support wide impacts. Instead, Riley (2018) finds that the main beneficiaries are the users themselves, who weather the aggregate shocks without declines in average consumption. Akram et al (2017) find general equilibrium effects connected with migration, showing that increased seasonal out-migration increases wages and the availability of jobs in migrant-sending villages while pushing up food prices. On net, rural households are helped directly by the earnings of migrants and indirectly through tightening village labor markets.

3 Sample and Randomization

The study starts with 815 rural household-urban migrant pairs randomized at the pair level in a dual-site design.[3] The study took place between 2014 and 2016, a window during which mobile money had spread widely enough that the networked service was useful for adopters—but not so widely that all markets had been fully served.

The two connected sites are: (1) Gaibandha district in Rangpur Division in northwest Bangladesh and (2) Dhaka District in Dhaka Division, the administrative unit in which the capital is located. We follow migrants in Dhaka and their families in rural Gaibandha. Gaibandha is in one of the poorest regions of Bangladesh, with a headcount poverty rate of 48 percent and, historically, exposure to the *monga*, a seasonal period of hunger in September through November (Bryan et al 2014, Khandker 2012). Even measured outside of the *monga* season, Gaibandha has lower rates of food consumption per capita than other regions in the country.

We conducted the experiment in cooperation with bKash, a subsidiary of BRAC Bank and the largest provider of mobile banking services in Bangladesh.[4] Most of the households had no previous experience with mobile banking.

3.1 Sampling Procedures

Participants were recruited between September 2014 and February 2015. To recruit participants, we took advantage of a pre-existing sampling frame from SHIREE, a garment worker training program run by the nongovernmental organization Gana Unnayan Kendra (GUK) with funding from the United Kingdom Department for International Development. GUK's criteria for targeting "ultra-poor" households included: (1) no ownership of cultivable land, (2) having to skip a meal during the lean season, (3) no financial/microfinance access, (4) residence in an environmentally fragile area, (5) household consumption under 2000 Tk per month (roughly \$25 per month at the nominal exchange rate), and (6) productive asset ownership valued no more than 8000 Tk (roughly \$100).[5] We restricted the sample to households in Gaibandha with workers in Dhaka. This yielded 341 household and migrant pairs.

3. A potential concern might be contamination or spillovers within villages which may lead to a SUTVA violation. In results detailed in Appendix B, we use variation in treatment density within villages to test for spillovers and find no evidence for this phenomenon, although we may be underpowered to test for this.

4. In July 2011, bKash began as a partnership between BRAC Bank and Money in Motion, with the International Finance Corporation (IFC) and the Bill and Melinda Gates Foundations later joining as investors. The service dominated mobile banking during our study period, but competition is growing with competitors including Dutch Bangla Bank.

5. The GUK project was named "Reducing Extreme Poor by Skill Development on Garment." For more, see http://www.gukbd.net/projects/. SHIREE is an acronym for Stimulating Household Improvements Resulting in Economic Empowerment, a program focused on ending extreme poverty. The program ended in late 2016. See www.shiree.org.

Beginning from this roster, we then snowball-sampled additional Gaibandha households with migrant members in Dhaka to reach a final sample size of 815 migrant-household pairs. The snowball sample was recruited by asking households in the rural SHIREE sample to suggest households that were similar to them in two dimensions: (1) having a household member that had migrated to Dhaka for work, and (2) that were also poor. These households were then contacted and asked to participate in the study. In Appendix C, we compare the subsamples. The two rural samples have identical rates levels of poverty (both 75%) and comparable baseline levels of consumption (63.1 taka daily per capita expenditure for SHIREE households and 61.6 for the snowball sample). The two urban subsamples also have comparable daily per capita expenditure (118.4 taka for SHIREE and 122.1 for the snowball sample), but migrants in the snowball sample differ on other dimensions. In particular, they were more likely to be in formal employment and male, and they earned more and sent more remittances at baseline. In Appendix sections C.3 and C.4 we estimate treatment effects separately for each subsample and find that the results are largely similar (with a few important differences discussed in Section 5), and the patterns from the combined sample are not consistently driven by one or the other of the samples.[6]

All rural households are from Gaibandha district, and roughly half are from Gaibandha *upazila* (subdistrict). The remaining families are from one of the six other *upazilas* within the district. The particular nature of our sample potentially limits the external validity of our results, although we note that our sample is similar in many respects to samples used in work by Bandiera et al (2017) and Bryan et al (2014).[7]

3.2 Randomization

We randomized which migrant-household pairs received treatment and which were in the control group following the min-max t-stat re-randomization procedure described in Bruhn and McKenzie (2009). The baseline survey was run from December 2014 to March 2015 and the endline survey followed one year later (February 2016 to June 2016). The intervention was started shortly after the baseline was completed, taking place in April and May 2015. In addition to the baseline and endline surveys, we obtained account-specific administrative data from bKash directly for the user accounts in the sample. These data allow us to determine whether user accounts were active at endline.

Attrition was very low. For the rural sample, we lost 2 of 815 households, an attrition rate of 0.2%. For the urban sample, we lost 6 of 815 migrants, an attrition rate of 0.7%. The final samples

6. While in the appendix we estimated treatment effects within the SHIREE and snowball subsamples to explore heterogeneity and robustness, the experimental design was not powered for these analyses.

7. For example, poverty rates in our sample are similar to those in the Bandiera et al (2017) study of an intensive "graduation" intervention with ultra-poor households in Bangladesh. See also footnote 8. Bryan et al (2014) also use a similar sample of ultra-poor households in Rangpur.

for analysis thus include 813 rural households and 809 migrants.

Baseline summary statistics for the sample by treatment status are shown in Table 2, showing balance on observables for assignment to treatment or control in the main experiment. Table 2 shows that treatment status is balanced on key observables, including ownership of a mobile phone, having a bank account, whether the migrant has a formal job, the urban migrant's income, the urban migrant's gender, and migrant age. The p-value of the F-test for joint orthogonality (0.954) shows balance. (Appendix Section C.1 also shows balance within the SHIREE and snowball subsamples separately.)

Nearly everyone (99% of individuals in the sample) had access to a mobile phone at baseline. Financial inclusion was low, however, as reflected by the 11% rate of bank accounts at baseline. About 90% of urban migrants are employed in the formal sector, about 70% are male, and the average age is 24. At baseline the treatment group earned on average 7830 taka (105 dollars) per month and sent a substantial portion of these earnings home as remittances. The variable "Remittances in past 7 months, urban" refers to remittances sent over a 7-month period (the current month and the past 6 months), so the average monthly remittances sent at baseline by migrants in the treatment group was $17356/7 = 2479$ Taka, which is nearly one third of monthly migrant income ($2479/7830 = 31.7\%$).

For rural households, the largest share of baseline household income (65%) came from wage labor; remittances from migrants formed the second largest contribution to household income (21%). Self-employment and agriculture contributed 7% and 5% of rural household income, respectively. Income from livestock and asset rental together accounted for only 2% of household income. The low level of income from agriculture is consistent with the fact that most of the rural ultra-poor households are functionally landless, possessing about 10 decimals of land (0.1 acre), essentially the size of their homestead, with no land to farm. Instead, they earn income by selling their labor. Among rural households, the average household size is 3.8 members while most households have fewer than two children resident, likely reflecting the fact that young migrants are now out of the household and are not yet married.

Three-quarters of rural households are poor as measured by the local poverty line in 2014 (the year of our baseline). The global $1.90 poverty line (measured at 2011 PPP exchange rates and converted to 2014 taka with the Bangladesh CPI) is 21% lower than the national line, and 51% are poor according to the global line. These poverty figures are comparable to the sample analyzed by Bandiera et al (2017) in which 53% of the Bangladesh "ultra-poor" sample was below the global poverty line at baseline.[8]

8. The Bandiera et al (2017) data are from a 2007 baseline and use the $1.25 global poverty line at 2007 international (PPP) prices (their Table 1). The $1.25 and $1.90 thresholds were chosen to deliver similar rates of poverty (globally) when using the associated PPP exchange rates. In our sample, the 2016 average exchange rate obtained from Bangladesh Bank is 1 USD = 78.4 Taka. The 2011 PPP conversion factor for Bangladesh from the World Bank is 23.145. The inflation factor for converting 2011 prices to 2016 prices is 1.335. The international poverty line at 2016 prices is thus $1.9 * 23.145 * 1.335 = 58.72$ Taka per person per day. (At baseline in 2014, we estimate the global threshold at 54.8 taka per person per day, and the median rural household member spent 54.5 taka per day.) As comparison,

Fewer than half of migrants (47% in the treatment group) completed primary schooling. Most migrants in the sample had moved to Dhaka in recent years, with the average migrant living fewer than three years in Dhaka prior to the study and working fewer than 2 years of tenure at their current job.

4 Experimental Intervention and Empirical Methods

The bKash mobile banking service has experienced rapid growth in accounts since its founding, and our study took place during a window before the service had fully penetrated the Gaibandha market. Since bKash was already available as a commercial product, we were not in a position to experimentally introduce it from scratch. Instead, we used an encouragement design in which adoption was facilitated for part of the sample.

The intervention that took place in April and May 2015 consisted of a 30 to 45 minute training about how to sign up for and use the bKash service. This training was supplemented with basic technical assistance with enrollment in the bKash service. If requested, our field staff assisted with gathering the necessary documentation for signing up for bKash and completing the application form. To minimize the risk of experimenter demand, we recruited fully local field staff and surveyors to implement the experiment, including research assistants.

The intervention aimed to reduce the main barriers to adoption of mobile banking. Most important, mobile banking services in Bangladesh use Unstructured Supplementary Service Data (USSD) menus which allow mobile banking services to be used on any mobile device. The menus, however, are in English, creating a large hurdle for poorer villagers in Gaibandha with only basic levels of numeracy and literacy even in Bangla (Bengali). The intervention responded by teaching the basic steps and protocols of bKash use, together with providing participants with practical, hands-on experience sending transfers at least five times to establish a degree of comfort (see Appendix F for the training materials used).

Within the treatment group, we also cross-randomized: (1) whether migrants were approached before or after their sending households (whether they were first or second movers) and (2) whether migrant-household pairs received a pro-social marketing message that emphasized the benefits of the technology for their family as well as for themselves as individuals. While recruitment was coordinated so that pairs were visited within a short time of each other, they were not primed in any way to transact with each other. We also cross-randomized whether households received a midline survey that measured willingness-to-pay that was priming respondents to think of bKash, or priming respondents to think of cash.

the 2016 Bangladesh urban poverty line is 92.86 Taka, and the 2016 Bangladesh rural poverty line is 74.22 Taka.

Table 2: Summary Statistics by Treatment Assignment (Baseline)

	Treatment Mean	Treatment SD	Treatment N	Control Mean	Control SD	Control N	Treatment-Control p-value
Any mobile, rural	0.99	0.10	413	0.98	0.13	402	0.340
Any bank account, urban	0.11	0.31	413	0.11	0.32	402	0.892
Formal employee, urban	0.91	0.28	413	0.88	0.32	402	0.161
Average monthly income, urban (‘000 Taka)	7.83	2.58	413	7.77	2.44	402	0.702
Female migrant	0.29	0.45	413	0.31	0.46	402	0.631
Age of migrant	24.1	5.3	413	24.0	5.1	402	0.987
Migrant completed primary school	0.47	0.50	413	0.45	0.50	402	0.402
Tenure at current job, urban	1.69	1.58	413	1.66	1.47	402	0.785
Tenure in Dhaka, urban	2.43	1.85	413	2.50	1.74	402	0.571
Remittances sent, past 7 months (‘000 Taka)	17.4	11.9	413	18.3	12.5	402	0.296
Daily per capita expenditure, urban	120.3	45.1	413	120.7	40.7	402	0.900
Household size, rural	3.8	1.6	413	3.8	1.6	402	0.547
Number of children, rural	1.2	1.0	413	1.2	1.1	402	0.380
Household head age, rural	47.3	13.0	413	46.2	13.4	402	0.243
Household head female, rural	0.12	0.33	413	0.13	0.34	402	0.721
Household head education, rural	0.19	0.39	413	0.16	0.37	402	0.229
Decimal of owned agricultural land, rural	9.4	28.6	413	10.8	30.8	402	0.498
Number of rooms of dwelling, rural	1.82	0.73	413	1.8	0.762	402	0.999
Dwelling owned, rural	0.94	0.23	413	0.94	0.24	402	0.807
Daily per capita expenditure, rural (Taka)	63.6	35.2	413	60.9	31.9	402	0.264
Poverty rate (national threshold), rural	0.73	0.44	413	0.77	0.42	402	0.188
Poverty rate (global $1.90 threshold), rural	0.49	0.50	413	0.53	0.50	402	0.341
Gaibandha subdistrict	0.50	0.50	413	0.53	0.50	402	0.456
Other subdistrict	0.50	0.50	413	0.47	0.50	402	0.456
p-value of F-test for joint orthogonality = 0.954.							

Notes: Summary statistics are means for the 815 households in the treatment and control groups. Initially two other households had been included in the baseline sample, but they were dropped because all household members had migrated from Gaibandha and were working in Dhaka. P-values are given for tests of differences in means by treatment status.

This paper focuses on the first randomization, that of assignment of a household-migrant pair to the bKash training intervention and control.[9]

The training materials were based on marketing materials provided by bKash, simplified to increase accessibility. Since the phone menus are in English, we also provided menus translated into Bangla (Bengali). The encouragement only included training on how to use mobile money. We took care to keep the treatment simple and narrow. The treatment did not include a text message between the rural and urban households. The recruiting teams did not explicitly coordinate but all visits were completed within 2 months. The households were not primed to transact with the other member of the pair.

Table 3 gives the breakdown of administrative, salary, and transportations costs per family (i.e., treating a family member in Gaibandha plus treating a migrant in Dhaka). Total costs were 885.84 taka., or US$11.36 at the prevailing exchange rate ($1 = 78 taka in mid-2015) per family-migrant pair. The costs include a small payment (200 taka, or approximately $2.50) given to each participant in the training to cover their time and to encourage participation (not made contingent on adoption of the bKash service). Other costs totalled 485.84 taka. These costs only cover the cost of introducing mobile banking to migrants and their families, not the cost of migration itself.

Table 3: Cost of intervention per family

	Cost
Costs in Taka:	
Participation payment x 2	400
Material cost (printed pictorial color poster on "how to use bKash") x 2	100
Trainer's salary + transportation (Gaibandha)	97.48
Trainer's salary + transportation (Dhaka)	178.34
Supervisor and RA time for administration	110.02
Total (Bangladesh Taka)	885.84 Tk
Total (US Dollars)	$11.36

Notes: Taka are converted to dollars at the June 30, 2015 exchange rate. One US Dollar equals about 78 Taka.

The household survey data collected in 2014/15 and 2016 were combined with administrative data from bKash to estimate impacts.[10] For most outcomes, we estimate intention-to-treat (ITT)

9. In ongoing work, we find that visiting households before migrants increased the takeup of mobile money by almost 20 percentage points for female migrants. The pro-social marketing messages increased takeup by approximately 10 percentage points for all migrants, male and female.

10. We did not follow a pre-analysis plan, but we show most main outcomes from the household survey. Results from all sections are described here, excluding the analysis of assets and social status (where standards were consistently large relative to estimates). The analysis of agriculture showed positive impacts, but the sample sizes were too small to draw reliable inferences.

effects using an Analysis of Covariance (ANCOVA) specification:

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

where $\mathbf{X}_i$ is a vector of baseline controls: gender, age, and primary school completion of household head or migrant, and 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 also estimate local average treatment effects (LATE) using instrumental variables (IV). We first define the variable *Active bKash account*, an indicator that takes the value 1 if the household 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 then instrument for *Active bKash account* using treatment assignment. The LATE parameters are treatment effects for households induced by the intervention to become active users. The exclusion restriction requires that any impact from the treatment acts through active use of bKash accounts.[11]

The surveys include questions on a range of outcome indicators, and we address problems of multiple inference by creating broad"families" of outcomes such as health, education, and consumption. 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 then test the overall effect of the treatment on the index (see Kling, Liebman, and Katz 2007).

For remittances and migrants' hours of work, we collected monthly data (for the current month and the previous six for remittances, as well as the current month month and the previous eleven for hours of work). To exploit the temporal variation in these variables within households, we estimate equation (2) on the stacked baseline and endline household-month level data:

$$Y_{i,t}=\beta_1 Endline_t+\beta_2 Treatment_i*Endline_t+\sum_{t=1}^{12}\beta_{3,t}Month_t+\beta_{4,i}+\epsilon_{i,t} \tag{2}$$

Here , $\beta_{3,t}$ captures month fixed effects and $\beta_{4,i}$ refers to household fixed effects. $Endline_t$ is an indicator for an endline observation. The coefficient of interest is β_2, the coefficient on the interaction between $Treatment_i$ and $Endline_t$. The coefficient captures the difference in the dependent variable

11. In Appendix D, we show robustness when varying the definition of active account use. Narrowing to active use in the past month in Appendix D inflates our LATE results because the implied first stage coefficient is much smaller, leading to a larger estimated treatment effect.

at endline between migrants in the treatment group and migrants in the control group, after controlling for differences between baseline and endline, household fixed effects, and month fixed effects. Standard errors for all regressions run using Equation (2) are clustered at the household level, while other specifications are not clustered because using the ANCOVA specification there is a single observation per household or migrant. Note that for all specifications in the rural analysis, the unit of observation is the household. For child education outcomes, variables are collapsed to the household level. For all of the migrant specifications, the unit of observation is the individual.

5 Results

5.1 Mobile Banking and Remittances Sent

The initial obstacles to signing up for mobile banking services were high for the poor in Gaibandha. As noted above, the bKash menus on the telephones are in English, although few members of the rural sample know written English. The training intervention thus provided Bangla-language translations, simple hands-on experiences with the mobile money service, and guidance on how to sign up for bKash.

Table 4: First Stage

	(1) Rural: Active bKash Account	(2) Rural: Active bKash Account	(3) Urban: Active bKash Account	(4) Urban: Active bKash Account
bKash Treatment	0.48	0.48	0.48	0.47
	(0.03)	(0.03)	(0.03)	(0.03)
R^2	0.23	0.24	0.23	0.25
Baseline Controls	No	Yes	No	Yes
Endline Control Group Mean	0.22	0.22	0.21	0.21
Observations	813	813	809	809

Standard errors in parentheses. “Active account use” 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 impact of the training intervention was substantial. Table 4 presents results on take-up from the first stage of the instrumental variable regressions. Columns (1) and (2) show that households in the rural treatment group were 48 percentage points more likely to have an actively-used bKash account than those in the control group, on a control mean base of 22%. Column (1) presents results without baseline controls, while the column (2) specification includes gender, age, and primary school completion of head of the household, and household size. Adding the baseline controls changes the point estimate in the third decimal place only, and both results are statistically significant at the 1% level. The result shows that the short intervention, together with facilitation of sign-up, not only led to a substantial increase in accounts but also to their active use. By the endline, 70% of the rural treatment group were active bKash users.

The results show a wide gap between access to financial services and their active use. The third and fourth columns of Table 4 give results for the urban migrants. Again, the treatment has a large impact on account use. Migrants in the urban treatment group were 47 percentage points more likely to have an active bKash account than those in the control group, on a control mean base of 21%. It is not surprising that the rural and urban numbers are very similar since sending and receiving urban-to-rural remittances is the primary use of mobile money in this context.

Table 5: Remittances Sent

	(1) Total, Taka (OLS)	(2) Total, Taka (IV)	(3) bKash, Taka (OLS)	(4) bKash, Taka (IV)	(5) Total, Share (OLS)	(6) Total, Share (IV)
Treatment * Endline	316.1		385.9		0.030	
	(163.0)		(130.1)		(0.016)	
Active Account * Endline		660.6		806.6		0.062
		(342.1)		(274.9)		(0.034)
Endline	-327.8	-466.2	-119.0	-287.9	-0.030	-0.043
	(121.7)	(181.1)	(96.76)	(144.7)	(0.012)	(0.017)
R^2	0.29	0.29	0.44	0.43	0.24	0.24
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Household Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Baseline Mean	2582	2582	1364	1364	0.28	0.28
Observations	10,526	10,526	10,526	10,526	10,526	10,526

Notes: Standard errors in parentheses, clustered by household. The dependent variable in columns (1) and (2) is total remittances (sent through any means) sent in the prior 7 months as self-reported by urban migrants. The dependent variable in columns (3) and (4) is remittances sent through bKash. The dependent variable in columns (5) and (6) is total remittances as a share of migrant income.

Table 5 gives regression results for remittances sent by migrants to the rural households, based on data on monthly remittances sent in the past seven months in baseline and endline surveys. All regressions control for household-level and month fixed effects. Column (1) shows the intention-to-treat impact of the treatment on remittances sent (from all sources); migrants in the treatment group sent 12% more remittances at endline (316.1 on a baseline mean of 2582) (statistically significant at a p-value of 0.053). Column (2) presents local average treatment effect results that account for active use of the bKash accounts. The 660.6 coefficient in the second row of column (2) indicates a 26% increase in the value of remittances sent by migrants induced by the experimental intervention to actively use bKash (661/2582). There is considerable heterogeneity in the samples, though, and the estimate is fairly noisy.[12]

The third and fourth columns of Table 5 present results for bKash remittances sent (in contrast to the results on remittances from all sources). Column (3) shows that migrants in the treatment group sent, on average, 385.9 Taka more in bKash remittances at endline in comparison to migrants in the control group, controlling for differences between baseline and endline, month fixed effects, and household fixed effects. The coefficient is slightly larger than that obtained for total remittances in column (1), and shows limited substitution from other means of remittances to bKash remittances. As such, the increase in total remittances from migrants in the treatment group is largely driven by an increase in new remittances rather than from substitution from other existing means of remittances to bKash. Columns (5) and (6) show that migrants also sent a substantially higher share of their income as remittances relative to the control group. The LATE results in column (6) show that the share of income sent as remittances increased by 26% relative to the control group mean (0.062/0.24).

While the value and composition of remittances changed, their frequency did not. In addition to remitting via mobile money (either through an own account or an agent's account), migrants also sent money through remittance services and through relatives and friends. Physically returning home to bring money back was also common, forming a large share of the "other" category in Figure 1. The top panel of Figure 1 shows a 27% (10540/8270) increase in the value of remittances sent using mobile money, which is similar to the 26% increase in the total value of remittances seen in Table 5.[13] The bottom panel of Figure 1 gives the frequency of remittances. Overall, there is no

12. One source of variation arises because some in the sample lack jobs and thus are not remitting money. To gauge the impact, we ran an exploratory regression adding a dummy variable for whether the migrant earned money in a given month, recognizing that employment is at least in part endogenous to the intervention. The coefficient on the dummy is -777, nearly eliminating the remittance impact for migrants without income (as expected), and the LATE parameter rose slightly to 834. In a study in the Philippines, Pickens (2009) found that one third of a sample of 1,042 users of mobile money services did not use remittances at all, using mobile money to purchase airtime. He found that about half of active users (52%) used the service twice a month or less while a "super-user" group (1 in every 11 mobile money users) made more than 12 transactions per month. In analyses of sub-samples in the appendix, we show that results for remittances are clearest for the SHIREE sub-sample and smaller and not significant for the snowball sub-sample. These regressions, though, are exploratory and the experimental design was not powered for these analyses.

13. It is notable that mobile money remittances form 52% of total remittances for the control group. There are two reasons. First, 21% of migrants in the control group have an active bKash account, for which they signed up of their own accord (i.e., without the experimental training intervention). Second, some respondents use a bKash agent to perform an agent-assisted (also known as over-the-counter or OTC) transaction. OTC transactions are not permitted by regulation and, for users, do not provide the speed, convenience, and privacy of user-to-user transactions. An active bKash account is not required for such a transaction. A comparison of the endline data and bKash administrative

significant difference in the total number of remittances sent between the treatment and control groups: on average, migrants sent one remittance every six weeks. The composition shifts, however, as migrants in the treatment group increased the number of remittances sent using mobile money by 22% (significant at the 10% level), while reducing the number of remittances sent using non-mobile money means by 19% (significant at the 5% level). This is primarily due to a reduction in the number of remittances sent using remittance services by 29% (significant at the 1% level).

5.2 Impacts on Rural Households

5.2.1 Direct Consumption Effect: Consumption, Poverty, Education, and Health

We show impacts on consumption directly first, then turn to impacts on poverty, education, and health. The roughly 26% increase in remittances sent by urban migrants in the treatment group (relative to the control group) transferred substantial resources back to families in Gaibandha. Figure 2 presents kernel density plots of per capita daily expenditure separately for the treatment and control groups. In line with the remittance flows, the distribution of per capita expenditure shifts to the right for the treatment group. A Kolmogorov-Smirnov test for equality of the distribution functions confirms the difference in distributions (p-value = 0.017).

The vertical line in Figure 2 marks the poverty line of 74.2 Taka in rural Bangladesh, adjusted to 2016 prices using the rural Consumer Price Index from the Bangladesh Bureau of Statistics. Most of the rural households fall substantially below the poverty line, consistent with the ultra-poor sample.

Given the extreme poverty of much of the sample, the increase in consumption was insufficient to bring many families over the rural poverty line, and column (1) of Table 6 shows the impacts on the poverty headcount are effectively zero and not statistically significant. To investigate impacts on extreme poverty, we tranform expenditure following the distributionally-sensitive Foster-Greer-Thorbecke (FGT) index. This squared poverty gap measure places greatest weight on the deprivations of the poorest households and is constructed for each rural household as follows:

$$P_i = \begin{cases} \left(\frac{z-y_i}{z}\right)^2 & \text{if } y_i < z \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

data confirms this for the control group. While we have access to administrative data, this does not give the complete picture of mobile money remittances due to over-the-counter bKash remittances (which are sent via the bKash platform but not through the senders own account). At endline, 73% of migrants in the treatment group reported over-the-counter transactions using an agents bKash account to send their last bKash remittance. The mean monthly remittance sent by migrants in the treatment group, conditional on sending remittances, is 3,529 Taka in the admin data, versus 4,595 Taka in the endline survey data. This difference likely reflects over-the-counter remittances.

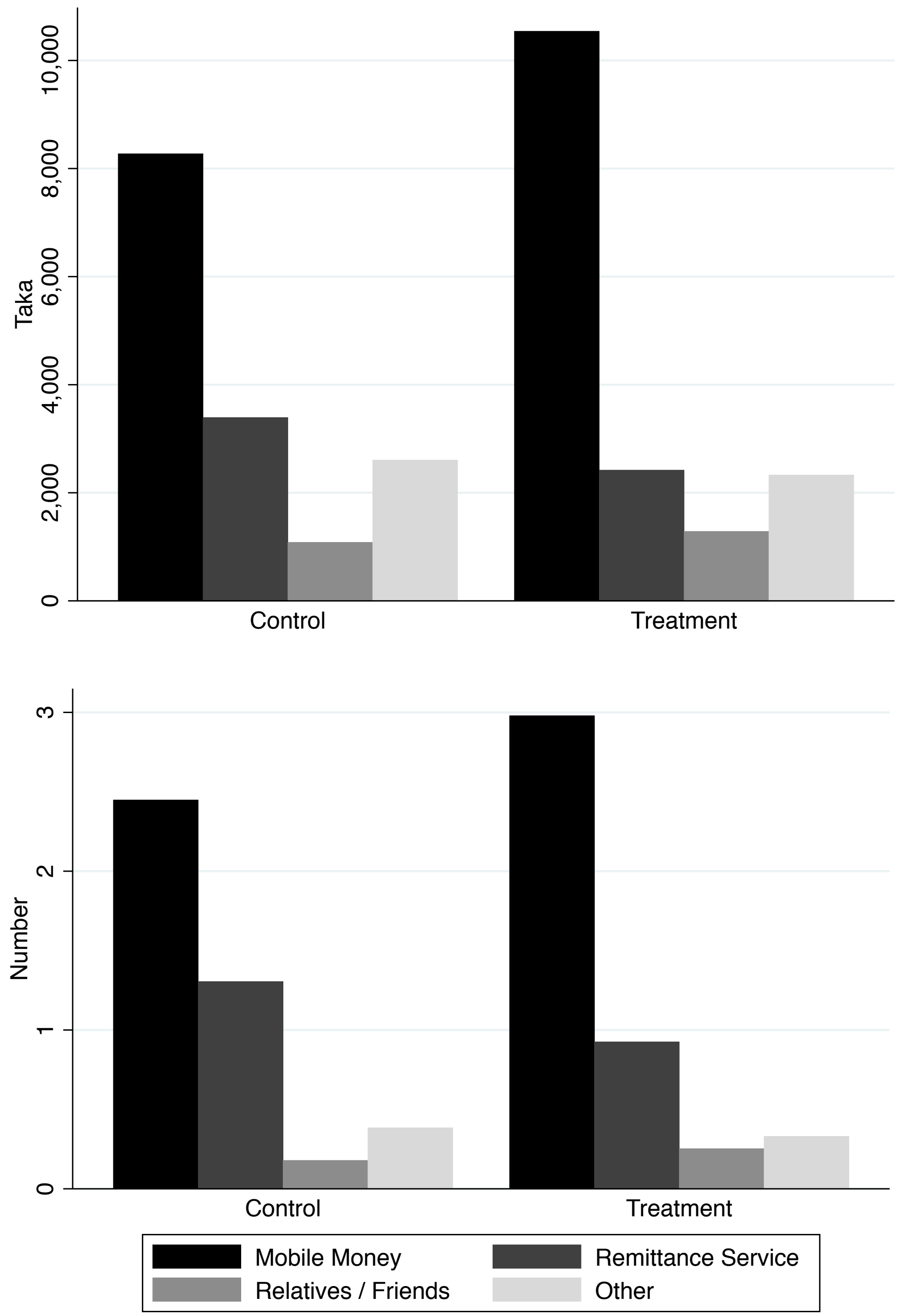

Figure 1: Value and Number of Remittances Sent over Last 7 Months (Endline)

The top panel shows the value of remittances in Taka. The bottom panel shows the number of remittances. The data are not conditional on using the particular mode.

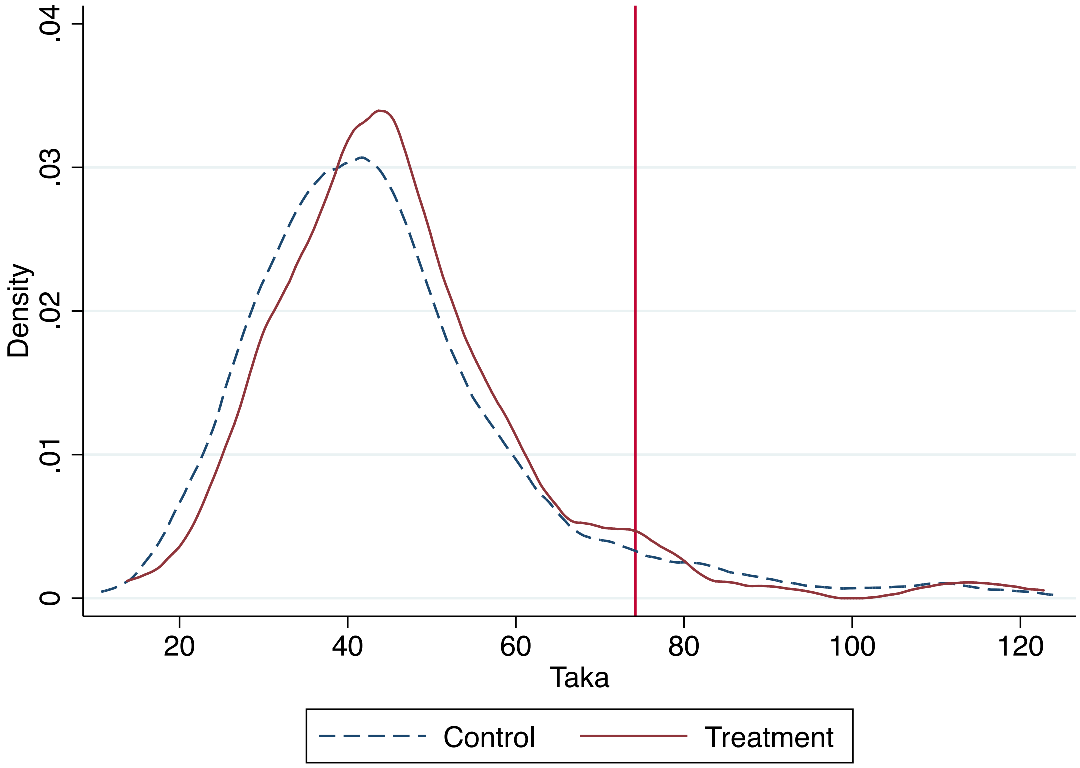

Figure 2: Kernel Density Plots of Rural Per Capita Daily Expenditure (Endline)

Note: The vertical line is the rural poverty line in Bangladesh (74.2 Taka per person in 2016 prices).

where P_i denotes the squared poverty gap, y_i denotes per capita daily expenditure, and z denotes the poverty line. Column (2) of Table 6 presents ITT and LATE regressions showing a LATE decrease in the extreme poverty metric by 0.038 relative to a baseline mean of 0.091, a decline of 42% (statistically significant at the 5% level).

Figure 3 presents intent-to-treat treatment effects on consumption, education, and health indicators. Coefficients are normalized relative to the baseline standard deviation, and the 90% and 95 % confidence intervals are displayed. The first row of the figure shows an intention-to-treat increase on the log of daily per capita expenditures of 0.09 of a standard deviation. All households ate three meals a day during regular seasons (i.e., not the lean season), and there was no variation across time or across samples. Calorie sufficiency improved, however, in the treatment group by 0.12 of a standard deviation or by almost 14,000 calories per month, although baseline calorie insufficiency for the household was high. As the rightward shift of the treatment distribution in Figure 2 shows,

Table 6: Rural Consumption, Poverty, Education, and Health

	(1) Poor?	(2) Squared Poverty Gap	(3) Consumption Index	(4) Education Index	(5) Health Index
Intention-to-treat:					
bKash Treatment	0.008	-0.018	0.117	0.096	0.004
	(0.016)	(0.009)	(0.047)	(0.066)	(0.026)
Local average treatment effect:					
Active bKash Account	0.016	-0.038	0.243	0.192	0.008
	(0.034)	(0.018)	(0.098)	(0.133)	(0.053)
R^2 (ITT)	0.04	0.18	0.43	0.15	0.03
R^2 (LATE)	0.04	0.16	0.42	0.13	0.03
Baseline Mean	0.75	0.09	0	0	0
Observations	813	813	813	397	813

Standard errors in parentheses. 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.

the treatment impact is largest at the bottom of the distribution, i.e. for the poorest households.[14]

The local average treatment effect in column (1) of Table 8 implies daily per capita expenditures 7.5% greater among compliers in the treatment group than the control. To summarize findings, we constructed a consumption index for each household using the three consumption variables in Figure 3 (and two consumption variables in Figure 4 below), with equal weight given to the normalized variables (z-scores standardized relative to their baseline distributions). Column (3) of Table 6 shows that the treatment increased the consumption index of households in the treatment group by 0.117 standard deviation units. The LATE estimate shows an increase in the consumption index by a relatively large 0.243 standard deviation units relative to the control group (statistically significant at the 5% level).

14. Calorie sufficiency was computed as the gap between the calorie needs and the calorie consumption of the household. We asked households about their monthly consumption of eggs, meat, fish, fruits, and milk. We then calculated the calorie consumption from these various food groups using calorie conversion factors provided by the Food and Agriculture Organization. Calorie needs were computed using the household roster and age and gender-specific calorie requirements provided by the United States Department of Agriculture (USDA). Accounting for member-specific needs is important since particular types of household members migrated more from treatment households for work. In particular, 70% of such migrants were male, and the average age of these migrants was 25. Males aged 25 have a USDA calorie requirement of 3,000 calories per day, one of the highest requirements of all ages and gender groups. (Only males aged 16-18 have a higher calorie requirement: 3200 calories per day.)

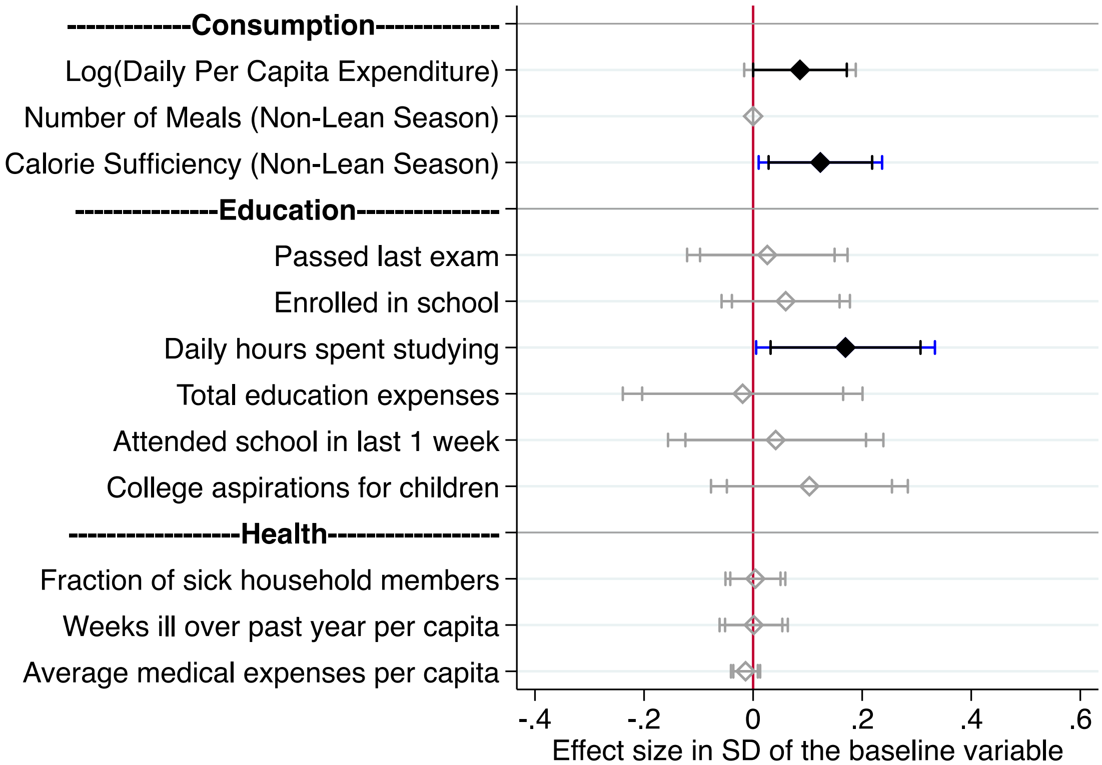

Figure 3: Impact on Rural Consumption, Education, and Health (ITT)

Notes: Intent-to-treat estimates. Each line shows the OLS point estimate and 90 and 95 percent confidence intervals for the outcome. The regressions are run with baseline controls as well as a control for baseline value of the dependent variable. Treatment effects are presented in standard deviation units of the baseline distribution for each variable. Consumption and health: 813 observations. Education: 397 observations (restricted to households with school-age children).

Table 7: Results for Consumption, Education and Health (Intent-to-treat)

Consumption: and Health:	(1) Log (Per Capita Daily Expenditure)	(2) Calorie Sufficiency (Non Lean Season)	(3) Fraction of Sick Household Members	(4) Average Medical Expenses Per Capita	(5) Weeks Ill Over Past Year Per Capita	
bKash Treatment	0.036	13.89	0.00110	-24.07	0.00184	
	(0.022)	(6.492)	(0.00736)	(23.69)	(0.0554)	
R^2	0.17	0.45	0.02	0.01	0.01	
Baseline Mean	4.03	-277.8	0.27	513.0	0.74	
Observations	813	813	813	813	813	

Education:	(6) Passed Last Exam	(7) Enrolled in School	(8) Daily Hours Spent Studying	(9) Total Education Expenses in Past 6 Months (Taka)	(10) Attended School in Last 1 Week	(11) College Aspirations for Children
bKash Treatment	0.010	0.023	0.298	-31.93	0.019	0.0513
	(0.029)	(0.023)	(0.146)	(186.0)	(0.047)	(0.0456)
R^2	0.04	0.21	0.04	0.04	0.04	0.04
Baseline Mean	0.83	0.81	2.99	2335.9	0.31	0.56
Observations	397	397	397	397	397	397

Standard errors in parentheses. All regressions are estimated with baseline control variables and the baseline dependent variable. “Calorie sufficiency” in column (2) is the monthly calorie sufficiency (difference between calorie consumption and calorie needs) for all household members, in thousands of calories. Regressions (6)-(11) are run at the household-level and are conditional on having a school-age child. For households with multiple children, hours spent studying and education expenses in columns (8) and (9) are averages across all school-aged children in the household, while the maximum value across school-aged children in the household was used for dependent variables in columns (6), (7), (10), and (11). Dependent variables in columns (6), (7), (10), and (11) are binary. “College aspirations for children” is 1 if households hope for children to attend college or higher.

Table 8: Results for Consumption, Education and Health (Local Average Treatment Effect)

Consumption: and Health:	(1) Log (Per Capita Daily Expenditure)	(2) Calorie Sufficiency (Non Lean Season)	(3) Fraction of Sick Household Members	(4) Average Medical Expenses Per Capita	(5) Weeks Ill Over Past Year Per Capita
Active bKash Account	0.0745	28.67	0.00228	-49.65	0.00384
	(0.0453)	(13.37)	(0.0151)	(48.68)	(0.115)
R^2	0.16	0.45	0.02	0.01	0.01
Baseline Mean	4.03	-277.8	0.27	513.0	0.74
Observations	813	813	813	813	813

Education:	(6) Passed Last Exam	(7) Enrolled in School	(8) Daily Hours Spent Studying	(9) Total Education Expenses in Past 6 Months (Taka)	(10) Attended School in Last 1 Week	(11) College Aspirations for Children
Active bKash Account	0.0206	0.0459	0.599	-64.42	0.0388	0.103
	(0.0588)	(0.0458)	(0.296)	(371.6)	(0.0931)	(0.0907)
R^2	0.04	0.20	0.01	0.04	0.04	0.04
Baseline Mean	0.83	0.81	2.99	2335.9	0.31	0.56
Observations	397	397	397	397	397	397

Standard errors in parentheses. All regressions are estimated with baseline control variables and the baseline dependent variable. "Calorie sufficiency" in column (2) is the monthly calorie sufficiency (difference between calorie consumption and calorie needs) for all household members, in thousands of calories. Regressions (6)-(11) are run at the household-level and are conditional on having a school-age child. For households with multiple children, hours spent studying and education expenses in columns (8) and (9) are averages across all school-aged children in the household, while the maximum value across school-aged children in the household was used for dependent variables in columns (6), (7), (10), and (11). Dependent variables in columns (6), (7), (10), and (11) are binary. "College aspirations for children" is 1 if households hope for children to attend college or higher.

The treatment effects on child education in Figure 3 and Tables 7 and 8 are from regressions run at the household-level for 397 households with at least one child aged 5-16 years. The ITT results in Figure 3show a positive treatment effect on the average number of hours spent studying per day (0.17 of a standard deviation). In absolute terms, the associated LATE regression in Table 8 shows that children of households in the treatment group that were induced to actively use bKash spent 0.6 hours more studying per day than children in the control group (baseline average 3 hours studying per day). The point estimates for school attendance, exam performance, and parents' aspirations for their children are consistently positive, but are not statistically significant at the 10% level. The mechanism for increased study hours is hard to pin down. One path is that parents could spend part of the increased remittances directly on child education. However, we do not see this in Figure 3. Second, children in treated households might study longer if they are in better health. We do not, however, find significant treatment impacts on child health. Third, children may be substituting study hours with time spent helping at home or in agriculture and/or other business activities of the household (although we see only a low incidence of paid child labor overall).

The final three rows of Figure 3 give treatment effects on health of rural households. Outcomes include the fraction of household members who were sick for a week or more over the past year, the number of weeks that individuals were ill (on average for each household), and the average household medical expenses per capita. All health coefficients are very close to zero.

Table 6 summarizes results on education and health indices using the variables in Figure 3 with equal weight given to the variables. The education index was only constructed for the 397 households with at least one child aged 5-16 years. The sign of the health index has been reversed so that a decrease in the fraction of sick household members, for example, is an improvement in the health index. Column (4) of Table 6 shows that children in the treatment group saw an increase in the education index by 0.082 standard deviation units (ITT) and 0.165 units (LATE), though noisily measured. Column (5) shows no overall treatment impact on health, consistent with Figure 3.

5.2.2 Shocks and liquidity: Borrowing, Saving, and Lean Season Consumption

Remittances can be used in place of credit or can be saved for later use. In times of particular need, like the lean season, well-timed remittances can also be a saving or insurance substitute. We would anticipate a decline in borrowing tied to increases in consumption during the lean season as a result of our intervention.

Figure 4 and Table 9 show that increased remittances from migrants sharply reduced the need of rural households to borrow. Households in the treatment group that were induced to actively use bKash accounts were 12.2 percentage points less likely to need to borrow than households in the control group (at baseline, 59.4% of households borrowed in the previous year). The total value of loans among treatment households also fell sharply: the average was 2960.5 Taka lower than the baseline mean of 6062 Taka. (The estimate combines the extensive and intensive margins of borrowing.) These large magnitudes are consistent with the magnitudes of transfers: the total size of loans taken over the last 12 months was 6665.5 Taka at baseline, and monthly remittances are large in comparison (2198/6665.5 = 33%).[15]

Figure 4 and Table 9 show significant positive impacts results on savings for rural households. Total savings are the sum of the value of various forms of saving plus bKash balances held at the time of endline survey. On the extensive margin, households in the treatment group were 44.3 percentage points more likely to save, relative to a baseline mean of 48%. This is because bKash can act as a savings device for households, in addition to the remittance facility it provides. This is seen in the month-end balances of households in the bKash administrative data. The results for the value of savings are not conditional on having saved, and thus combine the extensive and intensive margins of savings. Households in the treatment group saved roughly 143% more than households in the control group, with baseline levels of saving at 3358.6 Taka. Accounting for active use of the bKash accounts gives a LATE impact of 296%. The estimates are large, statistically significant, and driven by saving through bKash. The borrowing and saving results are summarized in the first four columns of Table 9.

Vulnerability to the lean season is one of the defining features of poverty in northwest Bangladesh (Khandker 2012, Bryan et al 2014), and the financial impacts are consistent with improvements in *monga* (lean season) consumption. The estimated coefficient for number of meals during the lean season is positive for the treatment group, but it is small and not statistically significant at the 10% level (Figure 4). However, households in the treatment group were more likely to consume sufficient calories relative to households in the control group (an improvement by 0.11 of a standard deviation) during the lean season. In absolute terms, households that actively used their bKash accounts in the treatment group saw a 10.3% improvement in calorie sufficiency during the lean season relative to the baseline mean (statistically significant at the 5% level). The improvement in calorie sufficiency during the lean season is consistent with improved timing of remittances sent through bKash, and it is also consistent with rural households saving more on their own.[16]

15. In analyses of sub-samples in the appendix, we show that results for borrowing are clearest for the snowball sub-sample and smaller and not significant for the SHIREE sub-sample. These regressions, though, are exploratory and the experimental design was not powered for these analyses.

16. We did not collect data on total consumption during the lean period, collecting data only on food-related measures.

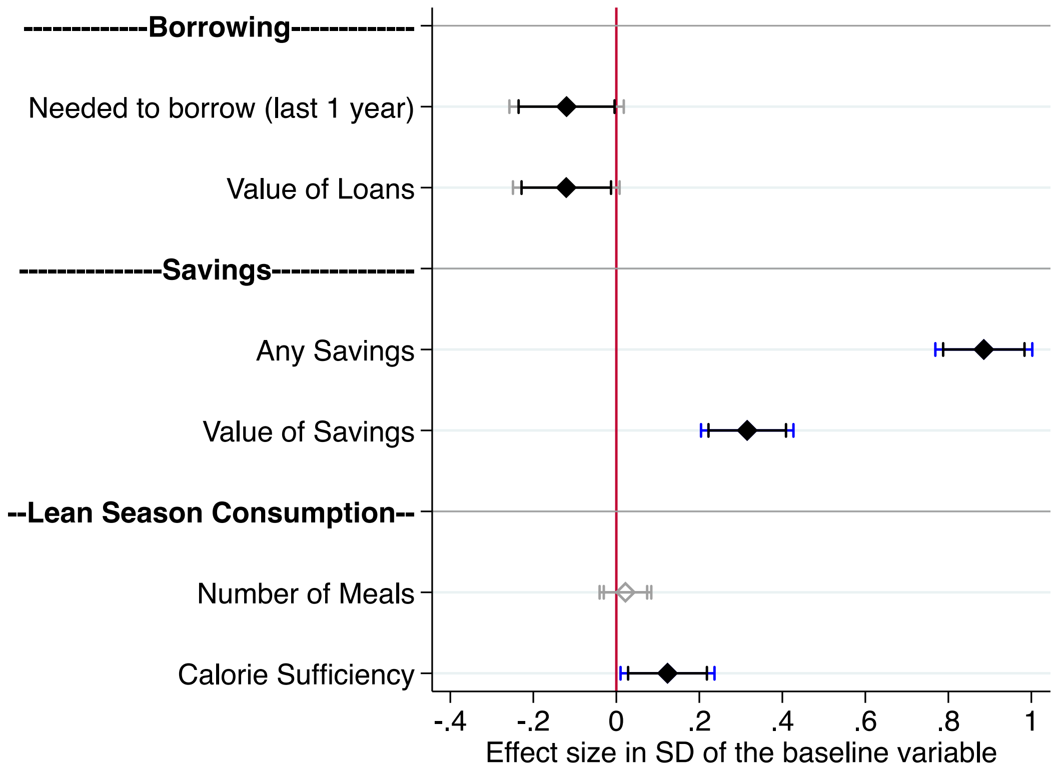

Figure 4: Impact on Rural Borrowing, Savings, and Lean Season Consumption (ITT)

Notes: Intent-to-treat estimates. Each line shows the OLS point estimate and 90 and 95 percent confidence intervals for the outcome. The regressions are run with baseline controls as well as a control for baseline value of the dependent variable. Treatment effects are presented in standard deviation units of the baseline distribution for each variable. 813 observations.

Table 9: Rural Borrowing, Saving, and Lean Season (Monga) Consumption

	(1) Any Borrowing?	(2) Loan Value	(3) Any Saving?	(4) Savings Value	(5) *Monga* Number of Meals	(6) *Monga* Calorie Sufficiency	(7) No *Monga* Problem?
Intention-to-treat:							
bKash Treatment	-0.0589	-0.553	0.443	1.426	0.00296	13.89	0.0443
	(0.035)	(0.300)	(0.030)	(0.256)	(0.00427)	(6.492)	(0.022)
Local average treatment effect:							
Active bKash Account	-0.122	-1.143	0.919	2.961	0.00613	28.67	0.0916
	(0.071)	(0.619)	(0.066)	(0.534)	(0.009)	(13.37)	(0.045)
R^2 (ITT)	0.02	0.05	0.22	0.05	0.01	0.45	0.01
R^2 (LATE)	0.02	0.04	0.11	0.03	0.00	0.45	0.00
Baseline Mean	0.59	5.08	0.48	4.28	2.98	-277.8	.
Observations	813	813	813	813	813	813	813

Standard errors in parentheses. All regressions are estimated with baseline control variables. All regressions with the exception of "No *Monga* Problem" are estimated with the baseline dependent variable, as this variable was not captured at baseline. Column (2) dependent variable is the inverse hyperbolic sine of total loan value. Column (4) dependent variable is the inverse hyperbolic sine of total savings value. Column (5) dependent variable is the number of meals per day during the *monga* season. Column (6) dependent variable is the monthly calorie sufficiency (difference between calorie consumption and calorie needs) for all household members, in thousands of calories. Column (7) dependent variable is an indicator for households reporting no difficulty during the lean (*monga*) season in response to a survey question about ways of coping during *monga*.

Column (5) of Table 9 summarizes the lean season impact. Households that actively used their bKash accounts in the treatment group were 9.2 percentage points more likely to declare that the lean season was not a problem. This result is in line with Batista and Vicente (2019) on the impact of mobile money in reducing hunger, as well as Jack and Suri (2014) on protecting consumption. Relative to the control mean of 8.2%, our estimate represents a large, 112% improvement.[17] For households that declared *monga* to still be a problem, the key coping strategies were purchasing goods on credit and drawing down savings, with no significant differences in strategies used by the treatment and control groups.

5.2.3 Investment and liquidity: Migration and Labor

The impacts on remittances can also be seen in rural investment. The surveys focus on three key contributors to rural household income: migration, wage labor, and self-employment. The increase in remittances facilitated the migration of other household members beyond the original migrant. The first column of Table 10 shows a local average treatment effect decrease in household size by 0.28 household members for the treatment group relative to the control group. This is consistent with the LATE result in column (2) showing increased migration by 0.24 people (this result excludes the "paired migrants" that were exposed to the initial treatment). The result is large relative to the baseline mean household size of 3.8 household members (a 7% change), and it is large relative to the baseline mean rate of migration of 0.692 household members (a 35% increase).[18]

There are at least five mechanisms (which cannot be isolated in the data). First, the larger remittances sent through bKash in the treatment group may help to finance the costs of migration. Migration to Dhaka is expensive: Bryan et al (2014) show that purchase of a bus ticket alone was enough to induce migration in 22% of the treated households, though their study focused on seasonal migration rather than long-term moves. The initial costs of housing and job search are also important. Second, household members in the treatment group could have revised their priors on expected income from migration upon observing the larger remittances received. When such migrants were asked at endline their primary reason for migrating for work, 90% noted the an expectation of a higher income was the main reason for migrating. Third, migrants in the treatment group may have built employment networks that could help other family members who migrate. Fourth, access to bKash makes sending remittances easier, raising the effective return to migration.

17. Note that we do not have baseline information for this indicator.

18. We observe migration of household members using two sources: (i) the household roster that tracks movement of individuals into and out of the household, and (ii) the employment history of each individual, which tracks their location and duration of work in each month for the past one year. Individuals who worked at least 312 days in the past year (at least 6 days per week) in Dhaka were classified as migrating for work. Migration here refers to permanent migration, not seasonal migration.

Fifth, migrants in the treatment group could have actively encouraged further migration to help shoulder the stress and burden of having to support rural families.

Table 10: Rural Household Size and Labor

	(1) Household Size	(2) Number Migrating For Work	(3) Any Wage Labor?	(4) Number Self-Employed	(5) Any Child Labor?
Intention-to-treat:					
bKash Treatment	-0.137	0.116	-0.060	0.037	-0.048
	(0.07)	(0.057)	(0.031)	(0.023)	(0.017)
Local average treatment effect:					
Active bKash Account	-0.284	0.240	-0.123	0.077	-0.095
	(0.159)	(0.119)	(0.063)	(0.047)	(0.035)
R^2 (ITT)	0.51	0.05	0.13	0.42	0.05
R^2 (LATE)	0.52	0.04	0.13	0.41	0.00
Baseline Mean	3.80	0.69	0.70	0.20	0.01
Observations	813	813	813	813	397

Standard errors in parentheses. Column (5) is restricted to households with at least one school-age child. All regressions are estimated with baseline control variables and the baseline dependent variable.

Column (3) of Table 10 presents results for the impact of the intervention on households engaged in any wage labor. A household is defined to engage in wage labor if at least one household member is engaged in wage labor. Notably, 71% of households at baseline engaged in some wage labor. Households in the treatment group that actively used bKash accounts were 12 percentage points, or 17% *less* likely to engage in any wage labor. The magnitude of the decline in the number of wage laborers in the treatment group is consistent with the magnitude of decrease in the household size due to migration for work. We see no treatment impact on the intensive margins of wage labor, i.e. number of wage laborers conditional on engaging in any wage labor, and the mean number of days worked by the wage laborers.

The bKash service may facilitate self-employment by providing capital for investment and by providing a financial cushion that encourages risk-taking. Column (4) of Table 10 presents results on the number of household members engaged in self-employment. The local average treatment effect estimate shows that households in the treatment group that actively used bKash accounts had 0.08 more household members engaged in self-employment relative to the control group. Relative to the baseline mean of 0.197, this represents a large, 42% increase in self-employment on the intensive margin. We do not observe statistically significant treatment impacts on the extensive margin on self-employment, although the estimated coefficients are consistently positive.

Few children were engaged in child labor (just 4 children out of 397 at baseline and 12 at endline), so interpretation of child labor results requires caution. Column (5) of Table 10 shows a relative decrease in the number of children working in the treatment group. The ITT results imply a large decrease in child labor in the treatment group relative to the 1% of households with children that were engaged in any child labor at baseline. These regressions are run only for the 397 households with at least one child aged 5-16 and results are statistically significant at the 1% level.[19]

5.3 Impacts on Urban Migrants

Urban migrants face their own struggles with liquidity and low incomes (e.g., Breza et al 2017). It is plausible that the treatment would reduce consumption by migrants (since increases in remittances would draw resources from consumption). We find the opposite, however. The increase in consumption and income of migrants found here is consistent with greater work intensity and an assumption of intrinsic reciprocity (Sobel 2005).

Column (1) of Table 11 shows that migrants in the treatment group that actively used their bKash accounts were 11 percentage points less likely to be below the poverty line, relative to a baseline mean of 21% (p-value = 0.055).[20] The large points estimates suggest that, taken at face value, bKash might serve as an effective poverty reduction tool for the urban poor, though below we note the costs associated with those gains.[21]

Column (2) of Table 11 presents treatment effects on employment in the garments and textiles industry. The LATE shows that migrants in the treatment group that were induced to actively use their bKash accounts were 11 percentage points more likely to be employed in the garments industry at endline than those in the control group, on a baseline mean of 55% (p-value = 0.12).[22]

19. The LATE result indicates that child labor is more than eliminated in the treatment group relative to the baseline control group average, a coefficient that seems "too large." But the treatment effect should be interpreted against the control trend. The number of child laborers in the treatment group increased from 0 at baseline to 2 at endline. In the control group, the increase was from 4 to 10 child laborers. The small sample size makes results particularly sensitive to outliers, and we would need a larger sample to be confident of the results despite the high level of statistical significance.

20. The rate of poverty in the control group is slightly higher than the latest urban poverty headcount ratio at national poverty line of 21.3% for Bangladesh, estimated by the World Bank.

21. As a robustness check, we re-analyzed Table 11, winsorizing the top and bottom 1% and 5%, and we do not see meaningful differences. We also repeated the poverty analysis using per capita income instead of expenditures, and obtained qualitatively similar estimates. We did not find significant reductions in poverty for extremely poor migrants, as measured by the squared poverty gap. These results come from the snowball sub-sample rather than the SHIREE sub-sample (Appendix Tables 10 and 18).

22. Due to the broad occupational classes used at baseline, we could not run the regressions in column 2 with a control for the baseline value of the dependent variable. There are two possible reasons for the result on garment work: it could either be the case that more migrants decided to move into garment work (higher entry), or more migrants decided to

Table 11: Migrant Poverty, Occupation, Saving, and Health

	(1) Poor?	(2) Garment Worker?	(3) Any Saving?	(4) Value of Saving	(5) Health Index
Intention-to-treat:					
bKash Treatment	-0.05	0.05	0.18	0.47	-0.17
	(0.03)	(0.03)	(0.024)	(0.27)	(0.09)
Local average treatment effect:					
Active bKash Account	-0.11	0.11	0.38	0.99	-0.35
	(0.06)	(0.07)	(0.05)	(0.56)	(0.19)
R^2 (ITT)	0.14	0.03	0.09	0.04	0.09
R^2 (LATE)	0.14	0.03	0.07	0.04	0.09
Baseline Mean	0.21	0.55	0.38	2.84	0
Observations	809	809	809	809	809

Standard errors in parentheses. 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. Column (4) dependent variable 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.

We show below that garment work pays well but involves substantial overtime work.

Column (3) presents results for the extensive margin on savings. The LATE shows an increase of 38 percentage points in the probability of saving, relative to a baseline mean of 38%. This is because many migrants in the treatment group that were induced to actively use their bKash accounts as a means of saving, as seen in their month-end balances in the bKash administrative data. The point estimate in column (4) suggests that migrants in the treatment group save 35% more than migrants in the control group scaled by the baseline mean. This result is not conditioned on having saved, and hence combines the extensive and intensive margins of savings.

stay on in their current jobs in the garment sector (lower exit). Given that we saw in Table 2 that the mean tenure at their current jobs among migrants in the treatment group was 1.7 years (longer than the duration of the intervention), it is likely that lower exit from the garments sector among migrants in the treatment group drives the above result.

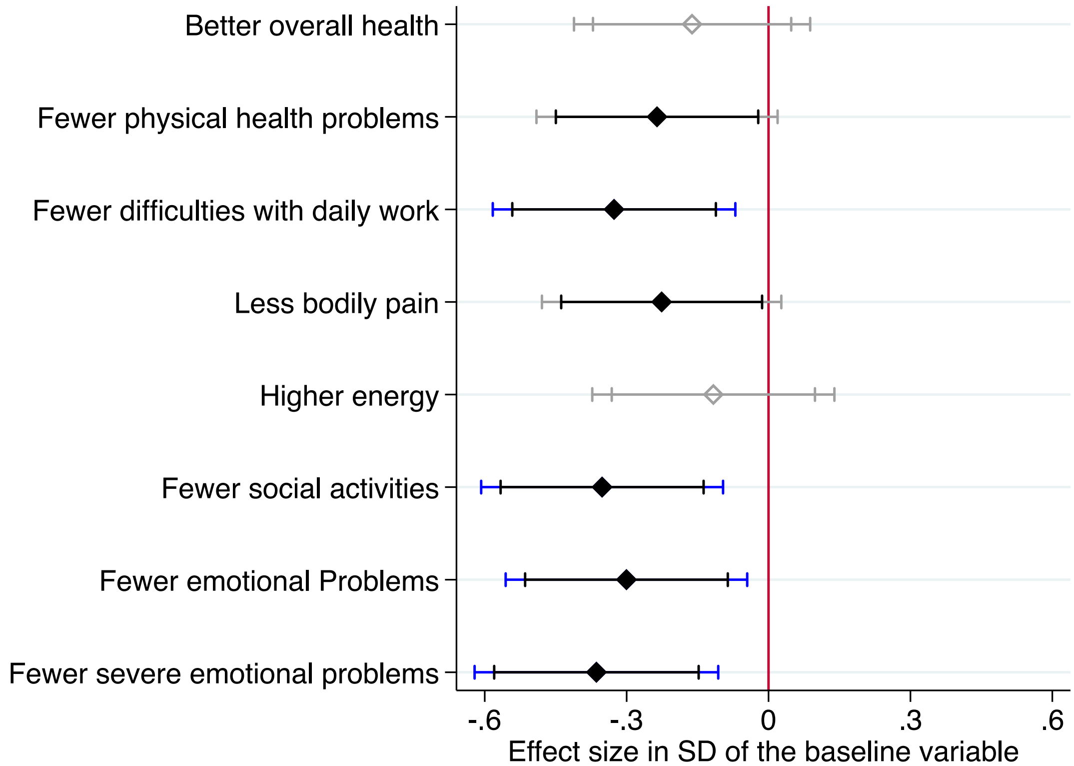

Figure 5: Impact on Migrant Health (ITT)

Notes: Each line shows the point estimate and 90 and 95 percent confidence intervals from an ordered logit specification. The regressions are run with baseline controls as well as control for baseline value of the dependent variable, and treatment effects are presented in standard deviation units of the control group. Intent-to-treat estimates are presented. All variables are self-reported and ordered on a scale of 1-5 with a reference frame of the past 4 weeks. "Better overall health" refers to a question on overall health of the respondent. "Fewer physical health problems" is in response to a question on the extent to which physical health problems limited usual physical activities. "Fewer difficulties with daily work" is in response to a question on difficulties doing daily work because of physical health. "Less bodily pain" is in response to a question on the extent of bodily pain. "Higher energy" is in response to how much energy the individual had over the reference frame. "Fewer social activities" is in response to a question on the extent to which physical health or emotional problems limited usual social activities with family or friends. "Fewer emotional problems" refers to a question on the extent to which the individual was bothered by emotional problems (including feeling anxious, depressed, or irritable). "Fewer severe emotional problems" refers to the extent to which personal or emotional problems kept the individual from doing usual work or other daily activities.

Table 12: Results for Migrant Health

	(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
Intent-to-treat:								
bKash Treatment	-0.162	-0.236	-0.327	-0.226	-0.117	-0.352	-0.300	-0.364
	(0.127)	(0.130)	(0.131)	(0.129)	(0.131)	(0.130)	(0.130)	(0.131)
Local average treatment effect:								
Active bKash Account	-0.214	-0.247	-0.352	-0.296	-0.0789	-0.328	-0.292	-0.352
	(0.164)	(0.169)	(0.170)	(0.194)	(0.136)	(0.149)	(0.136)	(0.143)
R^2 (ITT)	0.02	0.03	0.02	0.02	0.03	0.04	0.02	0.02
R^2 (LATE)	0.06	0.06	0.06	0.05	0.07	0.11	0.05	0.03
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

Standard errors in parentheses. All intent-to-treat regressions are run as ordered logit regressions. All variables as defined in Figure 5 are self-reported and ordered on a scale of 1-5 with a reference frame of the past 4 weeks. The regressions are estimated with baseline control variables and the baseline dependent variable.

As noted above, harder work and the 26% increase in remittances sent home came at a cost to migrants. Figure 5 and Table 12 present treatment effects on the physical and emotional health of migrants using an ordered logit specification that captures qualitative responses coded on a scale of 1-5 (e.g., options to the question on overall health were Poor, Fair, Good, Very Good, and Excellent).[23] "Fewer social activities" is in response to a question on the extent to which physical health or emotional problems limited usual social activities with family or friends. "Fewer emotional problems" refers to a question on the extent to which the individual was bothered by emotional problems, including feeling anxious, depressed, or irritable.

The treatment had negative impacts on the health of migrants across a series of measures. For example, migrants in the treatment group have notably more difficulties with daily work and more emotional problems. The negative health impact overall is shown in Column (5) of Table 11, which presents results for the health index variable, constructed with equal weight on each of the variables in Figure 5. The treatment decreased the health index by 0.17 standard deviation units, significant at the 10% level. The local average treatment effect estimate shows a large decrease in the health index by 0.35 standard deviation units (again only significant at the 10% level). However, note that baseline levels of self-reported health were high for many measures and that treated migrants still reported relatively good health. For example, in Table 12, we note that the baseline mean response to "fewer difficulties with daily work" was 4.84 (scored out of 5). The LATE effectively reduces this to 4.49.

One possible explanation for the health decline is that there was an increase in hours worked by garment workers in the treatment group. Over half of the migrants (58%) work in garments factories, a sector associated with worse health because of longer hours worked and more overtime work. This story is in line with results from financial diaries that provide a close look at the lives of 180 garment workers in Bangladesh (available at www.workerdiaries.org). The garment worker diaries show that the workers averaged 60 hours per week in the factories during the study period, and 53% of the time they worked beyond the 60-hour/week legal limit. Moreover, factory conditions tended to be harsh and financial stress high. Blattman and Dercon (2016) similarly show that workers randomly assigned to industrial jobs in Ethiopia, also an export hub for garments and textiles, had significant health problems after a year. The authors note the longer hours in these jobs as a mechanism for this deterioration in health. Similar results have been reported for factory workers in China (Akay et al 2012, Knight and Gunatilaka 2010) and Pakistan (Chen et al 2019).

To explore further, we present ITT and LATE regressions of the effect of the treatment on daily hours worked in Tables 13 and 14, respectively. The panel specification exploits data that captures

23. We obtain qualitatively similar results when the regressions are run using standard OLS. The estimates are more precise and the responses to "fewer physical health problems" and "less bodily pain" are no longer significant at the 10% level.

the average number of hours worked per day as self-reported by migrants in the prior 12 months. The regressions control for migrant-level and month fixed effects, with standard errors clustered by migrant. The labor supply data is conditional on working in the particular month given the likelihood that zero hours worked indicates that the migrant had temporarily returned home (14% of worker-months).

Column (1) of Table 13 presents the intent-to-treat impact on hours of work for all migrants, and we do not see an impact of the treatment on overall labor supply. Column (2) explores whether there are labor supply impacts among garment workers through an interaction term with a binary indicator for garments work. The coefficient in the second row is positive, indicating an additional 0.4 hours per day, but with a large standard error. Column (3) studies the treatment impact for female migrants. The coefficient implies that female migrants in the treatment group work an extra 0.5 hours per day relative to male migrants in the treatment group (significant at the 10% level). Column (4) turns to impacts for female workers in the garments sector (35% of workers in the garments sector), showing an ITT impact of an additional 0.6 hours per day (significant at the 10% level).

The local average treatment impacts are shown in Table 14. Column (3) shows that females induced to actively use bKash work an extra hour a day (significant at the 10% level). Column (4) shows slightly larger LATE impacts for females in the garments sector, specifically (an additional 1.2 hours worked per day, on average). On a baseline mean of 8.6 hours worked per day, this represents a sizeable 14% increase. Thus, although we do not see a significant impact of the treatment on the overall labor supply of migrants, we see a large (although not statistically significant) impact on garment workers, and a large and significant impact on women. The results align with the negative health results in Table 12, but are exploratory and additional studies are needed to establish a causal link.[24]

24. This analysis was not pre-specified as part of a pre-analysis plan, but was motivated by comments from the editor and referees.

Table 13: Results for Migrant Labor Supply (Intent-to-treat)

	(1) Daily Hours Worked	(2) Daily Hours Worked	(3) Daily Hours Worked	(4) Daily Hours Worked
Treatment $*$ Endline	-0.0517	-0.303	-0.188	-0.171
	(0.140)	(0.216)	(0.165)	(0.159)
Treatment $*$ Endline $*$ Garments Worker		0.365		
		(0.283)		
Treatment $*$ Endline $*$ Female Migrant			0.539	
			(0.311)	
Treatment $*$ Endline $*$ Female Garments Worker				0.596
				(0.326)
Endline $*$ Garments Worker		0.310		
		(0.208)		
Endline $*$ Female Migrant			-0.0685	
			(0.229)	
Endline $*$ Female Garments Worker				0.0226
				(0.263)
Endline	0.0912	-0.0912	0.110	0.0866
	(0.105)	(0.148)	(0.126)	(0.118)
R^2	0.272	0.274	0.273	0.273
Month Fixed Effects	Yes	Yes	Yes	Yes
Household Fixed Effects	Yes	Yes	Yes	Yes
Baseline Mean	8.56	8.56	8.56	8.56
Observations	17,270	17,270	17,270	17,270

Standard errors in parentheses, clustered by migrant. Regressions include month and migrant fixed effects. Dependent variable in columns (1) - (4) is the average number of hours worked per day in the prior 12 months as self-reported by urban migrants, conditional on working in the given month. Variables such as "Garments Worker", "Female Migrant", "Female Garments Worker", "Treatment $*$ Garments Worker", "Treatment $*$ Female Migrant", and "Treatment $*$ Female Garments Worker" are absorbed by the migrant fixed effects.

Table 14: Results for Migrant Labor Supply (Local Average Treatment Effect)

	(1) Daily Hours Worked	(2) Daily Hours Worked	(3) Daily Hours Worked	(4) Daily Hours Worked
Active Account ∗ Endline	-0.111	-0.749	-0.417	-0.375
	(0.301)	(0.544)	(0.368)	(0.351)
Active Account ∗ Endline ∗ Garments Worker		0.872		
		(0.655)		
Active Account ∗ Endline ∗ Female			1.130	
			(0.650)	
Active Account ∗ Endline ∗ Female Garments Worker				1.218
				(0.668)
Endline ∗ Garments		0.112		
		(0.329)		
Endline ∗ Female			-0.240	
			(0.308)	
Endline ∗ Female Garments Worker				-0.156
				(0.344)
Endline	0.115	0.0821	0.219	0.177
	(0.159)	(0.255)	(0.210)	(0.190)
R^2	0.271	0.272	0.271	0.271
Month Fixed Effects	Yes	Yes	Yes	Yes
Household Fixed Effects	Yes	Yes	Yes	Yes
Baseline Mean	8.56	8.56	8.56	8.56
Observations	17,270	17,270	17,270	17,270

Standard errors in parentheses, clustered by migrant. Regressions include month and migrant fixed effects. Dependent variable in columns (1) - (4) is the average number of hours worked per day in the prior 12 months as self-reported by urban migrants, conditional on working in the given month. Variables such as "Garments Worker", "Female Migrant", "Female Garments Worker", "Active Account ∗ Garments Worker", "Active Account ∗ Female Migrant", and "Active Account ∗ Female Garments Worker" are absorbed by the migrant fixed effects.

6 Conclusion

Rapid urbanization is one of the defining economic forces of our time. The movement of people to cities, together with the more efficient movement of money, suggests a possibility for improving rural conditions and reducing spatial inequality. We show that rural conditions can be improved by facilitating mechanisms to connect urban and rural areas financially. The study here is unique in following two (paired) groups simultaneously, one in rural Gaibandha in northwest Bangladesh and the other in Dhaka division, site of the country's capital and home to factories offering industrial jobs. The migrants in Dhaka are the adult children of families in Gaibandha.

Given the existence of the mobile banking network, the intervention we designed and tested was relatively inexpensive, costing under $12 per family for a 30-45 minute training intervention on how to use the bKash mobile banking service on a mobile telephone (carried out with family members in both urban and rural sites). The short intervention sharply increased take-up of bKash from 22% in the rural control group to 70% in the rural treatment group—itself a substantial result.

The high take-up rate is partly a function of the time and place. First, nearly all families have members with mobile telephones but adoption of mobile banking technologies was constrained by the use of English-language menus. In response, the intervention included teaching the basic steps and protocols, providing hands-on practice sending transfers five times to establish a degree of comfort, sharing translations of menus into Bangla (Bengali), and, if needed, facilitating the sign-up process. Second, the experiment was started when mobile money was still relatively new in Bangladesh, especially in poorer rural areas like Gaibandha. The nature of the service and use of English made the technology intimidating to villagers with limited education. Still, the experiment shows that the barriers were not insurmountable. As a result, the setting provided a window (now closing as bKash and its competitors penetrate widely) that made it possible to identify the impact of the new technology.

For "ultra-poor" villagers receiving remittances, the technology was a major help. Active users of bKash sent larger remittances home (relative to the control group), an increase of about 26%, both in value and as a fraction of the monthly income of migrants. As a result, extreme poverty fell in rural households in the treatment group. Households also reduced borrowing levels, increased savings, and had less difficulty during the *monga* (lean) season. Self-employment activity, agricultural investment and additional migration increased. As mobile banking spreads, we anticipate that general equilibrium effects and spillovers, both positive and negative, will become important (eg. Riley, 2018 and Akram et al., 2017), but we lack the statistical power to test for them here.

The migrants to Dhaka, though, had mixed experiences. We find increases in saving and reductions in poverty, but longer hours worked among women and declines in self-reported health status (a finding parallel to conclusions from financial diaires of garment workers in Bangladesh and analyses of factory workers in Ethiopia, Pakistan, and China). The result is in line with forms of altruism described by Sobel (2005) where technology can increase the efficiency of sacrifice and thus lead to more of it.

The study demonstrates that technology can bring social and economic improvements, but technology adoption cannot be taken for granted, especially for the poorest, least literate populations. When technology is adopted, its introduction can shift relationships within families, creating new expectations about what is possible and what is appropriate to expect of others. Our evidence suggests that, at least for urban migrants, those shifts came with costs.

At a mechanical level, the movements of people and money lead to broader questions about the nature of households. One common definition holds that a household is a group that lives together and regularly eats together. In the digital age, though, a son or daughter living in a city hundreds of miles away (or even in another country) may be in regular communication and may participate in their parents' economic lives in a day-to-day or week-to-week way. The growing speed and ubiquity of mobile banking transfers, together with relatively cheap communication, suggests that researchers may need to begin revising traditional notions of the household.

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