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

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Abstract

Moving to cities has long been a way for rural workers to find higher-paying jobs, but migration can be costly and remittance-sending inefficient. Against a background of rapid urbanization in Bangladesh, we estimate the impact of access to mobile banking in a sample of "ultra-poor" rural households paired to family members who had previously migrated to Dhaka. Mobile banking provides a reliable, fast, and relatively inexpensive technology for sending remittances, and we used an encouragement design that provided the treatment group with knowledge about how to sign up for and use mobile banking accounts. The intervention substantially increased rural mobile bank account use, from 22% in the control group to 70% in the treatment group, and remittances increased by 30% in value one year later (relative to the control group). The intervention brought few households over the poverty line, but extreme poverty fell. Rural households borrowed less, were more likely to save, and fared better in the lean season. The evidence is weak but positive that farmers were more productive, schooling improved, and the rate of child labor dropped. Rural health and overall poverty rates were unchanged. In the city, migrant workers exposed to the treatment were slightly more likely to be in garment work, saved more, and were less likely to be poor. However, they reported being in worse health. The results show that, in this setting, mobile banking imposed costs but improved rural social and economic conditions, partly by facilitating access to resources at key times.

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1 Introduction

In 1970, most of the world's population lived in rural areas, with just 37 percent in cities, but by 2016, 55 percent lived in urban areas (United Nations 2016). Migration has taken people, especially the young, from the periphery into the center, turning urban hubs into mega-cities, creating congestion and social challenges alongside economic opportunities. 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 27.4 million people (United Nations 2016, p. 15), and demographers estimate that Bangladesh's rural population has now started declining in absolute numbers.

In the face of rural poverty, within-country migration can be a powerful way to increase incomes, pushing workers to move with hopes of higher wages (Bryan et al 2014). In Dhaka migrants often aspire to jobs in garment factories, where tough working conditions accompany steady paychecks that can be shared with other family members (Lopez-Acevedo and Robertson 2016).

While migration pulls households apart, the easier movement of money brings households back together, at least financially. Much hope has been placed in mobile money as a technology that dramatically simplifies the process of sending money across distances (Gates Foundation 2013), but its 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 facilitated the use of mobile money based in a poor region of northwest Bangladesh using random assignment to treatment. The intervention led to a large increase in adoption (by about 50 percentage points), and we trace the impacts. The study follows both senders (urban migrants) and receivers (rural families), allowing measurement of impacts on both sides of transactions. The study shows large improvements in rural conditions. Migrants, though, report worse outcomes in a series of health measures.

The study covers 815 rural household-urban migrant pairs randomized at the individual level, and the dual-site design allows measurement of impacts in both rural and urban areas. The design involved providing the treatment group with training on mobile financial services and facilitating account set-up. The baseline survey took place in December 2014 and early 2015 and the endline in early 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 already been fully served. By the endline, 70% of the rural treatment group had an actively-used mobile financial service account relative to 22% of the control group.

The rural site is in Gaibandha district in northwest Bangladesh, part of Rangpur division, about 8 hours from Dhaka by bus (12-14 hours with stops and traffic). Rangpur is one of the poorest divisions of Bangladesh, and Gaibandha is historically vulnerable to seasonal food insecurity during the *monga* season (Khandker 2012, Bryan et al 2014). The potential impact of improved remittance services was thus high.

The Gaibandha sample includes rural households that had been identified as "ultra-poor."[1] As extreme poverty falls globally, the households that remain poor are increasingly like those in Gaibandha, facing the greatest social and economic challenges. In response, programs are being designed and tested that provide extra resources for especially disadvantaged populations, with strong positive results seen in Bangladesh (Bandiera et al 2016) and other countries (Banerjee et al 2015). These "ultra-poor" programs provide assets, training, and social support to facilitate income growth through self-employment.[2] The mechanism we explore is complementary. The focus here is on facilitating the sharing of gains from (urban) employment, rather than from promoting rural self-employment.

Migrants actively using mobile banking increased remittances by 30% in value one year after the intervention (relative to the control group). The intervention brought few households over the poverty line, but extreme poverty fell. Rural households borrowed less, were

[1] Bryan et al (2014) also focus on districts in Rangpur (although not Gaibandha), 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 (2016) 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.

more likely to save, and fared better in the lean season. The evidence is weak but positive that farmers were more productive, schooling improved, and the rate of child labor dropped. Rural health and overall poverty rates were unchanged.

The results for migrants to Dhaka show tradeoffs of these rural gains. Migrant workers exposed to the treatment were slightly more likely to be in garment work, saved more, and were less likely to be poor. But we find declines in self-reported health status, which may reflect longer work hours in the garments sector. Overall, the results suggest that, in this setting, adoption of mobile banking increases the welfare of rural households but has mixed effects on the welfare of migrant workers. We do not find evidence of spillovers to the control group. The results show that mobile banking imposed costs but improved rural social and economic conditions, partly by facilitating access to resources at key times.

2 Framework and Related Literature

Early theories of modernization and economic growth focused on the movement of workers from subsistence sectors to modern, industrial sectors, especially through rural-to-urban migration (e.g., Lewis 1954). In contrast, anti-poverty programs have tended to focus on bringing resources into rural areas, including interventions like farm mechanization, improved agricultural marketing, microfinance, and, recently, intensive "ultra-poor" interventions to foster microenterprise (e.g., Bandiera et al 2016, Banerjee et al 2015, Armendáriz and Morduch 2010).

Rapid urbanization, coupled with efficient money transfers, opens a different possibility to reduce rural poverty: promoting the rural-to-urban movement of people coupled with the urban-to-rural movement of money. Bryan et al (2014) also evaluate urban-rural migration using a randomized expriment in a rural sample in northwest Bangladesh (near the population we study). Their focus is on inducements to migrate temporarily during the lean agricultural season. The $8.50 incentive studied by Bryan et al (2014) was just 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 involves taking advantage of urban job opportunities while maintaining strong ties to rural villages. Bryan et al (2014) note that in 2005 data only 5% of households in vulnerable districts in northwest Bangladesh received domestic remittances, suggesting little development of migration-remittance mechanisms prior to the introduction of mobile money.

The idea behind our experiment is straightforward and parallels the mechanisms of international migration: As workers move from rural areas into towns and cities, they shift to higher-wage urban jobs, and rural households share the gains when money is remitted back to relatives in origin villages (Ellis and Roberts 2016, Suri and Jack 2016). 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 now used by at least one person in 96% of Kenyan households (Suri and Jack 2016).

Referred to as "mobile banking" or as "mobile money," these services penetrate 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.

Mobile money services in Bangladesh started later than in Kenya, but have grown rapidly. 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 (Bhuiyan 2017).

The spread of mobile banking has potential economic impacts through at least four channels: direct impacts on consumption; impacts on liquidity at critical times; impacts overcoming financing constraints (e.g., Angelucci 2015); and wider impacts on communities, including non-users.

Direct consumption impacts. Munyegera and Matsumoto (2016) investigate mobile money in rural Uganda with a difference-in-difference method and IV using the log of the distance to the nearest mobile money agents as an instrument for mobile money adoption (as well as propensity score matching methods). The identifying assumption is that distance is exogenous, conditional on control variables. Under that assumption, they find that the adoption of mobile money services led to a 13% increase in household per capita consumption and an increase in food consumption. They also present evidence of increased expenditure on non-food basic expenditures, education and health services, and social contributions including toward local savings and credit associations. 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.

Liquidity and timing. Jack and Suri (2014) and Suri and Jack (2016) use the plausible exogeneity of the timing and place of M-Pesa's expansion in Kenya to identify impacts. Jack and Suri (2014) show the impact of M-Pesa's mobile money service through reducing the transaction costs of risk sharing. They use the timing and location of M-Pesa's rollout in different parts of Kenya to estimate impacts, finding that, in the face of a negative shock, households that used mobile money 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 (2016) provide the only other RCT studying the impact of mobile money in financially-underserved areas. While they do not find an increase in the value of remittances in rural Mozambique, they find increases in remittances received by rural households. 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, and there was evidence of reduced investment in agriculture and business. Batista and Vicente (2016) recruited mobile money agents in the treatment area, essentially setting up the agent network in the villages. In contrast, we work in a setting already served by mobile money operations.

Liquidity and financing. Suri and Jack (2016) extend their analysis of M-Pesa to consider long-run impacts with five rounds of household panel data from 2008-2014. They find that access increased per capita consumption levels and lifted 194,000 (or 2% of) Kenyan households out of poverty. The impacts are more pronounced for female-headed households (the impact on consumption for female-headed households was more than twice the average impact). The impacts they find are driven by changes in financial behavior and labor market outcomes, again especially for women, who were more likely than others to move out of agriculture and into business. 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. Mbiti and Weil (2011) find that M-Pesa users send more transfers 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.

Wider impacts Riley (2016) 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, like us, Riley (2016) finds that the main beneficiaries are the users themselves, who weather the aggregate shocks without declines in average consumption.

3 Sample and Randomization

The experiment took place in two connected sites: (1) Gaibandha district in Rangpur Division in northwest Bangladesh and (2) Dhaka Dhaka Division, the administrative unit in which the capital is located. Bangladesh has a per capita income of 1212 dollars per year (World Bank, 2016) and headcount poverty rates of over 30 percent (World Bank, 2010). Gaibandha is in one of the poorest regions of Bangladesh, with a headcount poverty rate of 48 percent and, historically, exposure to the *monga* seasonal famine 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.

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. This program was targeted to the "ultra-poor" in and around Gaibandha.[3] We restricted the sample to households in Gaibandha with workers in Dhaka. Beginning from this roster, we then snowball-sampled additional Gaibandha households and with migrant members in Dhaka to reach a final sample size of 815 migrant-household pairs. 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).

Participants were recruited between September 2014 and February 2015. The baseline

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

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.

Baseline survey summary statistics for the sample by treatment status are shown in Table 1. P-values are given for tests of differences in means for these variables, showing balance on observables for assignment to treatment or control in the main experiment (and F-test similarly shows balance). Table 1 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 age, and many other variables of interest.

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 formal employees, 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 the treatment group was $17356/7 = 2479$ Taka, which is nearly one third of monthly migrant income ($2479/7830 = 31.7\%$).

Most rural households (75%) are poor as measured by the local poverty line in 2014. Moving to the global $1.90 poverty line (measured at 2011 PPP exchange rates and converted to 2014 taka with the Bangladesh CPI), 51% are poor, and the median spending level of rural households is approximately equal to the poverty threshold. These poverty figures are comparable to the sample analyzed by Bandiera et al (2016) in which 53% of the Bangladesh "ultra-poor" sample was below the global poverty line at baseline.[4]

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 less than three years in Dhaka prior to the study and working less than 2 years of tenure at their current job. 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.

At baseline, income from remittances was already an important income source for rural households. The largest share of rural household income (65%) came from wage labor, and remittances from the paired 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.

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.

[4] The Bandiera et al (2016) 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. As such, the international poverty line at 2016 prices = 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.) In comparison, the 2016 Bangladesh urban poverty line is 92.86 Taka, and the 2016 Bangladesh rural poverty line is 74.22 Taka.

Table 1: 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)	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	24.0	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 in past 7 months, urban (‘000)	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 upazila	0.50	0.50	413	0.53	0.50	402	0.456
Other upazila	0.50	0.50	413	0.47	0.50	402	0.456

p-value of F-test for joint orthogonality = 0.954.

4 Experimental Intervention and Empirical Methods

We conducted the experiment in cooperation with bKash, a subsidiary of BRAC Bank and the largest provider of mobile banking services in Bangladesh.[5] The bKash service has experienced rapid growth in accounts since its founding, and our study took advantage of a window before the service had reached high levels of penetration in 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; for example, if requested, our field staff assisted with gathering the necessary documentation for signing up for bKash and completing the application form. In addition to the training and technical assistance, a small amount of compensation (approximately three dollars) was provided for participating in the training, but this was not made contingent on adoption of the bKash service.

Mobile banking services in Bangladesh use Unstructured Supplementary Service Data (USSD) menus. The USSD menus provide a big advantage by allowing the 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 included learning the basic steps and protocols of bKash use, and practical, hands-on experiemce sending transfers five times to establish a degree of comfort.[6] The training materials were based on marketing materials provided by bKash and

[5] 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.

[6] 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

were simplified in order to be as accessible as possible to the target population. Since the phone menus are in English, we also provided menus translated into Bangla (Bengali).

The household survey data collected in 2014/15 and 2016 was combined with administrative data from bKash to estimate impacts. For most outcomes, we estimate intention-to-treat (ITT) effects using the following 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 treatment-on-the-treated (TOT) effects using an instrumental variables (IV) approach. 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 made by accounts in the study population. We then present IV regressions that instrument for *Active bKash account* using treatment assignment. The exclusion restriction here is satisfied as any impact from the treatment acts through active use of the bKash accounts.

In studying the impacts of the intervention on a range of outcome indicators, we address problems of multiple inference by creating broad"families" of outcomes such as health, education, and consumption. To do so, we transform outcome variables into z-scores and create

their family as well as for themselves as individuals. 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. This paper focuses on the first randomization, that of assignment of a household-migrant pair to the bKash training intervention and control.

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 earnings, we collected monthly data (for the current month and the previous six). To exploit the temporal variation in these variables within households, we estimate equation (2) on the stacked baseline and endline household-month level data:

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

Here , $\beta_{3,t}$ captures month fixed effects and $\beta_{4,i}$ refers to household fixed effects. $Endline_t$ is a dummy variable capturing an endline observation. The coefficient of interest is β_2, the coefficient on the interaction between $Treatment_i$ and $Endline_t$. This coefficient captures the difference in the dependent variable at endline between migrants in the treatment group and migrants in the control group, after controling 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.

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 together with simple hands-on experiences with the mobile money service. The focus on practical use of bKash (and specific guidance on how to sign up) were designed to overcome these barriers.

Table 2: 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***	0.48***
	(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.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The impact of the training intervention was substantial, partly reflecting the newness of mobile banking in Bangladesh, especially in Gaibandha and the poorer communities. Table 2 presents results from the first stage of the instrumental variables (IV) regressions. Columns (1) and (2) show that households in the rural treatment group were 48 percentage points more likely to have an active 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 treatent 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 third and fourth columns of Table 2 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.

The treatment group sent larger remittances than the control group, and Figure 1 shows monthly remittances (from all sources) drawn from the endline survey. While a large mass of migrants sent no remittances or very little in a given month (less than 1000 Taka = $13 in 2016), many sent large amounts, and migrants in the treatment group were more likely to send larger sums than migrants in the control group. A Kolmogorov-Smirnov test confirms that the distributions in Figure 1 are significantly different between the treatment and control groups at p-value = 0.04.

Figure 1: Monthly Remittances Sent

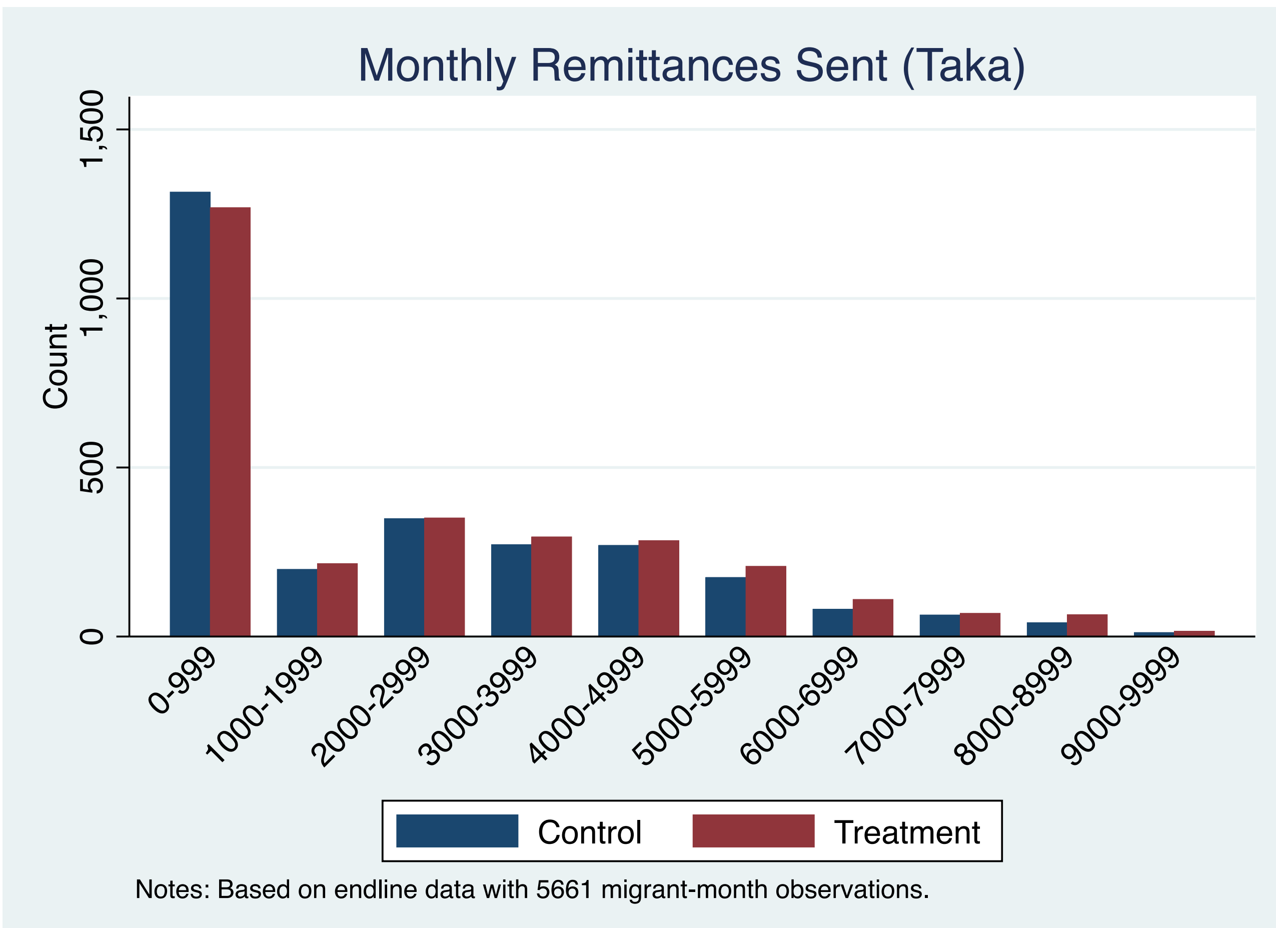


Table 3: Remittances Sent

	(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
Control Mean (Endline)	2198	2198	1162	1162	0.22	0.22
Observations	10,526	10,526	10,526	10,526	10,526	10,526

Standard errors in parentheses, clustered by household.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: 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.

The increase in remittances sent by migrants is summarized in Table 3. The table gives regression results for remittances sent by migrants to the rural households, based on data on monthly remittances sent in the past seven months data captured in baseline and endline surveys. All regressions control for household-level and month fixed effect. Column (1) shows a large intention-to-treat impact of the treatment on remittances sent (from all sources); migrants in the treatment group sent 14% more remittances at endline (316.1 on a control mean base of 2197.8) than migrants in the control group (statistically significant at a p-value of 0.053). Column (2) presents treatment-on-treated results that account for active use of the bKash accounts. The 660.6 coefficient in the second row of column (2) indicates a 30% increase in the value of remittances sent by migrants in the treatment group induced by the experimental intervention to use bKash (661/2198). There is considerable heterogeneity in the samples, though, and the estimate is fairly noisy.[7]

The third and fourth columns of Table 3 present results for bKash remittances sent (in contrast to the results on remittances from all sources). It is no surprise, given that the intervention focused on bKash, that the impacts here are large. 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, controling for differences between baseline and endline, month fixed effects, and household fixed effects. This number is slightly higher 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

[7] 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 TOT 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.

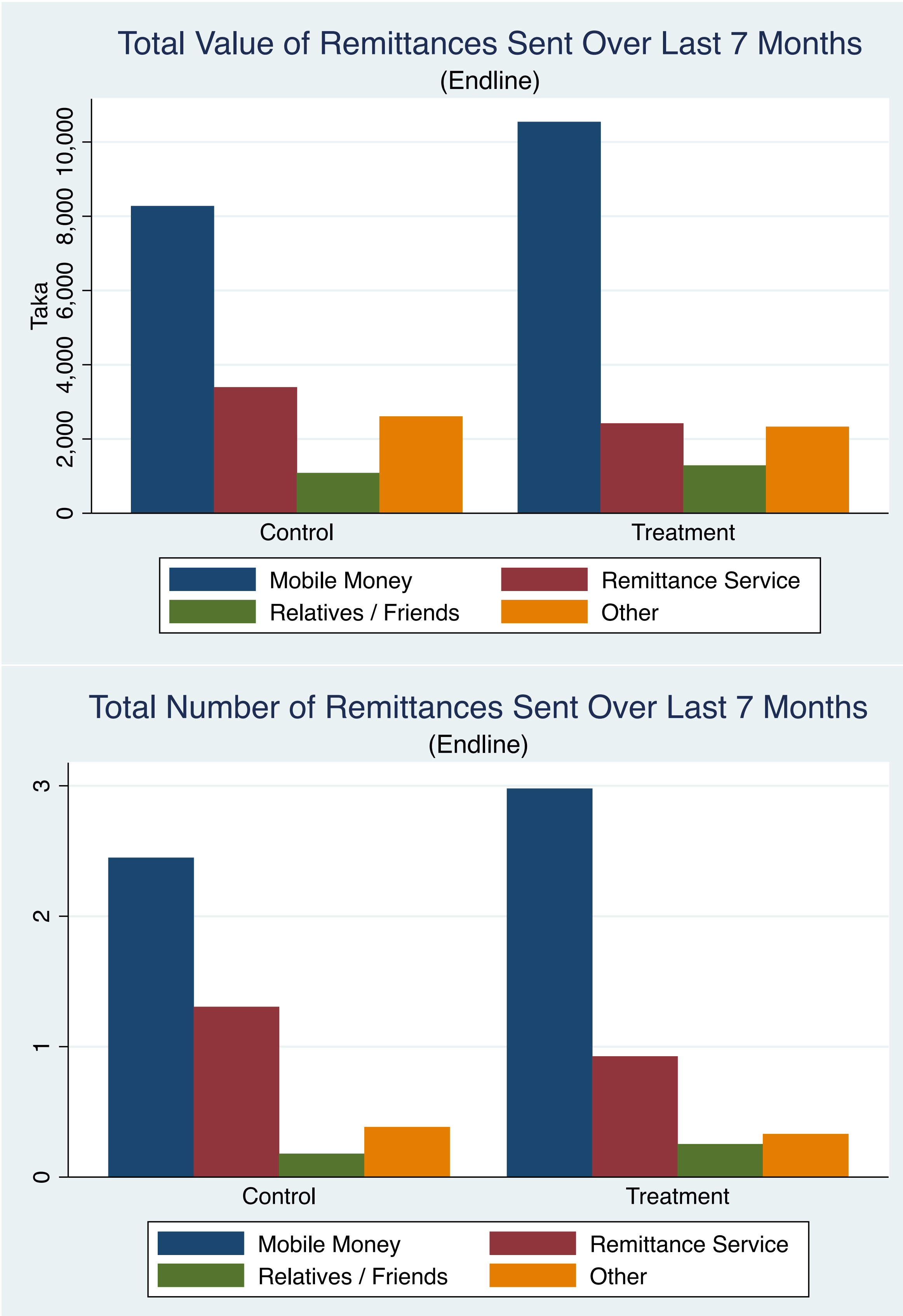
(6) show that migrants also sent a substantially higher share of their income as remittances relative to the control group. The TOT results in column (6) show that the share of income sent as remittances increased by 28% relative to the control group mean (0.062/0.22).

In addition to remitting via mobile money, 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 2.

The top panel of Figure 2 shows a 27% (10540/8270) increase in the value of remittances sent using mobile money, which is similar to the 30% increase in the total value of remittances seen in Table 3.[8] The bottom panel of Figure 2 gives the frequency of remittances. Overall, there is no 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). In sum, the value of remittances increased, but not their frequency.

[8] It is notable that mobile money remittances form 52% of total remittances for the control group, though only 21% of migrants in the control group have an active bKash account. There are two reasons. First, migrants with active bKash accounts in the control group chose to sign up for bKash of their own accord (i.e., without the experimental training intervention). Having an account thus signals particular interest in remitting money, and it is not surprising that they remit more than the average migrant in the treatment group with an active account. Second, there is likely some mis-classification in the self-reported data: some respondents said that they remitted money using "mobile money" when, in fact, they used a bKash agent to perform an agent-assisted (also known as over-the-counter) transaction. An active bKash account is not required for such a transaction. A comparison of the endline data and bKash administrative data confirms this for the control group.

Figure 2: Value and Number of Remittances Sent, By Type

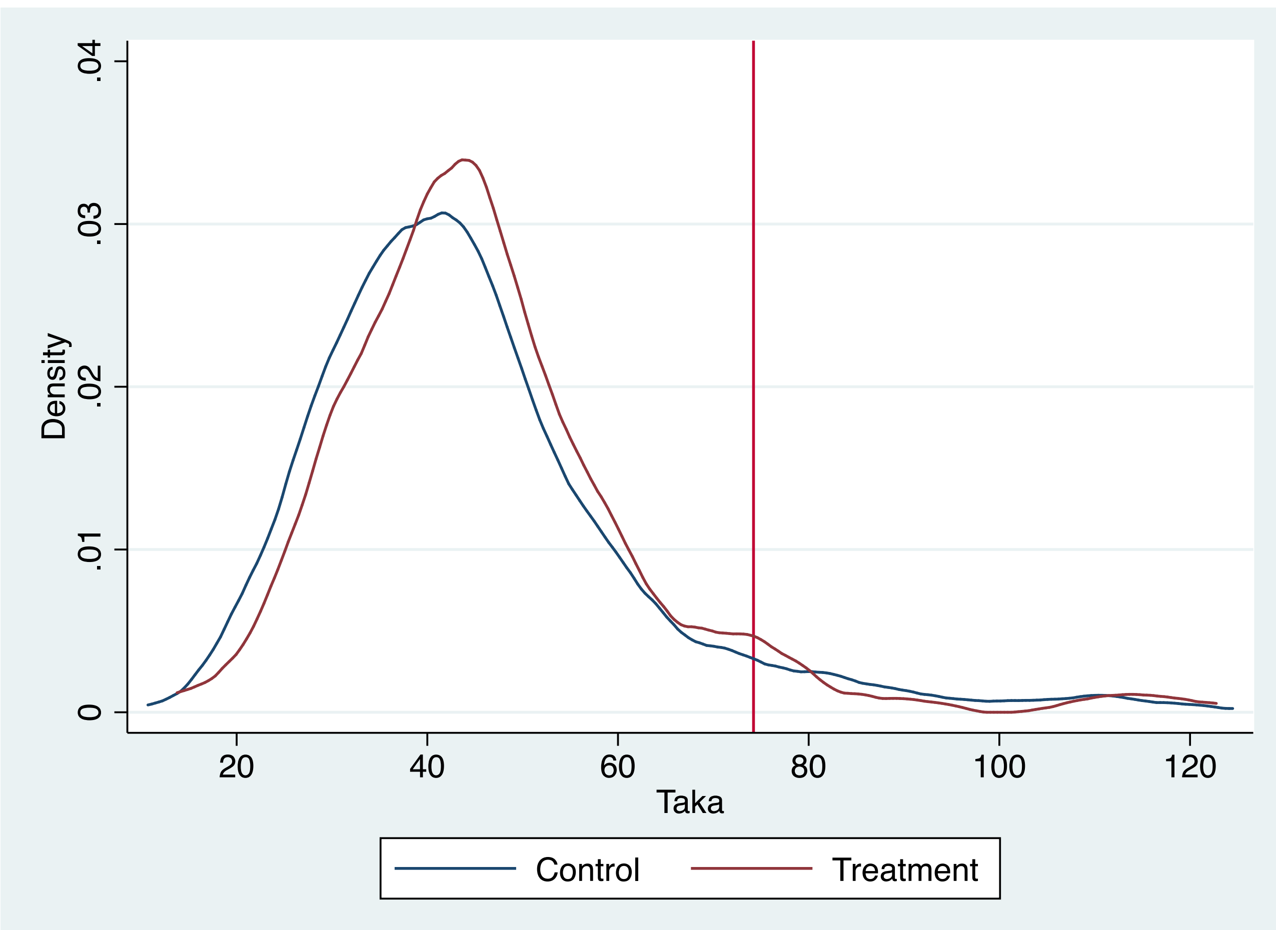


5.2 Impacts on Rural Households

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

The roughly 30% 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 3 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).

Figure 3: Kernel Density Plots of Per Capita Daily Expenditure (Endline)



The vertical red line in Figure 3 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 4 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:

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

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 4 presents ITT and TOT regressions showing a TOT decrease in the extreme poverty metric by 0.038 relative to a control mean of 0.20, a decline of 19% (statistically significant at the 5% level). These results could result directly from the large increase in remittances received by treatment households and from changes in economic activities (to be explored further below).

Table 4: 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**	0.14**	0.171*	0.022
	(0.02)	(0.009)	(0.053)	(0.094)	(0.068)
Treatment-on-treated:					
Active bKash Account	0.02	-0.038**	0.285**	0.35*	0.05
	(003)	(0.018)	(0.11)	(0.19)	(0.14)
R^2 (ITT)	0.02	0.18	0.39	0.03	0.02
R^2 (ToT)	0.04	0.16	0.38	0.02	0.02
Control Mean (Endline)	0.77	0.20	0	0	0
Observations	813	813	813	397	813

Standard errors in parentheses.

All regressions are estimated with baseline control variables and the baseline dependent variable.

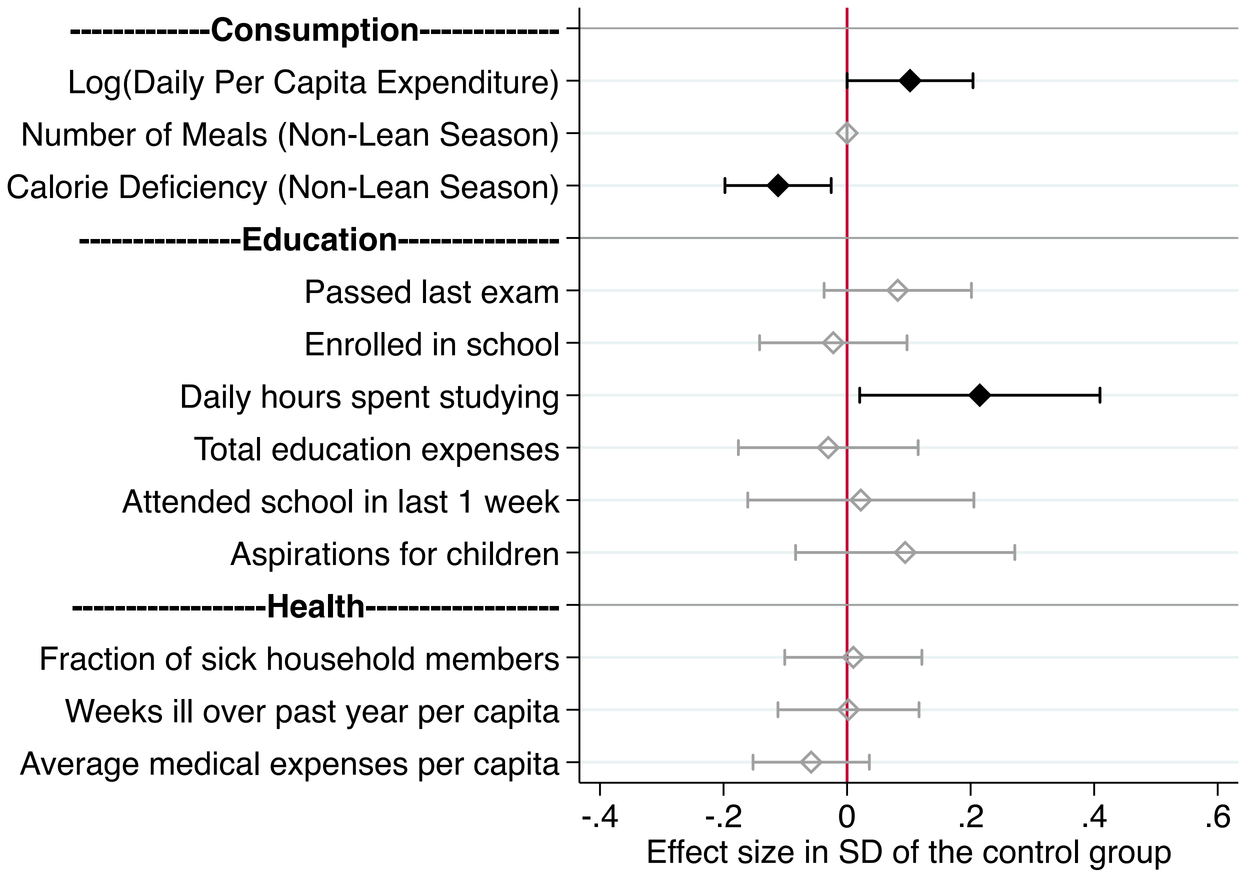
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 4 presents treatment effects on consumption, education, and health. The first row of the figure shows an intention-to-treat increase on the log of daily per capita expenditures of 0.1 of a standard deviation. The associated treatment-on-treated coefficient implies daily per capita expenditures 7.5% greater in the treatment group than the control. 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 deficiency was reduced, however, in the treatment group by 0.11 of a standard deviation (a reduction of 10.4%). As the rightward shift of the treatment distribution in Figure 3 shows, the treatment impact is largest at the bottom of the distribution, i.e. for the poorest households. [9]

We constructed a consumption index for each household using the three consumption variables in Figure 4 and two consumption variables in Figure 5, with equal weight given to the variables. The index is standardized to reflect standard deviation units of the control group. The signs of the calorie deficiency variable were reversed so that a decrease in calorie deficiency is an improvement in the consumption index. Column (3) of Table 4 shows that the treatment increased the consumption index of households in the treatment group by 0.14 standard deviation units. The TOT result shows an increase in the consumption index by a relatively large 0.29 standard deviation units relative to the control group (statistically significant at the 5% level).

[9] 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). Calorie deficiency was then computed as the difference between the calorie needs and the calorie consumption of the household. Calorie deficiency provides a more accurate measure of the nutritional status of the household as opposed to calorie consumption, as it takes into account household member-specific calorie needs. This is important, as 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.) Failing to take into account this difference in calorie needs between treatment and control groups will result in an inaccurate picture of the nutritional status of the rural households.

Figure 4: Impact on Consumption, Education, and Health



Notes: Each line shows the OLS point estimate and 90 percent confidence interval for the outcome. 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. Consumption and health: 813 observations. Education: 397 observations.

The treatment effects on child education in Figure 4 are from regressions run at the household-level for 397 households with at least one child aged 5-16 years. All regressions were run using standard OLS, with the exception of aspirations for child education, which was run using an ordered logit over a list of ordered categories that included high school, college, and post-graduate studies.[10] We see a positive treatment effect on the average number of hours spent studying per day (0.21 of a standard deviation). In absolute terms, children of households in the treatment group that actively used bKash spent 0.52 hours more studying per day than children in the control group (baseline control average 2.55 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.

There are at least three ways through which the intervention could have caused children in treated households to increase their study hours. First, it is possible that parents used remittances sent via bKash to increase expenditure on child education. However, we do not see this in Figure 4. 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, it is possible that children may be substituting study hours with time spent helping out in agriculture and/or other business activities of the household, consistent with the evidence on the fall in child labor.

The final three rows of Figure 4 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 per capita, and the average medical expenses per capita. We do not see any significant treatment impacts on these variables.

Table 4 presents results on education and health indices using the variables in Figures 4, with equal weight given to the variables. The education index was only constructed for the

[10]We obtain a larger coefficient and smaller p-value when standard OLS is used instead.

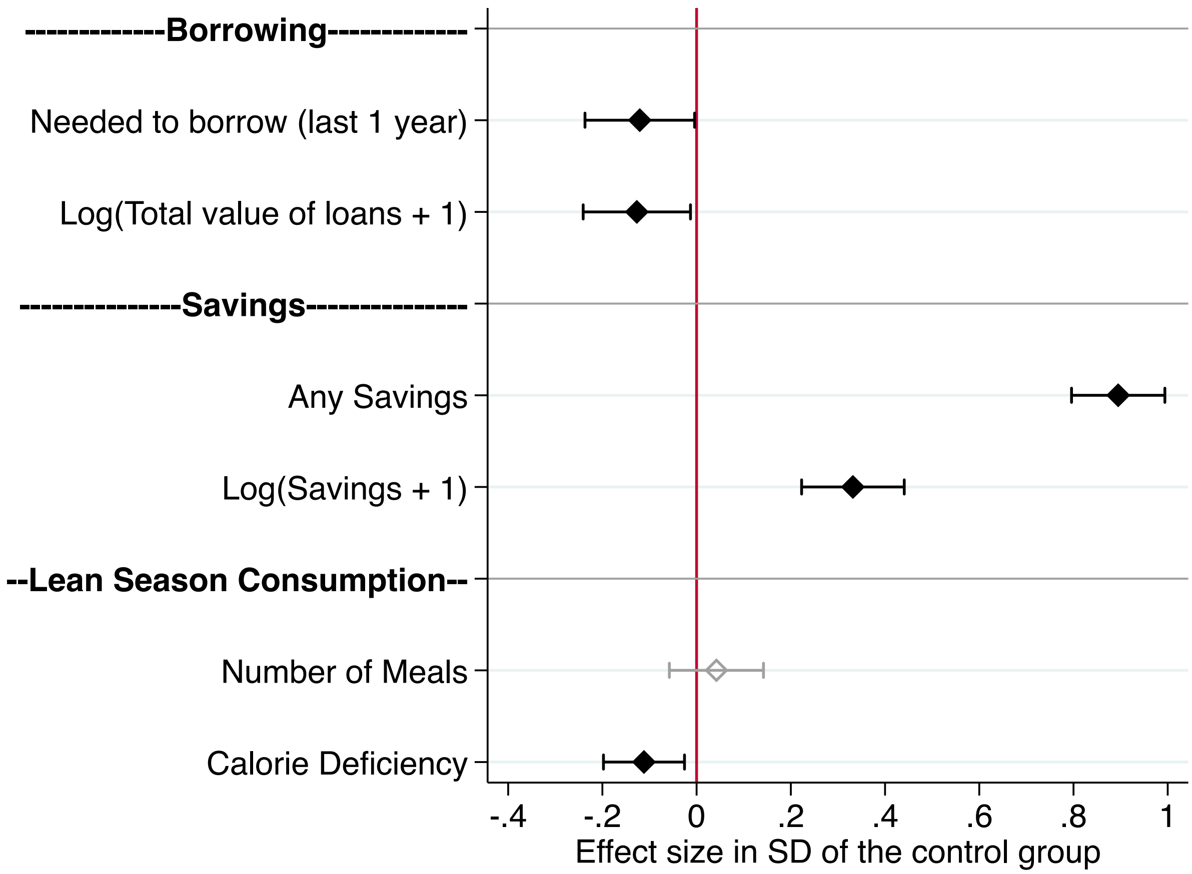
397 households with at least one child aged 5-16 years. The sign of the health index has been reversed so that a decrease in the fraction of sick household members, for example, is an improvement in the health index. Column (4) of Table 4 shows that children in the treatment group saw an increase in the education index by 0.17 standard deviation units (ITT) and 0.35 units (TOT), though noisily measured. Column (5) shows no overall treatment impact on health, consistent with Figure 4.

5.2.2 Liquidity and Timing Effects: Borrowing, Saving, and Lean Season Consumption

Figure 5 presents treatment effects on borrowing by rural households. Households that actively used bKash accounts in the treatment group were 12.2 percentage points less likely to need to borrow than households in the control group (at endline, 60.9% of households in the control group borrowed in the previous year). The total value of loans among treatment households was 882 Taka lower than that among the control group, on a control mean base of 4039.5 Taka. The use of log(total value of loans + 1) as shown in the figure combines the extensive and intensive margins of borrowing. The results indicate that easier access to transfers from migrants sharply reduced the need of rural households to borrow. These large magnitudes are consistent with the magnitudes of transfers: the total size of loans taken over the last 12 months was 6798 Taka at baseline, and monthly remittances are large in comparison (2198/6798 = 32.3%).

Figure 5 shows 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, on a control mean base of 42%. This is because bKash acts 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 log(savings + 1) are not conditional on having saved, and thus combine the extensive and intensive margins of savings. Households in the treatment group saved 120% more than households in the control group. Accounting for active use of the bKash accounts gives a TOT impact of 248%. These estimates are large and statistically significant at the 1% level. The borrowing and saving results are summarized in the first four columns of Table 5.

Figure 5: Impact on Borrowing, Savings, and Lean Season Consumption



Notes: Each line shows the OLS point estimate and 90 percent confidence interval for the outcome. 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.

Table 5: Borrowing, Saving, and Lean Season (*Monga*) Consumption

	(1) Any Borrowing?	(2) Log Loan Value	(3) Any Saving?	(4) Log Savings	(5) No *Monga* Problem?
Intention-to-treat:					
bKash Treatment	-.059*	-0.51*	0.44***	1.20***	0.044**
	(0.035)	(0.28)	(0.03)	(0.23)	(0.021)
Treatment-on-treated:					
Active bKash Account	-0.122*	-1.05*	0.92***	2.48***	0.092**
	(0.071)	(0.571)	(0.066)	(0.047)	(0.045)
R^2 (ITT)	0.02	0.05	0.22	0.04	0.01
R^2 (ToT)	0.02	0.04	0.11	0.03	0.00
Control Mean (Endline)	0.61	4.56	0.42	2.53	0.082
Observations	813	813	813	813	813

Standard errors in parentheses.

All regressions are estimated with baseline control variables and the baseline dependent variable.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Column (2) dependent variable is logarithm(total loan value +1).

Column (4) dependent variable is logarithm(total savings value + 1).

Column (5) 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*.

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 5). However, households in the treatment group had less of a calorie deficiency than households in the control group (a reduction by 0.11 of a standard deviation) during the lean season. In absoute terms, households that actively used their bKash accounts in the treatment group saw a 11% decrease in calorie deficiency during the lean season relative to the control group (statistically significant at the 5% level).The decrease in calorie deficiency during the lean season is consistent with the bility that bKash provides migrants to more easily time remittances during the lean season when households are hit the hardest, but it is also consistent with rural households saving more on their own.

Column (5) of Table 5 summarizes the lean season impact with a result on the proportion of households who no longer found *monga* (the lean season) to be a problem. 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. On a control mean base of 8.2%, this represents a large, 112% increase. For households that declared *monga* to still be a problem, the key coping strategies were purchasing goods on credit and drawing down savings. We found no significant differences in strategies used by the treatment and control groups.

5.2.3 Liquidity and financing effects: Migration and Labor

Remittance income can re-shape economic choices, possibly financing investment and overcoming financing constraints. In this section, we focus on three key contributors to rural household income: migration, wage labor, and self-employment. One channel of impact for mobile banking is through facilitating the migration of other household members beyond the original migrant. The first column of Table 6 shows a treatment-on-treated decrease in household size in household size by 0.28 household members for the treatment group relative to the control group. This is consistent with the TOT 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 control group mean household size at endline of 4.02 household members (a 6% change), and it is large relative to the control group mean rate of migration of 0.60 household members (a 42% increase).[11]

There are at least five mechanisms. 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. Transport costs aside, the initial costs of housing and job search are also important considerations in the migration decision. Second, household members in the treatment group could have revised their priors on expected income from migration upon observing larger remittances received. When such migrants were asked at endline their primary reason for migrating for work, 89.8% said that an expectation of a higher income was the main reason for migrating. Third, migrants in the treatment group may have been able to form stronger employment networks, thereby inducing further migration to Dhaka. In line with this, we show below that that migrants in the treatment group are more likely to find employment in certain sectors, particularly in garments work. Fourth, access to bKash makes sending remittances easier, raising the effective return to migration. Fifth, migrants in the treatment group could have encouraged further migration to help shoulder the stress and burden of having to remit more money home. We are not able to disentangle the relative importance of the five factors.

[11]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 more than or equal to 312 days in the past year (more than or equal to 6 days per week) in Dhaka were classified as migrating for work. (Migration here refers to permanent migration, as opposed to seasonal migration, which is very common in Bangladesh.)

Table 6: 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)
Treatment-on-treated:					
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 (ToT)	0.52	0.04	0.13	0.41	0.00
Control Mean (Endline)	4.02	0.60	0.71	0.17	0.05
Observations	813	813	813	813	397

Standard errors in parentheses.

All regressions are estimated with baseline control variables and the baseline dependent variable.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Column (3) of Table 6 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 1 household member is engaged in wage labor. Notably, 71% of households in the control group at endline engaged in some wage labor. We see that households in the treatment group that actively used bKash accounts were 0.12 percentage points, or 17% less likely to engage in any wage labor. This is driven by a decrease in the number of wage laborers in households in the treatment group, though this decrease is only significant at a p-value of 0.13. 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 sel-employment by providing capital for investment and by providing a financial cushion that encourages risk-taking. Column (4) of Table 6 presents results on the number of household members engaged in self-employment. The treatment-on-treated 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 control group mean of 0.17, this represents a large, 45% 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 12 of 397 at endline), so analysis of child labor is exploratory. Column (5) of Table 6 shows a relative decrease in the number of households engaged in any child labor in the treatment group, although on a very low base. The ITT results imply that child labor decreased by 88% in the treatment group relative to the 5.4% of households with children in the control group 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.[12]

5.2.4 Liquidity and financing effect: Agriculture

Most workers in the rural sample are involved in wage work, but some are farmers. The results on agriculture should be seen as exploratory since sample sizes are small: 27 observations in the *Aman* season sample and 60 observations in the *Boro* season sample. As a result of the the small samples, standard errors are large and outliers are a concern. Still, we see suggestive evidence that remittances are especially large during the *Boro* season, the irrigated rice season requiring outlays for irrigation and related inputs.

Figure 6 uses administrative data from bKash to show patterns of remittances within

[12]The TOT result seems to show that child labor is more than eliminated in the treatment group, a coefficient that seems "too large" in the context here, but the treatment effect should be interpreted against the control trend. The number of child laborers increased from 0 to 2 in the treatment group and from 4 to 10 in the treatment group. We would need a much larger sample to say anything precise about child labor and the statistical significance here is likely a function of the small sample, rather than an accurate assessment of precision.

the year sent by the treatment group. Figure 6 reveals significant seasonality in the value of remittances sent per active account. The spikes in remittances roughly coincide with the harvest periods of the agricultural seasons: *Aman* planting (July and August), *Aman* harvest (rainfed, November), and *Boro* (irrigated, January-June). These remittances may help to offset labor and other costs incurred during the harvest and planting periods. A decrease in remittances sent is seen in the months immediately after the Eid festivals, possibly due to a decrease in income earned during the festival months or because migrants returned home during Eid bringing gifts.

Figure 6: Total Value of bKash Remittances Sent Per Active Account in Treatment Group

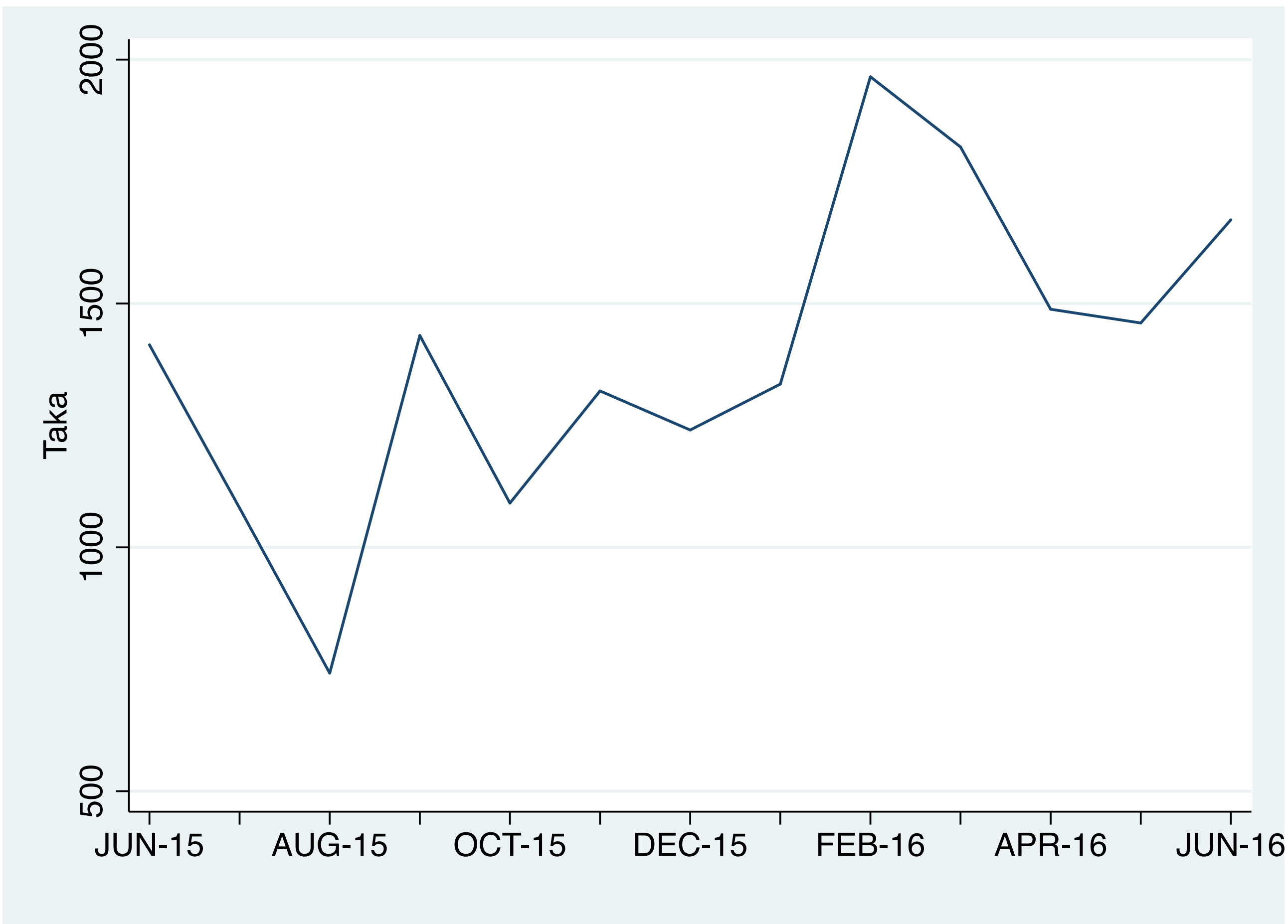
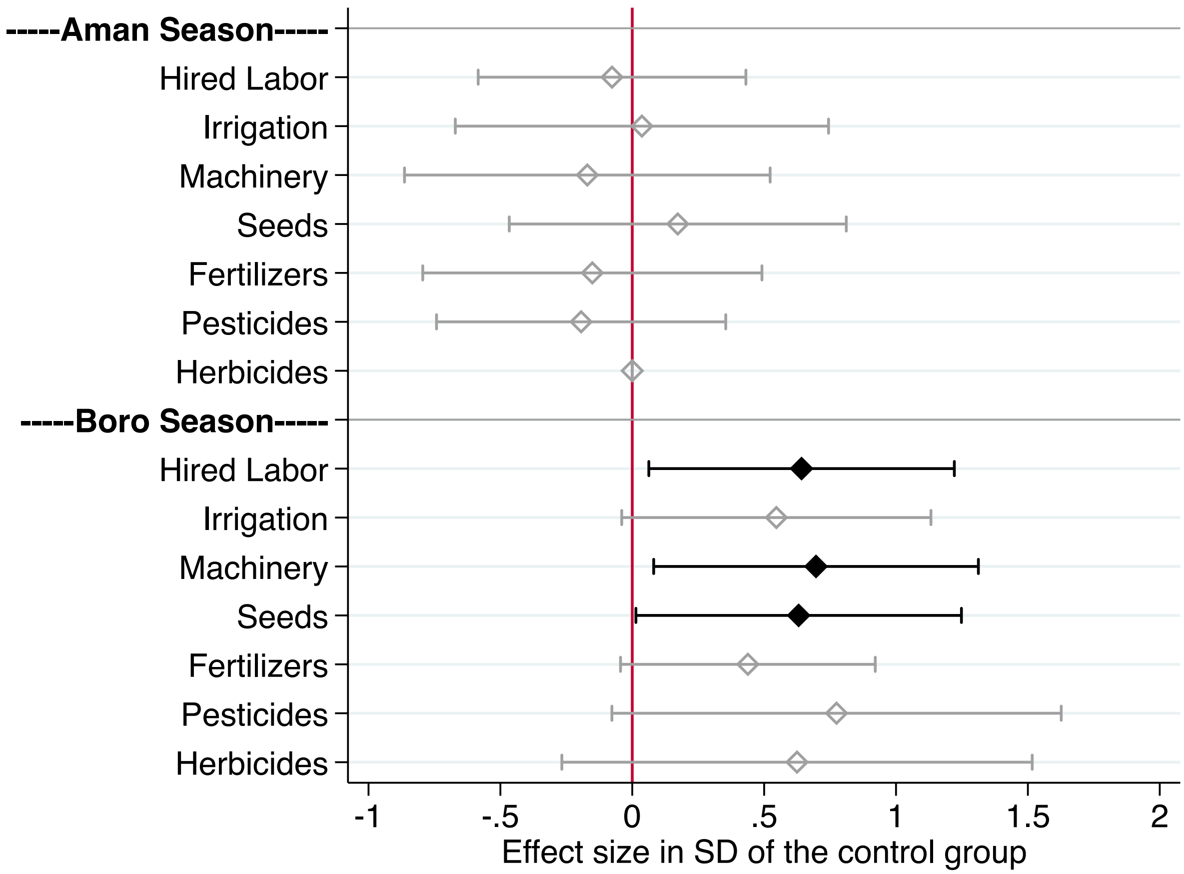


Figure 7: Expenditure on Agricultural Inputs



Notes: Each line shows the OLS point estimate and 90 percent confidence interval for the outcome. 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. Regressions for the *Aman* season have 27 observations. For *Boro*: 60 observations.

Figure 7 presents the impacts on the intervention on agriculture during the two main agricultural seasons, *Aman* and *Boro*. *Aman* season, which typically runs from July to December, is rain-fed and requires fewer purchased inputs. *Boro* season, which typically runs from January to June, is irrigation-fed and requires substantially more inputs, such as High Yielding Variety (HYV) seeds. Since the ultra-poor nature of the sample means that few households owned land sufficient to farm on a meaningful scale (excluding wage labor on agricultural plots for others), the results should be treated with caution as the regressions run are conditional on farming (and that, itself, may be endogenous).

We see little impact of the treatment during the *Aman* season. Coefficients are a mix of positive and negative coefficients and confidence intervals are wide. In contrast, however, all coefficients on inputs during *Boro* are positive, and some are very large. For example, the regressions show an increase in expenditures on hired labor by 0.64 standard deviation, machinery by 0.70, and seeds by 0.63 during the *Boro* season, all of which are statistically signifiant. The small sample sizes (27 observations for *Aman* farming and 60 for *Boro*) and correspondingly wide standard errors mean that the results on expenditures on irrigation, fertilizers, and pesticides are not statistically significant at the 10% level (p-values are 0.12, 0.13, and 0.13 respectively). Taken together, households engaged in agriculture during the *Boro* season in the treatment group invest more in agricultural inputs relative to the control group. Panel A of Table 7 shows that the *Boro* input index increased substantially by 0.86 standard deviation units (significant at the 10% level).

To explore whether the increase in inputs was due to the timing of remittances, we investigate whether migrants in the treatment group whose paired households engaged in Boro cultivation at endline sent more remittances during the months of the *Boro* season. Given the small sample, we regard these regressions as exploratory. For the results presented in Panel B of Table 7, we supplement the panel regression specification (2) with dummies for *Boro* month and any *Boro* cultivation, as well as all possible interactions between the variables Endline, Treatment, *Boro* Month, and Any *Boro* Cultivation.

Table 7: Results for Agriculture

Panel A:		
	(1)	(2)
	Aman Input Index (OLS)	*Boro* Input Index (OLS)
bKash Treatment	-0.0808	0.863*
	(0.354)	(0.450)
R^2	0.091	0.161
Baseline Controls	Yes	Yes
Baseline Dependent Variable Control	Yes	Yes
Endline Control Group Mean	0	0
Observations	27	60

Panel B:		
	(1)	(2)
	Value of Remittances (OLS)	Value of Mobile Money Remittances (OLS)
Treatment $*$ Endline $*$ *Boro*	1243.0^{+}	1146.1^{+}
Month $*$ Any *Boro* Cultivation	(848.7)	(734.9)
R^2	0.291	0.442
Baseline Controls	No	No
Month Fixed Effects	Yes	Yes
Household Fixed Effects	Yes	Yes
Endline Control Group Mean	2197.8	1161.6
Observations	10526	10526

Notes: Controls in Panel B include Endline, Treatment, *Boro* Month, Any *Boro* Cultivation, and all possible interactions between these variables. *Boro* Months are January to to June (inclusive). Standard errors in parentheses. Standard errors clustered by household in Panel B only.

$^{+}$ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Panel B of Table 7 shows that the coefficient on the quadruple interaction term is large in columns (1) and (2), though not statistically significant at conventional p-values. The value of remittances increases by 1243 taka relative to a control endline mean of 2198 taka. This implies that migrants in the treatment group send substantially larger remittances during the months of the *Boro* season when their paired households are engaged in *Boro* cultivation at endline.[13] The results provide suggestive evidence that both the value and timing of remittances matter for the results on agriculture.

5.2.5 Wider impacts: Spillovers to non-users

As Riley (2016) argues based on her work in Tanzania, the impacts of mobile money may spill widely since the technology facilitates movement of money into rural areas, including during times of generalized shortages. The benefits of liquidity may filter through the community from users to non-users.

There is a second concern which is specific to the experimental set-up. Randomization took place at the individual level, not at the village level. Thus, there might be spillovers from the treatment group to the control group. Those spillovers may be good for the control group but problematic for interpretation of the results above since the control group is contaminated in a statistical sense.

In this section, we check for potential spillovers in the rural and urban samples using variation in treatment density to assess the likelihood of spillovers. Treatment density here is defined as the ratio of the number of treatment households to total households surveyed in a given geographic unit. We study two key outcome variables of interest, bKash adoption and active bKash accounts, obtained from the bKash administrative data. Evidence of increased bKash adoption or use within the control group in areas with higher treatment density would indicate spillovers from the treatment group to the control group.

[13]We do not observe similar results for the number of remittances sent, although the estimated coefficients are positive. Although it is possible that "Any *Boro* Cultivation" could be endogenous, we do not observe a treatment impact on this variable.

Table 8 presents results for the spillover analysis for rural households. Here treatment density was defined at the village level.[14] Column (1) presents results for bKash adoption and column (2) presents results for active bKash accounts.[15] Control group households in villages with a higher treatment density were not more likely to adopt bKash or have active bKash accounts. In fact, all the point estimates are negative in Panel A, showing that if anything, control group households in villages with a higher treatment density were *less* likely to adopt bKash and have active bKash accounts. As a further check, we ran the regressions using logit and probit specifications, and the results remained insignificant. As such, we see no significant spillovers owing to bKash adoption and active use in the rural sample.

It is also possible that spillovers occur in villages with higher treatment density due to sharing of incoming remittances (Emma Riley, 2016). We can directly test for this in the data, and the results are in column 3 of Panel A. As Riley (2016) found, there is no evidence of consumption spillovers. In fact, the point estimates are negative when we consider potential spillovers to daily per capita expenditures.

[14]We repeated the analysis at a higher geographic level, the union level, and the results remained insignificant. Households in the study were part of 281 villages in 35 unions in Bangladesh.

[15]We were only able to obtain bKash administrative data for the one-year period from June 2015 to June 2016, while the intervention took place in April and May 2015. As such, we are unable to control for the baseline values of the dependent variables in this analysis.

Table 8: Spillover Analysis

	(1) Adopted bKash?	(2) Active bKash Account?	(3) Daily per capita Spending	(4) Consumption Index
Panel A: Rural				
Treatment Density	-0.038	-0.027	-1.21	0.54
	(0.098)	(0.088)	(11.41)	(0.55)
R^2	0.01	0.02	0.20	0.46
Control Mean (Endline)	0.30	0.22	44.8	0
Observations	402	402	402	402
Panel B: Rural				
Nearest neighbor	0.017	0.092		
adopted bKash	(0.080)	(0.089)		
R^2	0.01	0.00		
Control Mean (Endline)	0.30	0.22		
Observations	402	402		
Panel C: Urban				
Treatment Density	0.01	0.09		
	(0.17)	(0.16)		
R^2	0.07	0.05		
Control Mean (Endline)	0.23	0.22		
Observations	397	397		

Standard errors in parentheses.
First and third row coeffcients are from OLS regressions estimated with baseline control variables. Second row coeffcients are from IV regressions estimated with baseline control variables.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

As a further check, Panel B presents results that use the status of treatment assignment, bKash adoption, and active use of the nearest neighbor for each rural household. GPS co-ordinates of each rural household were recorded during our surveys, and this allows us to conduct the following analysis. In particular, we ask the following questions: (i) Are control group households whose nearest neighbor in our sample adopted bKash also more likely adopt bKash? (ii) Are control group households whose nearest neighbor in our sample actively used bKash also more likely to actively use bKash? Households whose nearest neighbor in our sample adopted or actively used bKash were not significantly more likely to adopt or actively use bKash. Taken together with the results on treatment density, the analysis shows no evidence of spillovers to the control group. These results speak to both the internal validity of our experiment, as well as the barriers to adoption of bKash in our setting.

We turn to the spillover analysis for urban migrants in Panel C of Table 8. Treatment density is defined at the city-*upazila* level, the lowest geographic level at which data was collected for migrants. Again, control group migrants in city-upazilas with a higher treatment density were not more likely to adopt bKash or have active bKash accounts. These results are robust to the use of logit and probit specifications.

5.3 Impacts on Urban Migrants

We next turn attention from rural households to urban migrants. Figure 8 presents kernel density plots of per capita daily expenditure separately for the treatment and control groups. The vertical red line depicts the urban poverty line of 98.6 Taka, which was constructed in a similar manner to the rural poverty line. The distribution of per capita expenditure has shifted to the right for the treatment group around the poverty line, but we cannot reject equality of the distribution functions. Figure 8 shows the basis for finding a drop in the poverty headcount – a decrease in the share of the urban treatment group (relative to control) with per capita daily expenditures below the poverty line.

Figure 8: Kernel Density Plots of Per Capita Daily Expenditure (Endline)

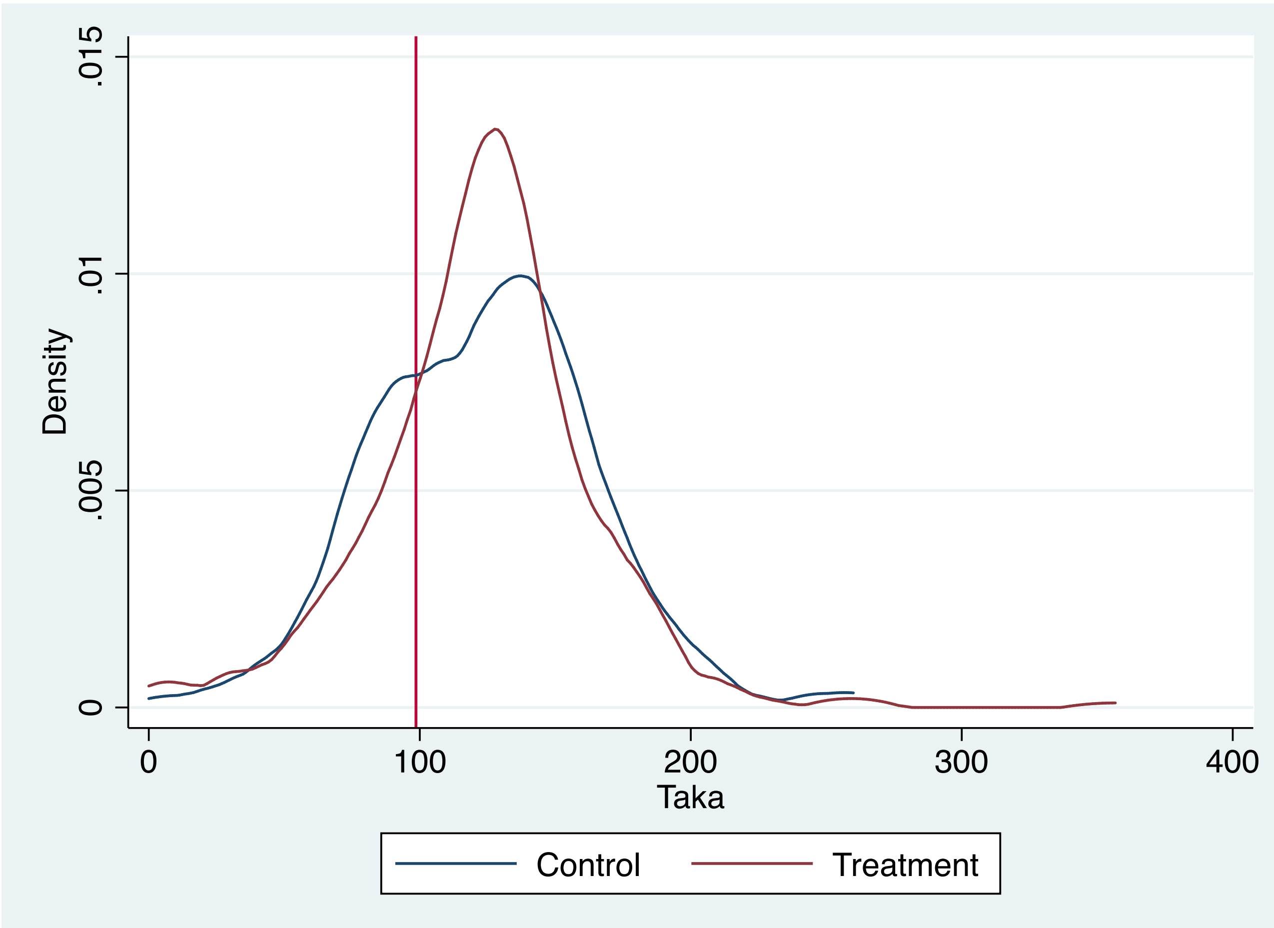


Table 9: Urban Labor, Poverty, Saving, and Health

	(1) Garment Worker?	(2) Poor?	(3) Any Saving?	(4) Log Saving	(5) Health Index
Intention-to-treat:					
bKash Treatment	0.053	-0.052*	0.180***	0.376	-0.129*
	(0.03)	(0.027)	(0.024)	(0.249)	(0.069)
Treatment-on-treated:					
Active bKash Account	0.11	-0.110**	0.381*	0.797	-0.275*
	(0.07)	(0.057)	(0.052)	(0.526)	(0.146)
R^2 (ITT)	0.03	0.14	0.09	0.04	0.09
R^2 (ToT)	0.03	0.14	0.07	0.04	0.09
Control Mean (Endline)	0.55	0.24	0.76	5.68	0
Observations	809	809	809	809	809

Standard errors in parentheses.

All regressions are estimated with baseline control variables and the baseline dependent variable. Column (4) dependent variable is logarithm(total savings value + 1).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Column (1) of Table 9 presents treatment effects on employment in the garments and textiles industry. Migrants in the treatment group that actively used 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 control mean base of 55% (p-value = 0.12).[16] (Below, we explore income and hours in the garment sector.)

Column (2) of Table 9 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, on a control mean base of 24.2% (p-value = 0.055).[17] The large points estimates suggest that bKash might serve as an effective poverty reduction tool for the urban poor, though below we note the costs associated with those gains.[18]

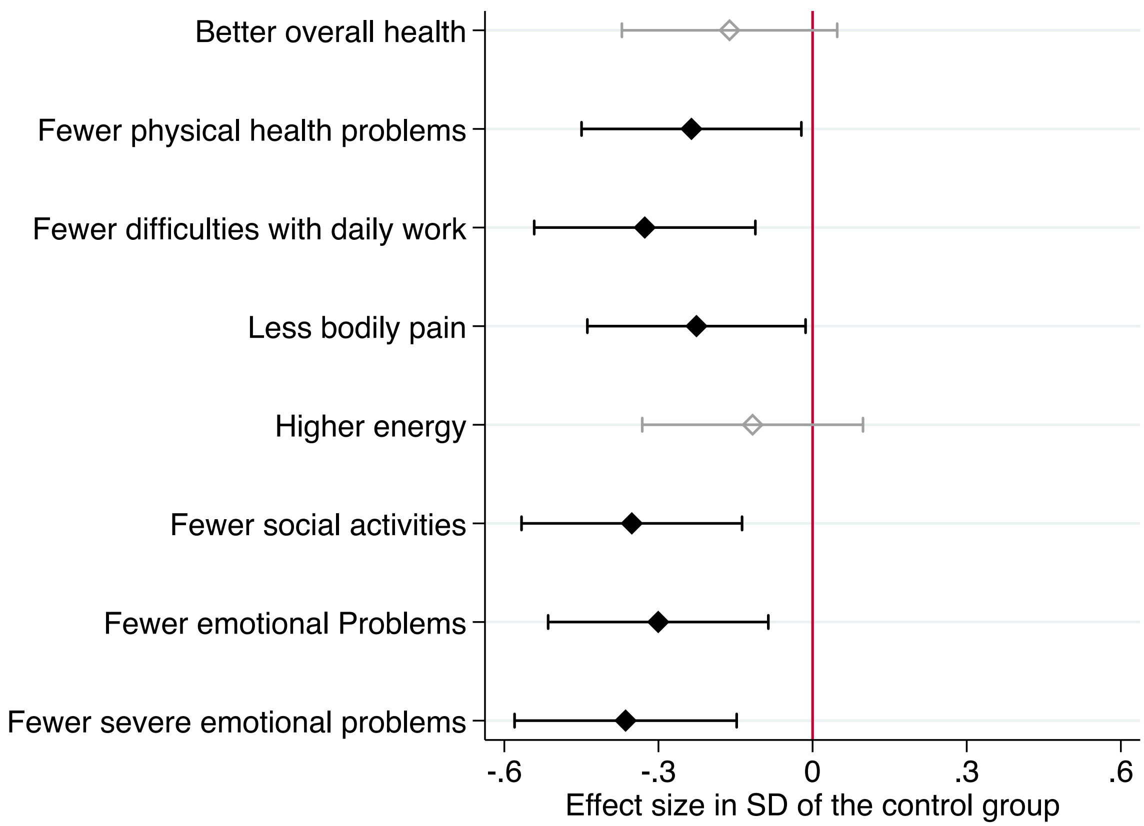
Column (3) presents results for the extensive margin on savings. Migrants in the treatment group that used their bKash accounts were 38 percentage points more likely to save, on a control mean base of 76%. This is because many migrants in the treatment group use their bKash accounts as a means of saving, 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 37.6% more than migrants in the control group (p-value = 0.09 without baseline controls, 0.13 with baseline controls). This result is not conditioned on having saved, and hence combines the extensive and intensive margins of savings.

[16] We did not collect occupation data at baseline and thus did not run these regressions 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 stay on in their current jobs in the garment sector (lower exit). Given that we saw in Table 1 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. An OLS regression of tenure in the current job on garments work, treatment indicator, and an interaction term between garments work and treatment yields a positive coefficient on the interaction term.

[17] The rate of poverty in the control group is very close to the latest urban poverty headcount ratio at national poverty line of 21.3% for Bangladesh, estimated by the World Bank.

[18] As a robustness check, we repeated the BPL exercise using per capita income instead of expenditures, and obtained qualitatively similar estimates. (We did not, however, find significant reductions in poverty for extremely poor migrants, as measured by the squared poverty gap.)

Figure 9: Impact on Migrant Health



Notes: Each line shows the point estimate and 90 percent confidence interval 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.

Figure 9 presents treatment effects on health of migrants using an ordered logit specification that captures qualitiative responses (e.g., options to the question on overall health were Poor, Fair, Good, Very Good, and Excellent).[19]

The treatment had negative impacts on the health of migrants. For example, migrants in the treatment group have more difficulties with daily work and more emotional problems. The negative health impact overall is shown in Column (5) of Table 9 below, which presents results for the health index variable, constructed with equal weight on each of the variables in Figure 9. The treatment decreased the health index by 0.13 standard deviation units, significant at the 10% level. The treatment-on-treated estimate shows a large decrease in the health index by 0.28 standard deviation units.

One channel for the negative health impact could arise from the increased stress of having to remit money home. We saw that migrants remit more money home by two means: (i) by remitting a greater fraction of their income home at endline in comparison to migrants in the control group (in the TOT results, the increase was an estimated 28%), and (ii) by choosing to stay in higher-paying occupations such as garment work (Table 10). However, garment work is a demanding occupation, and can having negative consequences for health.

To explore further, we present correlational regressions that describe garment workers. Table 10 shows that while garment workers earn more overtime income and work longer, they do so at the expense of their health (results are large and significant at the 1% level.) In particular, migrants in the garments sector receive 322% more overtime pay than migrants in other sectors (column 2). However, this comes at the expense of their health, as migrants in the garments sector have a worse health index than migrants employed in other sectors (column 4).

[19]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.

Table 10: Overtime Income, Hours Worked, and Health of Garment Workers

	(1) Log (1+ Income) (OLS)	(2) Log (1+Overtime Income) (OLS)	(3) Hours Worked Weekly (OLS)	(4) Health Index (OLS)
Garments Worker	1.368***	3.215***	1.789***	-0.161**
	(0.158)	(0.302)	(0.166)	(0.0702)
R^2	0.143	0.312	0.164	0.095
Baseline Controls	Yes	Yes	Yes	Yes
Baseline Dep. Var. Control	Yes	Yes	Yes	Yes
Endline Control Group Mean	11.0	4.74	9.75	0
Observations	809	809	809	809

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

While garments workers worked longer in general, garments workers in the treatment group worked significantly longer hours at endline (p-value = 0.12). The additional 0.8 hours per week on a base of 9.1 hours represents an additional 9% increase. We do note, however, that the variable *Garments Worker* is endogenous. Nevertheless, these results together provide suggestive evidence that longer work hours in the garments sector could be a potential mechanism for the negative health impacts on migrants in the treatment group.

These results are 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 during the study period, and 53% of the time they worked beyond the 60-hour/week legal limit. Moreover, factory conditions could 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 also note the longer hours in these jobs as a mechanism for this deterioration in health.

6 Conclusion

The movement of people and money suggests the possibility of broadening ways to improve rural conditions. We show that rural conditions can be improved by facilitating engagement with urban jobs and opportunities – and with mechanisms to connect urban and rural areas financially.

At a mechanical level, the movements of people and money lead to 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 be a central participant in their parents' economic lives, even in a day-to-day way. The growing speed and ubiquity of mobile banking transfers, together with relatively cheap communication, suggests that the traditional view of households requires revisiting.

The study here is unique in following two (paired) groups simultaneously, one in rural Gaibandha in northwest Bangladesh and the other in Dhaka division, home to factories offering industrial jobs. The migrants in Dhaka are the children of household heads in Gaibandha.

The intervention at the heart of the randomized controlled trial was a 30-45 minute training intervention on how to use the bKash mobile banking service on a mobile telephone. Education levels are low in the sample, and, while most families have members with a mobile telephone, technology adoption is limited, especially by the use of English-language menus. The intervention was designed to reduce barriers by giving people a hands-on experience with bKash. The intervention included learning the basic steps and protocols, sending transfers five times to establish a degree of comfort, translation of menus into Bangla (Bengali), and, if needed, facilitation with the sign-up process. The short intervention increased take-up of bKash from 22% in the rural control group to 70% in the rural treatment group–itself a surprising result.

The substantial take-up is in part a function of the time and place. 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, especially the English-language menus, made the technology intimidating to villagers with limited education. Still, the experiment shows that the barriers were not insurmountable. As a result, the context provides a window (now closing as bKash and its peers penetrate widely) that made it possible to identify the impact of the new technology in both rural and urban settings. 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 30%, both in value and as a fraction of monthly income of migrants. As a result, rural households in the treatment group reduced borrowing levels, increased savings, and had less difficulty during the *monga* (lean) season. In this setting, mobile money services facilitated the transfer of substantial net resources to rural Gaibandha. The migrants to Dhaka, though, had mixed experiences. We find increases in garment work, and reductions in poverty, but declines in self-reported health status (a finding parallel to conclusions from financial diaires of garment workers in Bangladesh and analysis of factory workers in Ethiopia by Blattman and Dercon 2016). Technology is capable of bringing great social and economic improvements, but traditional challenges – relating to labor and health conditions especially – remain.

References

Akay, A., Bargain, O., & Zimmerman, K. (2012). Relative concerns of rural-to-urban migrants in China. *Journal of Economic Behavior and Organization*, *81*(2), 421-441.

Angelucci, M. (2015). Migration and financial constraints: Evidence from Mexico. *Review of Economics and Statistics*, *97*(1), 224-228.

Armendáriz, B., & Morduch, J. (2010). *The economics of microfinance, 2nd edition.* MIT Press.

Bandiera, O., Burgess, R., Das, N. C., Gulesci, S., Rasul, I., & Sulaiman, M. (October 2016). Labor markets and poverty in village economies. *CEPR Discussion Paper*(DP11554).

Banerjee, A., Duflo, E., Goldberg, N., Karlan, D., Osei, R., Parienté, W., ... Udry, C. (2015). A multifaceted program causes lasting progress for the very poor: Evidence from six countries. *Science*, *348*(6236).

Batista, C., & Vicente, P. C. (September 2013). Introducing mobile money in Rural Mozambique: Initial evidence from a field experiment. *NOVAFRICA Working Paper Series*, *1301*.

Bauchet, J., Morduch, J., & Ravi, S. (2015). Failure vs. displacement: Why an innovative anti-poverty program showed no net impact in South India. *Journal of Development Economics*, *116*, 1 - 16.

Berg, C., & Emran, M. S. (June 2017). Microfinance and vulnerability to seasonal famine in a rural economy: Evidence from monga in Bangladesh. *MPRA*(79818).

Bhuiyan, M. M. (January 23, 2017). Mobile financial services gather pace further. *The Financial Express*.

Bilkis, S., & Khan, M. M. R. (December 2016). Are mobile financial services promoting financial inclusion in Bangladesh: An assessment study. *Bangladesh Bank Working Paper*(1623).

Blattman, C., & Dercon, S. (2018). The impacts of industrial and entrepreneurial work on income and health: Experimental evidence from Ethiopia. *American Economic*

Journal: Applied Economics (forthcoming).

Blumenstock, J., Callen, M., Ghani, T., & Koepke, L. (2015). Promises and pitfalls of mobile money in Afghanistan: Evidence from a randomized control trial. *Proceedings of the 7th IEEE/ACM International Conference on Information and Communication Technologies and Development*.

Breza, E., Kanz, M., & Klapper, L. (2017). Scarcity at the end of the month: A field experiment with garment factory workers in Bangladesh. *International Growth Centre brief 31400*.

Bruhn, M., & McKenzie, D. (2009, October). In pursuit of balance: Randomization in practice in development field experiments. *American Economic Journal: Applied Economics*, *1*(4), 200-232. doi: 10.1257/app.1.4.200

Bryan, G., Chowdhury, S., & Mobarak, A. M. (2014). Underinvestment in a profitable technology: The case of seasonal migration in Bangladesh. *Econometrica*, *82*, 1671-1758.

Chen, J., Kosec, K., & Mueller, V. (2017, June). *Moving to despair? Migration and well-being in Pakistan* (Working Paper No. 10853). IZA Institute of Labor Economics.

Ellis, P., & Roberts, M. (2016). Leveraging urbanization in South Asia: Managing spatial transformation for prosperity and livability. *Washington, DC: World Bank*.

Gates Foundation. (2013, September). *Fighting poverty, profitably: Transforming the economics of payments to build sustainable, inclusive financial systems* (Report). Financial Services for the Poor.

Jack, W., & Suri, T. (2014, January). Risk sharing and transactions costs: Evidence from Kenya's mobile money revolution. *American Economic Review*, *104*(1), 183-223.

Khandker, S. (2012). Seasonality of income and poverty in Bangladesh. *Journal of Development Economics*, *97*, 244-256.

Kikulwe, E. M., Fischer, E., & Qaim, M. (2014, 10). Mobile money, smallholder farmers, and household welfare in Kenya. *PLOS ONE*, *9*(10), 1-13.

Kirui, O. K., Okello, J. J., Nyikal, R. A., & Njiraini, G. W. (2013). Impact of mobile phone-based money transfer services in agriculture: Evidence from Kenya. *Quarterly Journal of International Agriculture*, *52*(2), 141-162.

Knight, J., & Gunatilaka, R. (2010). Great expectations? The subjective well-being of rural-urban migrants in China. *World Development*, *38*(1), 113-124.

Lewis, W. A. (1954). Economic development with unlimited supplies of labor. *Manchester School*, *22*, 139-91.

Lopez-Acevedo, G., & Robertson, R. (2016). *Stitches to riches? Apparel employment, trade, and economic development in South Asia*. World Bank.

Mbiti, I., & Weil, D. N. (2011, June). *Mobile banking: The impact of M-Pesa in Kenya* (Working Paper No. 17129). National Bureau of Economic Research.

Morawczynski, O., & Pickens, M. (2009). Poor people using mobile financial services: Observations on customer usage and impact from M-PESA. *CGAP brief. Washington, DC: World Bank*.

Munyegera, G. K., & Matsumoto, T. (2016). Mobile money, remittances, and household welfare: Panel evidence from Rural Uganda. *World Development*, *79*, 127 - 137.

Pickens, M. (2009). Window on the unbanked: Mobile money in the Philippines. *CGAP brief. Washington, DC: World Bank*.

Riley, E. (July 28, 2016). Mobile money and risk sharing against aggregate shocks. *Oxford University CSAE Working Paper WPS/20*.

Suri, T., & Jack, W. (2016). The long-run poverty and gender impacts of mobile money. *Science*, *354*(6317), 1288–1292.

U.N. (2016a). Urbanization and migration in Bangladesh. *Dhaka: UNFPA Bangladesh Country Office*.

U.N. (2016b). *The world's cities in 2016: Data booklet* (No. ST/ESA/ SER.A/392).