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Poverty and migration in the digital age

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

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Abstract

Migration in search of urban jobs provides a path to higher income for poor rural residents, but migration can be costly and remittance-sending inefficient. We experimentally estimate the impact of mobile banking coupled with migration in Bangladesh, using a sample of rural households paired to family members who migrated to Dhaka. We provided the treatment group with knowledge about how to sign up for and use mobile banking accounts. The training induced a substantial increase in rural mobile bank account use, from 22% in the control group to 70% in the treatment group, and migrants increased remittances by 30% in value. As a result, rural households borrowed less, were more likely to save, and experienced significant and substantial positive impacts on health, education and agricultural productivity. Treatment households that experienced negative health conditions and agricultural productivity shocks were better insured than those in the control group (and positive agricultural productivity shocks were more fully exploited). Migrant workers exposed to the treatment were 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 improved rural social and economic conditions, partly by playing an insurance role. The impact on migrant welfare was mixed.

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1 Introduction

Early theories of international development 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 tilted toward 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. The theory is straightforward: As workers move from rural areas into towns and cities, they shift to higher-wage urban jobs, and rural households can share the gains when money is remitted back to relatives in origin villages (Ellis and Roberts 2016, Suri and Jack 2016).

Sending remittances can involve logistical and economic burdens, however, undermining the sharing of gains. 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 randomly assigned access to training on the use of mobile money. The intervention led to a large jump in adoption, and we trace the impacts. The study follows both senders (urban migrants) and receivers (rural families), allowing measurement of impacts on both sides of the transactions. The study, based in a poor region of northwest Bangladesh, shows large improvements in rural conditions. Migrants, though, report worse outcomes in a series of health measures.

In 1970, most of the world's population lived in rural areas, with just 37 percent in cities; 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. In Dhaka migrants often aspire to jobs in garment factories, where tough working conditions accompany steady paychecks (Lopez-Acevedo and Robertson 2016).

While migration pulls households apart, the easier movement of money can bring households back together, at least financially. The flows of remittances back to rural families are made easier by the spread of mobile financial services. Kenya's M-Pesa mobile money service, for example, started 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). 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 (Bhuiyan 2017).

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 households 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.

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).

While Jack and Suri (2014) and Suri and Jack (2016) can use the plausible exogeneity of the timing and place of M-Pesa's expansion in Kenya to identify impacts, other studies must rely on stronger assumptions. The selection problem is that the use of mobile money is generally positively correlated with broader levels of economic activity, leading to a risk of upwardly-biased impact estimates. 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.

The study closest to ours is Batista and Vicente (2016) who run an RCT in rural Mozambique. Like us, they investigate the impact of mobile money in financially-underserved areas. While they do not find an increase in the value of remittances sent, 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. Blumenstock et al (2015) also run an RCT, focusing on the impact of paying salaries via mobile money rathern 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.

Bryan et al (2014) also evaluate urban-rural migration using a randomized expriment in a rural sample in northwest Bangladesh (similar to 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) led 22% of their sample to out-migrate seasonally, and 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. Their focus is on facilitating migration, while we focus on overcoming barriers to sending remittances.

Our study covers 817 rural household-urban migrant pairs randomized at the individual level. The dual-site design allows measurement of impacts in both rural and urban areas. The "encouragement design" involved introducing the treatment group to mobile financial services and facilitating account set-up. 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 baseline survey took place in December 2014 and early 2015 and the endline in early 2016.

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). Gaibandha is in one of the poorest sections of Bangladesh, an area historically vulnerable to seasonal food insecurity during the *monga* season (Khandker 2012, Bryan et al 2014), and the Gaibandha sample includes rural households that had been identified as "ultra-poor." As extreme poverty falls globally, the households that remain poor are increasingly those 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.[1] 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.

We find that rural households in the treatment group reduced borrowing levels, increased savings on the extensive margin, and experienced significant and substantial positive impacts on health, education and agricultural productivity. Treatment households that were hit by negative agricultural productivity shocks were better insured than those in the control group, and we find a similar result for negative health conditions as long as the migrant worker is not simultaneously experiencing poor health. The results also suggest that positive agricultural productivity shocks are exploited more in treatment households. Taken together, the results suggest that mobile money services facilitate the transfer of substantial net resources to rural areas and improve insurance against shocks. We do not find evidence of spillovers to the control group.

The results for migrants to Dhaka show tradeoffs of these rural gains. We find increases in

[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. 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.

garment work, but declines in self-reported health status, which may reflect longer work hours in the garments sector. Savings on the extensive margin also increase among migrant workers. 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.

2 Background and Experimental Design

Mobile technologies have rapidly expanded in the developing world, spreading information and creating the potential to serve as a distribution platform for services and products, including broadly accessible banking services (Aker and Mbiti, 2010; Aker, 2010; Jensen, 2007). Referred to as "mobile banking" or as "mobile money," these services can penetrate markets previously unreached by traditional banks due to the relatively high costs of bank branching, particularly in rural areas. Mobile money allows individuals to deposit, transfer, and withdraw funds to and from electronic accounts or "mobile wallets" based on the mobile phone network, as pioneered by the popular M-Pesa mobile service in Kenya, introduced in 2007. Individuals can transfer funds securely to friends and family members at a relatively low cost and cash in or cash out with the help of designated agents.

We conducted the experiment in cooperation with bKash, the largest provider of mobile banking services in Bangladesh. The company is a subsidiary of BRAC Bank and commands a leading share of the mobile money market in Bangladesh, in which there are a number of alternative providers.[2] The 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 market.

The experiment took place in two connected sites: (1) Gaibandha, a district in Rangpur Division in northwest Bangladesh and (2) Dhaka Dhaka Division, the administrative unit in

[2] 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.

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 seasonal famine in September through November known as *monga* (Bryan et al 2014). Even measured outside of the *monga* season, Gaibandha has lower rates of food consumption per capita than other regions in the country. Internal migration is common in Bangladesh, as is international migration.

To recruit participants, we initially took advantage of a pre-existing sampling frame from SHIREE, a garment worker training program run by the nongovernmental organization Gana Unnayan Kendra with funding from the United Kingdom Department for International Development. This program was targeted to the "ultra-poor" in and around Gaibandha. We restricted the sample to household with workers in Dhaka who were already sending remittances home. Beginning from this roster, we then snowball-sampled additional households and with migrant members in Dhaka to reach a final sample size of 817 migrant-household pairs.[3] 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).

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. Treatment households received training on the use of bKash and technical assistance with the enrollment process.[4] The intervention

[3]Rural respondents over-stated the number of days worked: 99% of respondents reported working the same number of days in each of the past 12 months at endline, despite seasonality which leads to monthly ups and downs of work in Gaibandha. As a result, measured per capita incomes were more than double that of per capita expenditures in the rural sample. Expenditure-based poverty measures yield that 90% of the rural sample is poor, which lines up with the recruitment protocol to target ultra-poor households.

[4]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. 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.

consisted of a simple 30 to 45 minute training designed to inform study participants in the treatment arm of how to sign up for and use the bKash service. The training materials were based on marketing materials provided by bKash and 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 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.

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.

3 Data

We recruited participants between September 2014 and February 2015. 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.

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.

About 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 by the treatment group was 17279/7 = 2468 Taka, which is nearly one third of monthly migrant income (2468/7830 = 31.5%).

Most rural households (90%) are poor as measured by the local poverty line in 2014, and the median spending level of rural households is 85% of the poverty threshold. Moving to the global $1.90 poverty line (measured at 2011 PPP exchange rates and converted to 2014 taka with the Bangladesh CPI), 70% are poor. These figures show a slightly greater extent of poverty than 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.[5]

Fewer than half of migrants (47% in the treatment group) have completed primary schooling. Most migrants had a relatively short tenure in Dhaka prior to the study, with the average migrant living less than three years in Dhaka and working less than 2 years of tenure at their current job. Among rural households, the average household size is 4.4 members while

[5]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 spent 46.4 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.

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.

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	415	0.98	0.13	402	0.336
Any bank account, urban	0.11	0.31	415	0.11	0.32	402	0.873
Formal employee, urban	0.91	0.28	415	0.88	0.32	402	0.154
Average monthly income, urban (‘000)	7.83	2.58	415	7.77	2.44	402	0.717
Female migrant	0.29	0.46	415	0.30	0.46	402	0.709
Age of migrant	24.0	5.3	415	24.1	5.1	402	0.970
Migrant completed primary school	0.47	0.50	415	0.45	0.50	402	0.439
Tenure at current job, urban	1.69	1.58	415	1.66	1.47	402	0.797
Tenure in Dhaka, urban	2.42	1.85	415	2.50	1.74	402	0.559
Remittances in past 7 months, urban (‘000)	17.3	11.9	415	18.3	12.5	402	0.256
Daily per capita expenditure, urban	120.3	45.1	415	120.7	40.7	402	0.886
Household size, rural	4.4	1.6	415	4.4	1.6	402	0.687
Number of children, rural	1.2	1.0	415	1.3	1.1	402	0.356
Household head age, rural	47.2	13.1	415	46.2	13.4	402	0.286
Household head female, rural	0.12	0.33	415	0.13	0.34	402	0.702
Household head education, rural	0.19	0.40	415	0.16	0.37	402	0.209
Decimal of owned agricultural land, rural	9.4	28.5	415	10.8	30.8	402	0.483
Number of rooms of dwelling, rural	1.82	0.73	415	1.8	0.762	402	0.938
Dwelling owned, rural	0.94	0.23	415	0.94	0.24	402	0.793
Daily per capita expenditure, rural (Taka)	50.5	18.3	415	49.0	18.3	402	0.262
Poverty rate (national threshold), rural	0.89	0.32	415	0.90	0.30	402	0.604
Poverty rate (global $1.90 threshold), rural	0.68	0.47	415	0.72	0.45	402	0.194
Gaibandha	0.50	0.50	415	0.53	0.50	402	0.455
Other upazila	0.50	0.50	415	0.47	0.50	402	0.455

p-value of F-test for joint orthogonality = 0.952.

4 Empirical Methods

We use the household survey data and administrative data from bKash to estimate impacts on a range of outcomes. For most outcomes, we estimate intention-to-treat (ITT) effects using the following Analysis of Covariance (ANCOVA) specification:

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

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 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:

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

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.

To estimate treatment impacts when rural households are hit with shocks, we estimate Equation (3):

$$\begin{aligned} Y_{i,h,t+1} =& \beta_0 + \beta_1 Treatment_i + \beta_2 NoShock_{i,h,t+1} + \beta_3 NoShock_{i,h,t} + \\ & \beta_4 Treatment_i * NoShock_{i,h,t+1} + \beta_5 Y_{i,h,t} + \mathbf{X}_{i,h} + \epsilon_{i,h,t+1} \end{aligned} \tag{3}$$

Here households in the omitted (base) group are households in the control group that are hit by shocks. As such, we are interested in the coefficient β_1, which gives the relevant comparison. The subscript h emphasizes that the sample is restricted to rural households. Since we estimate the impact of the treatment on $Y_{i,h,t+1}$ *conditional* on $NoShock_{i,h,t+1}$, we control for both $Y_{i,h,t}$ and $NoShock_{i,h,t}$ to be consistent with the ANCOVA estimation strategy.

We then exploit the unique paired rural household - urban migrant structure of the data to study the impact of the intervention when rural households are hit with shocks, and the paired urban migrants are hit with shocks as well. In particular, we compare outcomes of households in the treatment group hit by shocks whose paired migrants are also hit with shocks, with households in the control group hit by shocks whose paired migrants are hit with shocks. To do so, we estimate Equation (4):

$$\begin{aligned} Y_{i,h,t+1} =& \beta_0 + \beta_1 Treatment_i + \beta_2 NoShock_{i,h,t+1} + \beta_3 NoShock_{i,m,t+1} + \beta_4 NoShock_{i,h,t} + \\ & \beta_5 NoShock_{i,m,t} + \beta_6 Treatment_i * NoShock_{i,h,t+1} + \beta_7 Treatment_i * NoShock_{i,m,t+1} + \\ & \beta_8 NoShock_{i,h,t+1} * NoShock_{i,m,t+1} + \beta_9 NoShock_{i,h,t} * NoShock_{i,m,t} + \\ & \beta_{10} Treatment_i * NoShock_{i,h,t+1} * NoShock_{i,m,t+1} + \beta_{11} Y_{i,h,t} + \mathbf{X}_{i,h} + \epsilon_{i,h,t+1} \end{aligned} \tag{4}$$

The subscripts h and m refer to the rural households and urban migrants, respectively. Here households in the omitted (base) group are households in the control group that are hit by shocks whose migrants are hit by shocks as well. As such, we are interested in the coefficient β_1, which gives the relevant comparison. Note that in addition to $Y_{i,h,t}$, we also control for $NoShock_{i,h,t}$, $NoShock_{i,m,t}$, and the interaction $NoShock_{i,h,t} * NoShock_{i,m,t}$ to be consistent with the ANCOVA estimation strategy.

Finally, we estimate the impact of the intervention when rural households are hit with shocks, but the paired urban migrants are not hit with shocks. To do so, we estimate Equation (5), where again, β_1 gives the relevant comparison:

$$\begin{aligned} Y_{i,h,t+1} =& \beta_0 + \beta_1 Treatment_i + \beta_2 NoShock_{i,h,t+1} + \beta_3 Shock_{i,m,t+1} + \beta_4 NoShock_{i,h,t} + \\ & \beta_5 Shock_{i,m,t} + \beta_6 Treatment_i * NoShock_{i,h,t+1} + \beta_7 Treatment_i * Shock_{i,m,t+1} + \\ & \beta_8 NoShock_{i,h,t+1} * Shock_{i,m,t+1} + \beta_9 NoShock_{i,h,t} * Shock_{i,m,t} + \\ & \beta_{10} Treatment_i * NoShock_{i,h,t+1} * Shock_{i,m,t+1} + \beta_{11} Y_{i,h,t} + \mathbf{X}_{i,h} + \epsilon_{i,h,t+1} \end{aligned} \tag{5}$$

5 Results

5.1 First Stage

Table 2: First Stage of IV - Rural Household Sample

	(1) Active bKash Account	(2) Active bKash Account
bKash Treatment	0.483***	0.484***
	(0.0306)	(0.0306)
R^2	0.235	0.242
Baseline Controls	No	Yes
Observations	815	815
Endline Control Group Mean	0.219	0.219

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2 presents results from the first stage of the instrumental variables (IV) regressions for rural households. Households in the 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 column (2) includes gender, age, and primary school completion of head of the household, and household size as controls. 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 impact is substantial, and reflects the newness of mobile banking in Bangladesh, especially in Gaibandha and the poorer communities. The result also reflects the obstacles to signing up for mobile banking services in this context. The bKash menus on the telephones are in English, although few members of the rural sample have much comfort in 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 to adoption.

Table 3: First Stage of IV - Urban Migrant Sample

	(1) Active bKash Account	(2) Active bKash Account
bKash Treatment	0.477***	0.474***
	(0.0307)	(0.0304)
R^2	0.230	0.252
Baseline Controls	No	Yes
Observations	811	811
Endline Control Group Mean	0.207	0.207

Standard errors in parentheses

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

Table 3 presents results for the urban migrants. Again, the treatment has a large impact on account use. Migrants in the 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 treatment effect and control mean base are very similar in the rural and urban samples, given that remittance flows from urban migrants to rural households constitute the primary use of bKash accounts. The result shows that the 30-45 minute treatent intervention 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.

5.2 Urban Households: Remittances

Figure 1: Monthly Remittances Sent

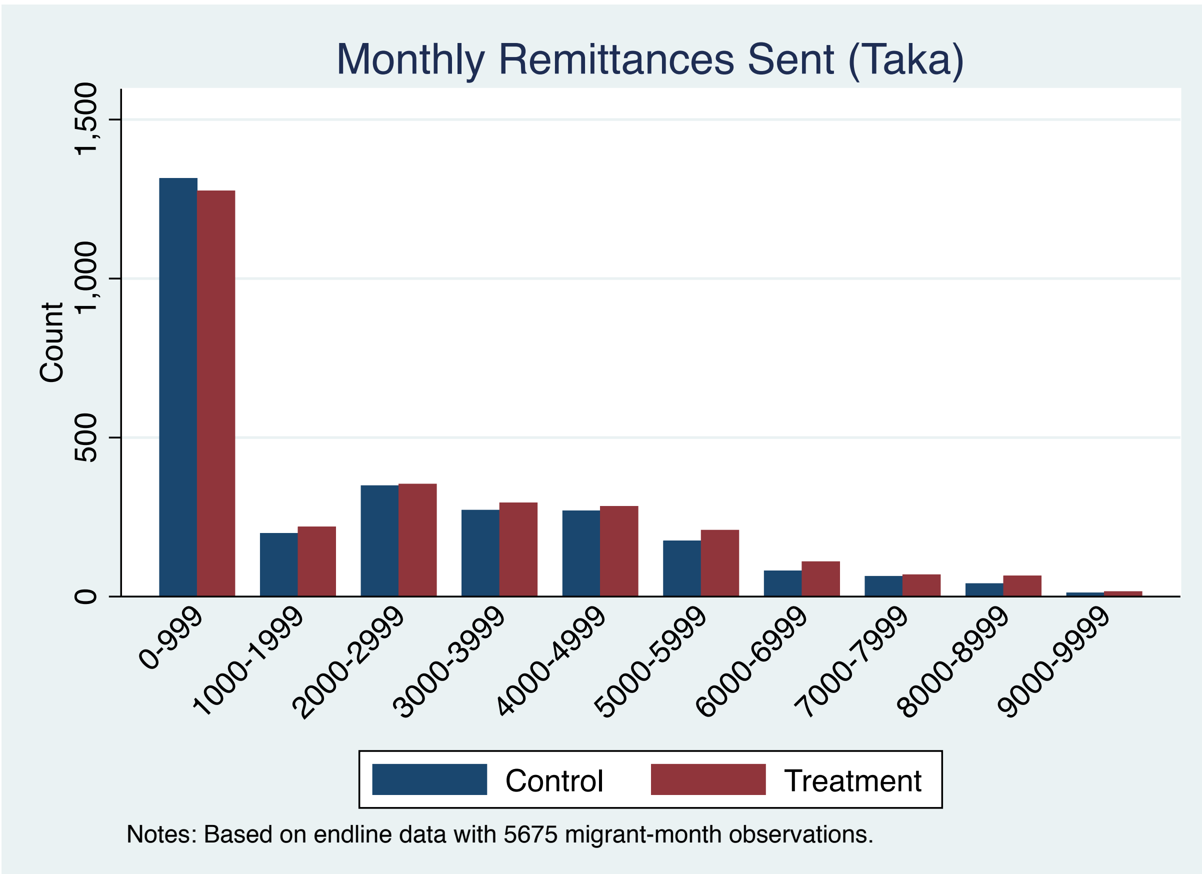


Figure 1 presents data on monthly remittances drawn from the endline survey. While a large mass of migrants sent no remittances or very little in a given month (less than 1000 Taka = $13 in 2016), many sent large amounts. A Kolmogorov-Smirnov test confirms that the distributions of the monthly remittances sent are significantly different between the treatment and control groups at p-value = 0.046. The treatment group in particular was more likely to send larger sums than the control group.

Table 4: Total Remittances Sent

	(1) Total Remittances Sent, Taka (OLS)	(2) Total Remittances Sent, Taka (IV)	(3) Total Remittances Sent, Taka (IV)
Treatment * Endline	320.1**		
	(162.8)		
Active Account * Endline		667.7*	715.1**
		(341.0)	(326.2)
Endline	-327.1***	-467.1**	-696.3***
	(121.6)	(181.0)	(174.8)
No Income			-1406.6***
			(74.38)
R^2	0.290	0.289	0.308
Baseline Controls	No	No	No
Month Fixed Effects	Yes	Yes	Yes
Household Fixed Effects	Yes	Yes	Yes
Observations	10547	10547	10547
Endline Control Group Mean	2197.8	2197.8	2197.8

Standard errors in parentheses and clustered by household

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

Table 4 above presents regression results for remittances sent by migrants to the rural households. The estimation exploits the monthly remittance data captured at both baseline and endline. Column (1) shows a large ITT impact of the treatment on remittances sent; migrants in the treatment group sent an estimated 15% more remittances at endline (320.1 on a control mean base of 2197.8) than migrants in the control group, controling for differences between baseline and endline, month fixed effects, and household fixed effects. Columns (2) and (3) present TOT results that account for active use of the bKash accounts. The 667.7 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 (668/2198). There is considerable heterogeneity in the samples, though, and the estimate is fairly noisy. One source of variation arises because some in the sample lack jobs and thus are not remitting money. Column (3) investigates the impact by including an indicator for whether the migrant earned income that month. The size of the cofficient in the second row remains large and negative, slightly increasing the TOT impact estimate and reducing the standard error. Since employment is plausibly at least in part endogenous to the intervention, we view column (3) as giving an exploratory sense of variation in the data, rather than providing an improved causal estimate.[6]

Table 5 presents results for total bKash remittances sent, drawing on the administrative data. It is no surprise, given that the intervention focused on bKash, that the impacts here are large. The most important finding is that Table 4 and Table 5 taken together suggest that most of the action in Table 4 is coming via new remittances rather than from substitution from other means of remittances to bKash:

[6]Pickens (2009) found that one third of a sample of 1,042 users of mobile money services in the Philippines did not use remittances at all, using mobile money to purchase airtime. About half of active users (52%) used the service twice a month or less. There was also a "super-user" group (1 in every 11 mobile money users) that made more than 12 transactions per month.

Table 5: Total bKash Remittances Sent

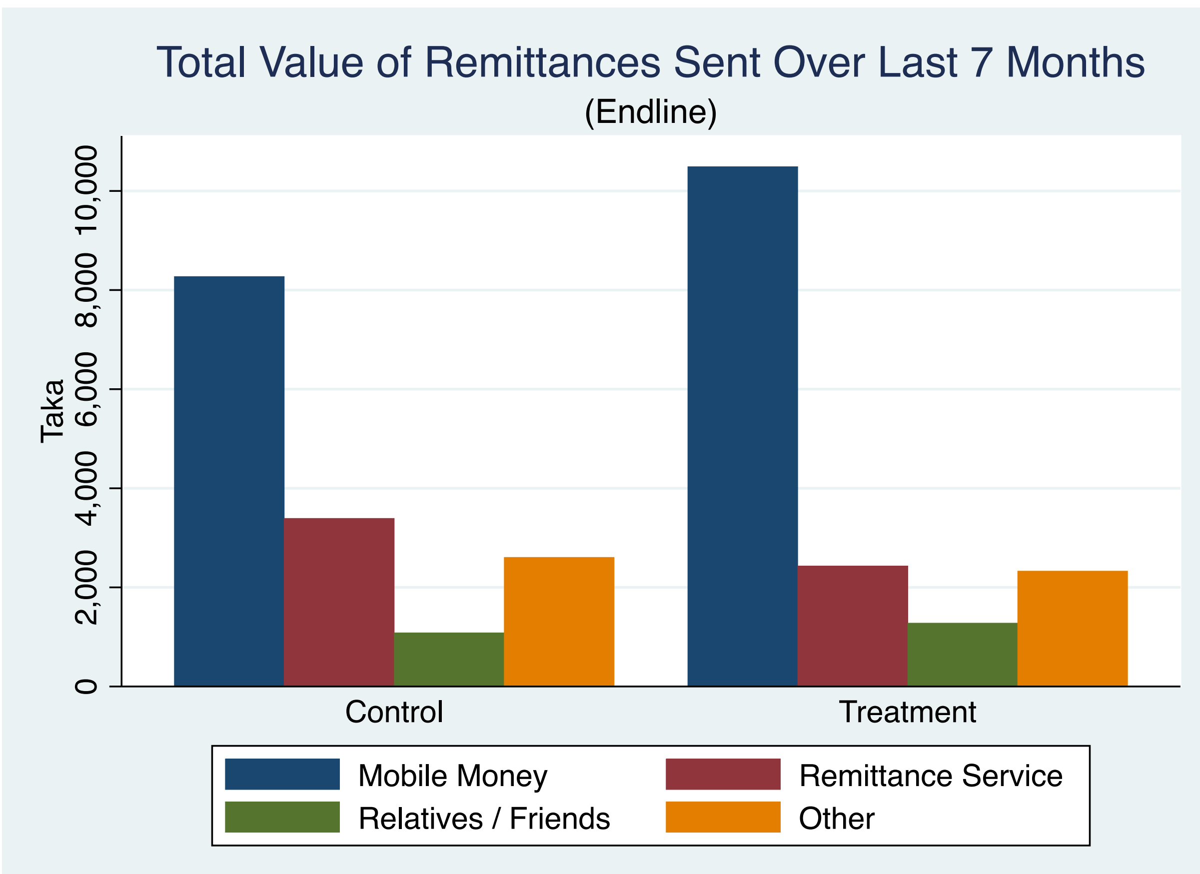
	(1) Total bKash Remittances Sent, Taka (OLS)	(2) Total bKash Remittances Sent, Taka (IV)	(3) Total bKash Remittances Sent, Taka (IV)
Treatment * Endline	384.1***		
	(129.9)		
Active Account * Endline		801.2***	827.3***
		(273.9)	(269.5)
Endline	-119.0	-286.9**	-413.4***
	(96.75)	(144.6)	(144.5)
No Income			-775.7***
			(62.11)
R^2	0.438	0.434	0.446
Baseline Controls	No	No	No
Month Fixed Effects	Yes	Yes	Yes
Household Fixed Effects	Yes	Yes	Yes
Observations	10547	10547	10547
Endline Control Group Mean	1161.6	1161.6	1161.6

Standard errors in parentheses and clustered by household

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

Column (1) shows that migrants in the treatment group sent, on average, 384.1 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) of Table 4 above, 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 bKash remittances. We also see this in Figure 2 below:

Figure 2: Total Value of Remittances Sent, By Type



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. Figure 2 shows a 27% (10490/8270) increase in the value of remittances sent using mobile money, close to the point estimate reflecting a 33% increase in Table 5. The substantial increase in the value of mobile money remittances and the evidence of little substitution away from other means of remittances drive the 30% increase in the total value of remittances seen in Table 4.[7]

The tables above show increases in remittances by value. Migrants also sent a substantially higher fraction of their income as remittances relative to the control group. In the TOT results presented in column (2), the increase is an estimated 28% (0.063/0.223). Again, column (3) is an exploratory look at the impact of jobless months, and again the treatment effect increases slightly and is estimated more precisely.

[7]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 (consistent with the bKash administrative data in Figure 3). 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.

Table 6: Fraction of Income Remitted

	(1) Fraction of Income Remitted (OLS)	(2) Fraction of Income Remitted (IV)	(3) Fraction of Income Remitted (IV)
Treatment * Endline	0.0301*		
	(0.0163)		
Active Account * Endline		0.0628*	0.0723**
		(0.0340)	(0.0312)
Endline	-0.0300**	-0.0432**	-0.0891***
	(0.0117)	(0.0174)	(0.0164)
No Income			-0.282***
			(0.00720)
R^2	0.241	0.241	0.311
Baseline Controls	No	No	No
Month Fixed Effects	Yes	Yes	Yes
Household Fixed Effects	Yes	Yes	Yes
Observations	10547	10547	10547
Endline Control Group Mean	0.223	0.223	0.223

Standard errors in parentheses and clustered by household

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

Figure 3 uses administrative data from bKash to show patterns of remittances within the year. Figure 3 reveals significant seasonality in the value of remittances sent per active account. The increases in remittances roughly coincide with the harvest periods of the agricultural seasons: Aus (August-September), Aman planting (July and August), Aman harvest (rainfed, November), local Boro (February-June), and high-yielding Boro (irrigated, 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. The figure shows that households in the control group generally have a higher value of remittances sent per active account. Since this chart only plots the bKash account data, the households with active bKash accounts in the control group have chosen to sign up for bKash of their own accord (i.e., without the experimental training intervention). Having an account signals particular interest in remitting money, and, conditional on having an active account, it is not surprising that the average control group member remits more (by value) conditional on using bKash. Members of the treatment group, though, are far more likely to have active accounts.

Figure 3: Total Value of bKash Remittances Sent Per Active Account

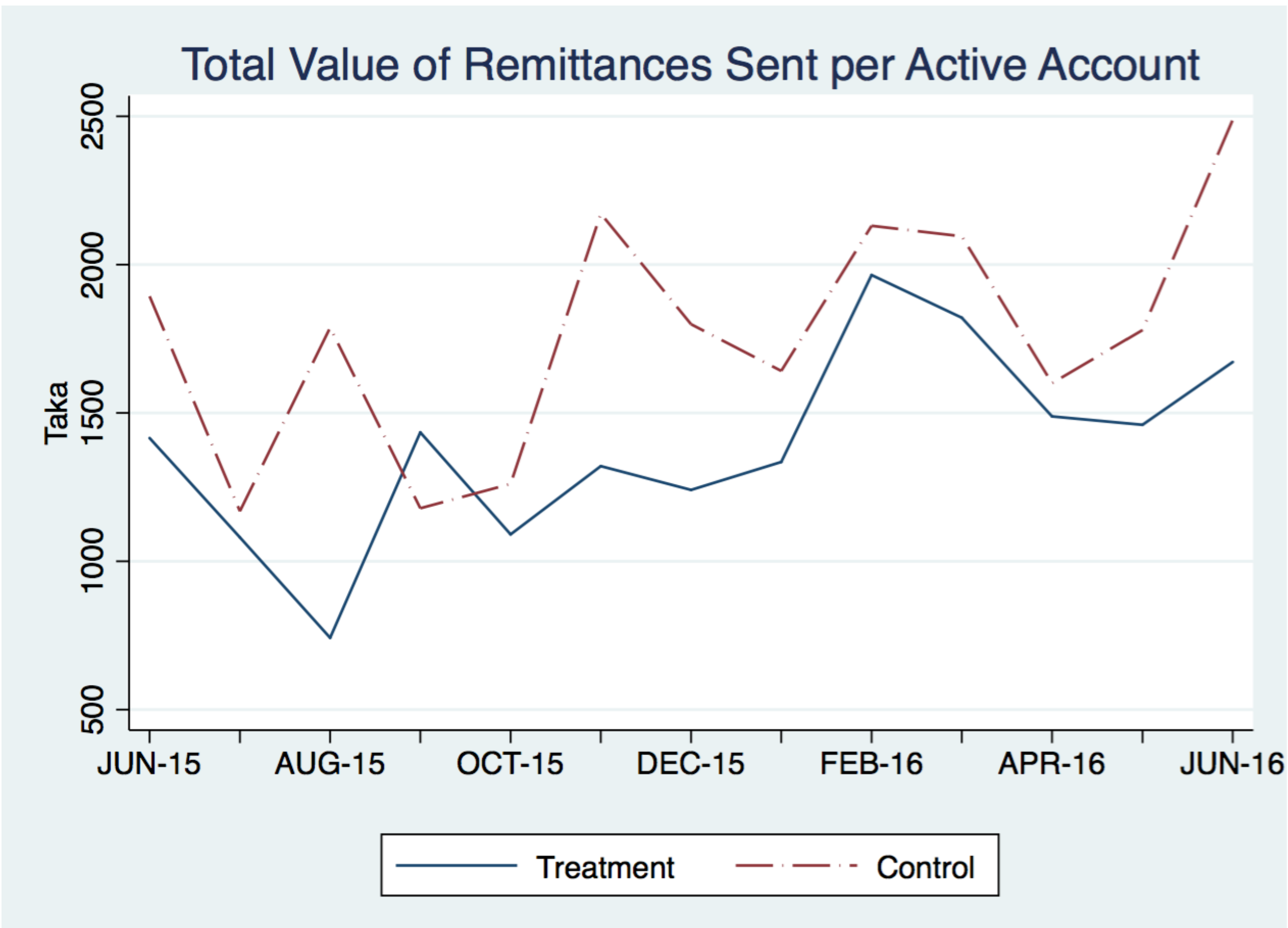
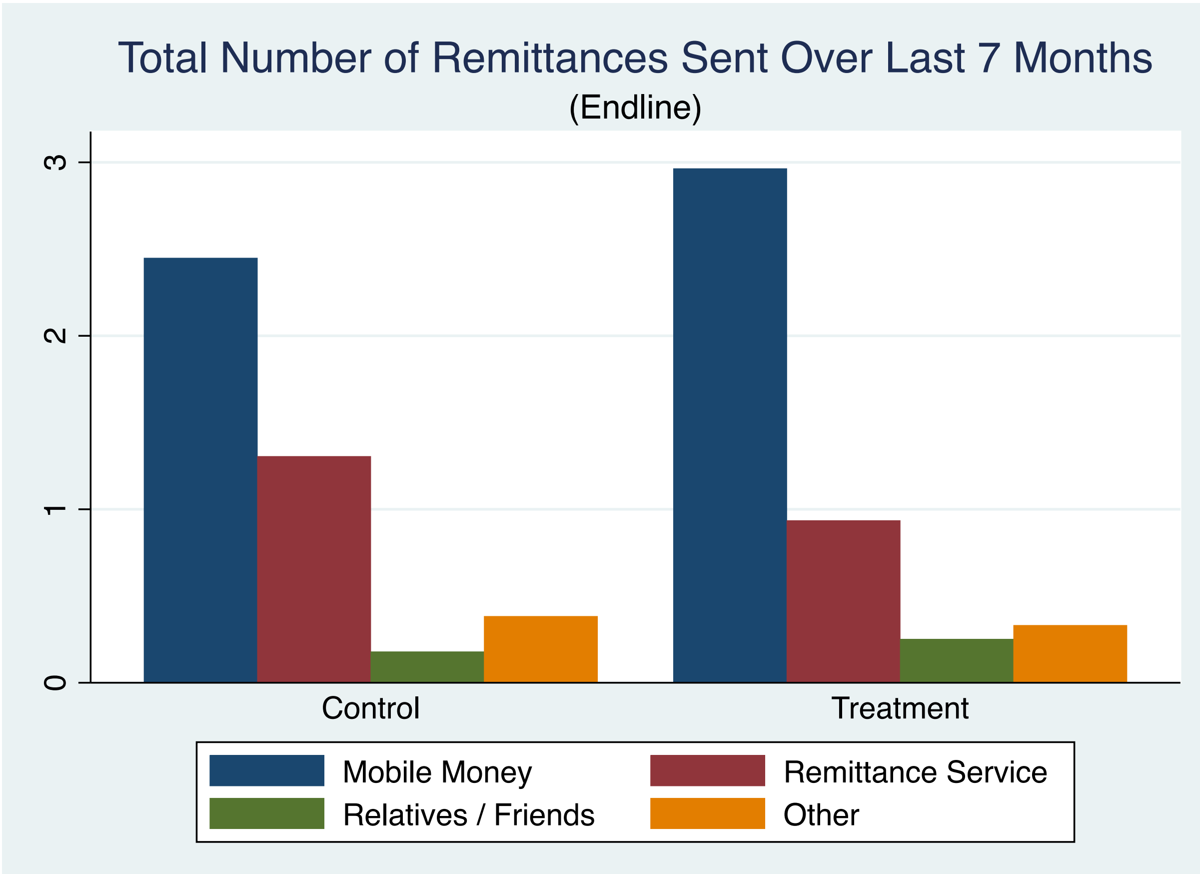


Figure 4 turns to the frequency of remittances sent:

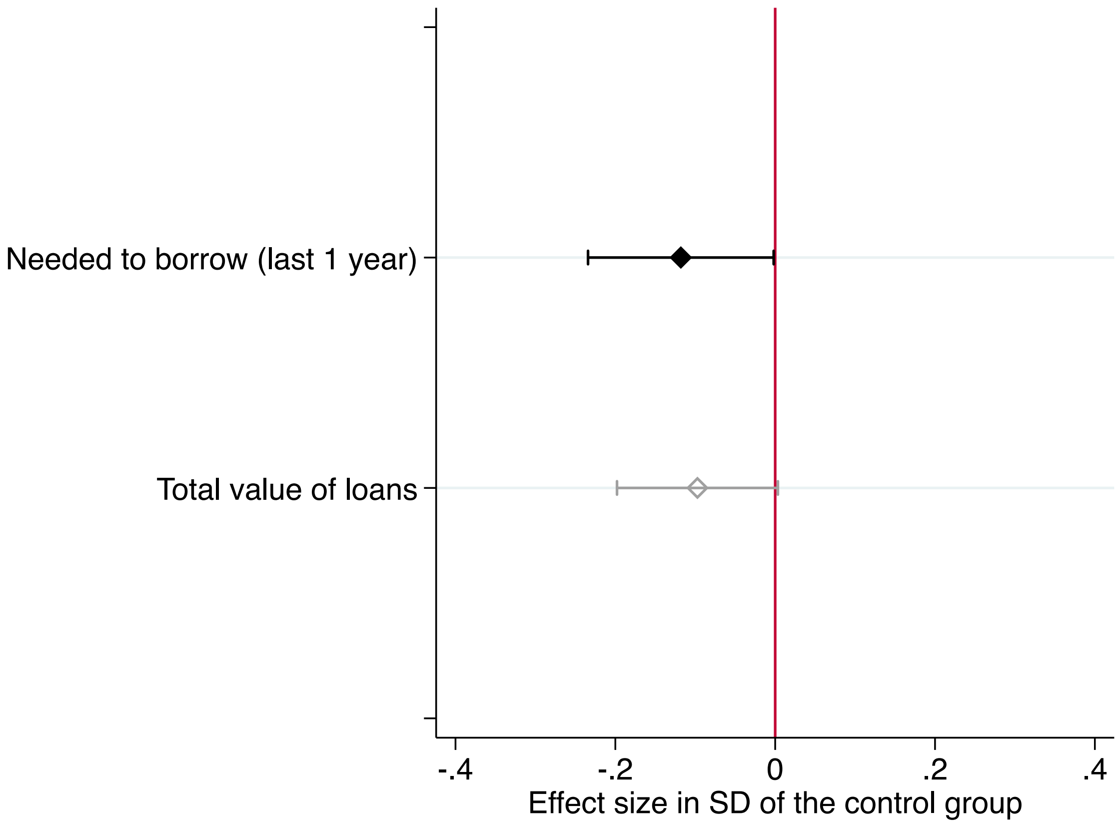
Figure 4: Total Number of Remittances Sent, By Type



We see a shift in the composition of number of remittances sent by migrants in the treatment and control groups. In particular, migrants in the treatment group increased the number of remittances sent using mobile money by 21% (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 28% (significant at the 1% level). 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.

5.3 Rural Households: Borrowing and Saving

Figure 5: Impact on Borrowing



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.

Figure 5 presents treatment effects on borrowing by rural households. Households in the treatment group were significantly less likely to report needing to borrow in the past year. In particular, households in the treatment group were 5.9 percentage points less likely to need to borrow than households in the control group. At endline, 60.9% of households in the control group needed to borrow in the last one year. Furthermore, 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 (p-value = 0.11 with controls, 0.09 without baseline controls). The result on total value of loans is not conditioned on having borrowed, and hence combines the extensive and intensive margins of borrowing. The results indicate that easier access to transfers from migrants reduced the need of rural households to borrow. The large magnitudes we obtain are also consistent with the magnitudes of transfers. At baseline, the total size of loans taken over the last 12 months was 6798 Taka. As such, monthly remittances are large in comparison to the size of total loans (2198/6798 = 32.3%).

We constructed a borrowing index for each household using the two variables in Figure 5, with equal weight given to the variables. The index is standardized to reflect standard deviation units of the control group. Table 7 below presents these results:

Table 7: Results for Borrowing Index

	(1) Borrowing Index (OLS)	(2) Borrowing Index (OLS)	(3) Borrowing Index (IV)	(4) Borrowing Index (IV)
bKash Treatment	-0.132**	-0.128*		
	(0.0668)	(0.0663)		
Active bKash Account			-0.272**	-0.263*
			(0.138)	(0.137)
R^2	0.009	0.037	0.002	0.028
Baseline Controls	No	Yes	No	Yes
Baseline Dep. Var. Control	Yes	Yes	Yes	Yes
Observations	815	815	815	815
Endline Control Group Mean	0	0	0	0

Standard errors in parentheses

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

Columns (1) and (2) show that the treatment was successful in reducing the borrowing index of households in the treatment group by 0.13 standard deviation units. This intention-to-treat (ITT) results are statistically significant at the 5% and 10% levels, without and with baseline controls, respectively. Columns (3) and (4) present results from IV regressions, highlighting the treatment-on-the-treated (TOT). The TOT treatment reduced the borrowing index of treated households by 0.27 standard deviation units.

Table 8: Results for Savings

	(1) Any Savings	(2) Any Savings	(3) Log(Savings+1)	(4) Log(Savings+1)
bKash Treatment	0.437***		1.247***	
	(0.0296)		(0.240)	
Active bKash Account		0.908***		2.592***
		(0.0658)		(0.504)
R^2	0.221	0.104	0.040	0.015
Baseline Controls	Yes	Yes	Yes	Yes
Baseline Dep. Var. Control	Yes	Yes	Yes	Yes
Observations	815	815	815	815
Endline Control Group Mean	0.43	0.43	2.58	2.58

Standard errors in parentheses

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

Table 8 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. Columns (1) and (2) present results for the extensive margin of savings. Households in the treatment group were 43.7 percentage points more likely to save, on a control mean base of 43%. 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.

Columns (3) and (4) present results for overall savings that does not condition on having saved, thus combining the extensive and intensive margins of savings. Households in the treatment group saved 125% more than households in the control group. Accounting for active use of the bKash accounts in column (4) gives a TOT impact of 259%. These estimates are large and statistically significant at the 1% level.

5.4 Rural Households: Education

Figure 6: Impact on Education

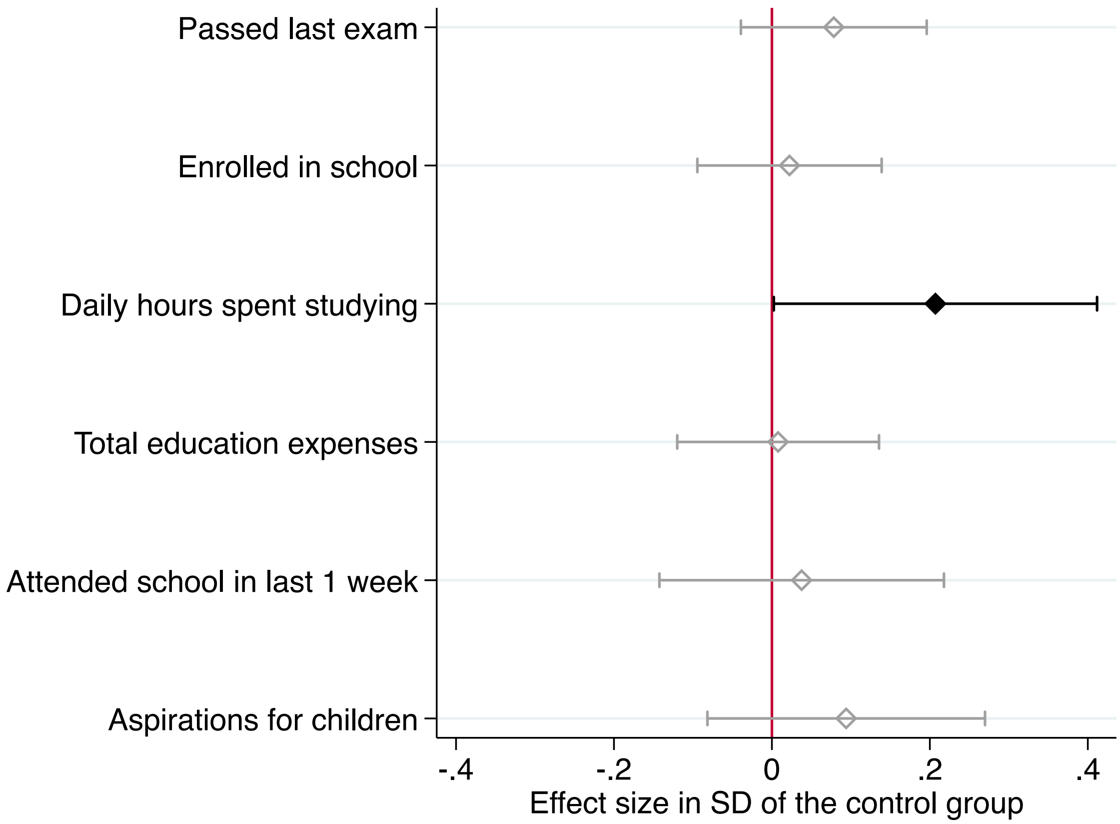


Figure 6 presents treatment effects on child education in rural households. All regressions were run using standard OLS, with the exception of aspirations for child education, which was run using an ordered logit because the responses to the question on aspirations were in the form of a list of ordered categories that included high school, college, and post-graduate studies[8]. The estimates show a statistically significant positive treatment effect on daily hours spent studying. In particular, children in the treatment group spent 0.25 hours more studying per week than children in the control group, who spent on average 2.5 hours studying per week. In addition, the point estimates for school attendance, enrollment, performance, and parents' aspirations for their children are positive. Taken together, the

[8]In fact, we obtain a larger coefficient and smaller p-value when standard OLS is used instead.

results suggest that the treatment had a positive impact on child education. This is confirmed in the ITT and TOT regressions using the education index, constructed using the variables in Figure 6 with equal weight given to the variables:

Table 9: Results for Child Education Index

	(1) Education Index (OLS)	(2) Education Index (OLS)	(3) Education Index (IV)	(4) Education Index (IV)
bKash Treatment	0.139**	0.140**		
	(0.0664)	(0.0665)		
Active bKash Account			0.287**	0.289**
			(0.138)	(0.137)
R^2	0.016	0.024	0.010	0.017
Baseline Controls	No	Yes	No	Yes
Baseline Dep. Var. Control	Yes	Yes	Yes	Yes
Observations	815	815	815	815
Endline Control Group Mean	0	0	0	0

Standard errors in parentheses

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

Columns (1) and (2) of Table 9 show that the treatment was successful in improving the education index of households in the treatment group by 0.14 standard deviation units, significant at the 5% level. Columns (3) and (4) show that the treatment improved the education index of treated households by 0.29 standard deviation units.

Parents are not using remittances sent via bKash to increase expenditure on child education. Rather, the significant increase in hours spent studying and increases in school attendance, enrollment, and performance suggest that children may be substituting study hours with time spent helping out in agriculture and/or other business activities of the household.[9] Another possible channel could be through the treatment impacts on health. Notably, controlling for child health in the above regressions lead to insignificant impacts of the treatment on education.

[9]We asked about child labor in the surveys, but only 3 households reported that their children participated in economic activities at endline, perhaps worried about being caught engaging in child labor.

5.5 Rural Households: Health

Figure 7: Impact on Health

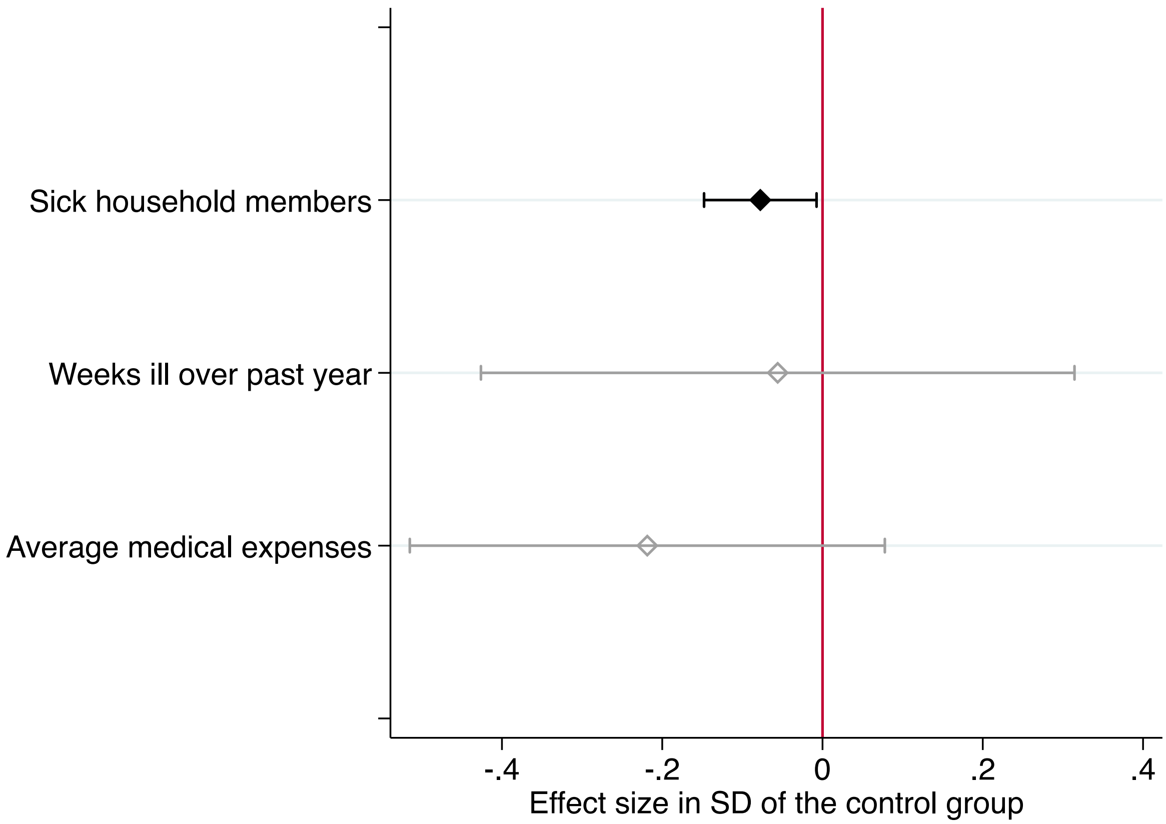


Figure 7 presents treatment effects on health of rural households. The number of household members who were sick for a week or more over the past year fell significantly. In particular, households in the treatment group had 0.12 fewer household members who were sick, in comparison to households in the control group. At endline, on average, 4.2 household members were sick in households in the control group. The point estimate for the number of weeks that individuals were ill is negative, but the standard error bars are too wide to detect statistically significant effects here. The average medical expenses across all household members also decreased. The results on weeks ill and medical expenses are not conditioned on falling ill, and hence combine the extensive and intensive margins of the health impacts.

Next, we construct a health index for each household using the variables in Figure 7, with equal weight given to the variables. The signs have been flipped so that a decrease in the number of sick household members, for example, is an improvement in the health index.

Table 10: Results for Health Index

	(1) Health Index (OLS)	(2) Health Index (OLS)	(3) Health Index (IV)	(4) Health Index (IV)
bKash Treatment	0.117*	0.103**		
	(0.0613)	(0.0482)		
Active bKash Account			0.243*	0.212**
			(0.128)	(0.0997)
R^2	0.171	0.493	0.160	0.488
Baseline Controls	No	Yes	No	Yes
Baseline Dep. Var. Control	Yes	Yes	Yes	Yes
Observations	815	815	815	815
Endline Control Group Mean	0	0	0	0

Standard errors in parentheses

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

Column (2) of Table 10 shows that the treatment was successful in improving the health index of households in the treatment group by 0.1 standard deviation units, significant at the 5% level. Column (4) shows that the treatment improved the health index of treated households by 0.21 standard deviation units.

5.6 Rural Households: Agriculture

Figure 8: Impact on Agriculture

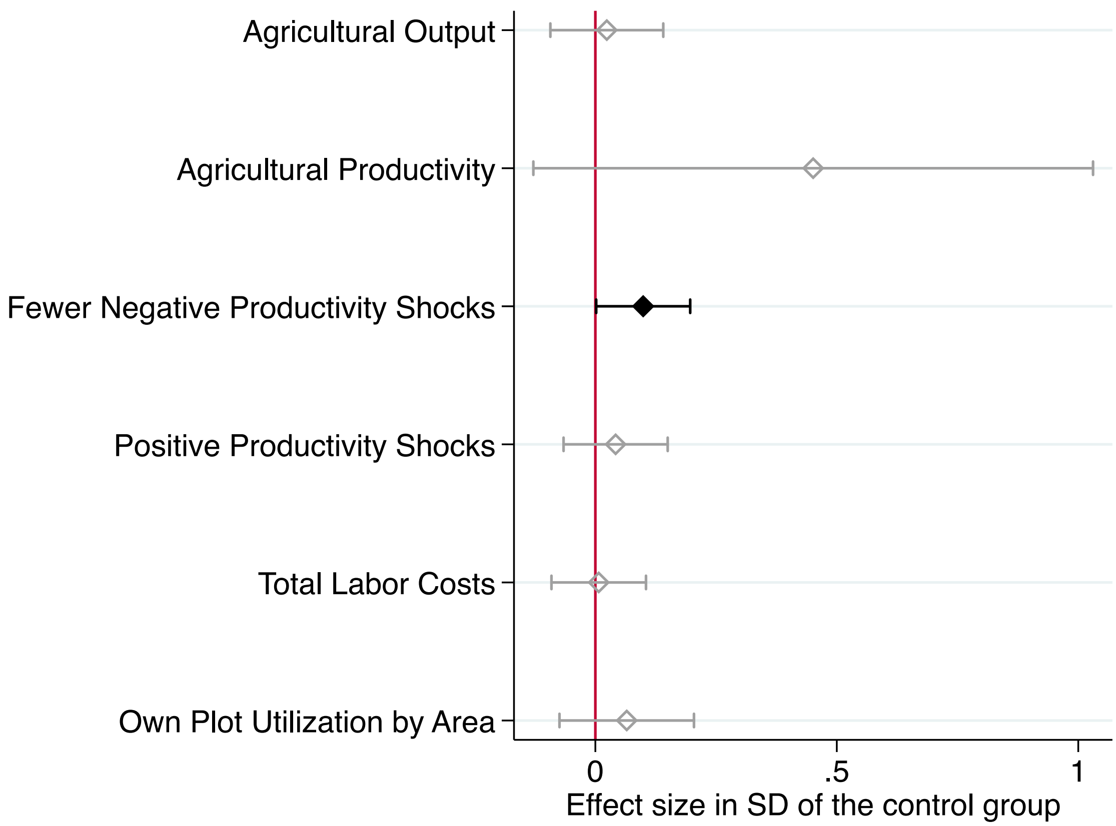


Figure 8 presents treatment effects on agricultural outcomes of interest for rural households. The figure reflects variables in the underlying Cobb-Douglas production function:

$$Y = AK^{\alpha}L^{\beta} \tag{6}$$

where Y refers to agricultural output, A represents agricultural productivity, K refers to land area and L represents labor. Agricultural productivity is estimated as the residual from a regression of output on land and labor (in logs).

Overall, we see positive treatment impacts on agriculture, although the point estimates are not always statistically significant. We estimate a large and positive point estimate of 0.45 standard deviation units on agricultural productivity, though estimated with wide standard error bars. We do, however, find that the incidence of negative productivity shocks is significantly lower among households in the treatment group. In particular, households in the treatment group were 1.6 percentage points less likely to be hit by a negative productivity shock. We return to the negative and positive productivity shocks in greater detail in Section 5.8.

Table 11: Results for Agriculture Index

	(1) Agriculture Index (OLS)	(2) Agriculture Index (OLS)	(3) Agriculture Index (IV)	(4) Agriculture Index (IV)
bKash Treatment	0.100	0.0935		
	(0.0683)	(0.0681)		
Active bKash Account			0.208	0.193
			(0.142)	(0.141)
R^2	0.122	0.135	0.114	0.129
Baseline Controls	No	Yes	No	Yes
Baseline Dep. Var. Control	Yes	Yes	Yes	Yes
Observations	815	815	815	815
Endline Control Group Mean	0	0	0	0

Standard errors in parentheses

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

Table 11 presents treatment effects on an agricultural index for rural households, where the index is constructed using the variables in Figure 8. Overall, we see that the treatment had a positive impact on the index (p-value = 0.14 without controls).

5.7 Rural Households: Consumption

Figure 9: Impact on Consumption

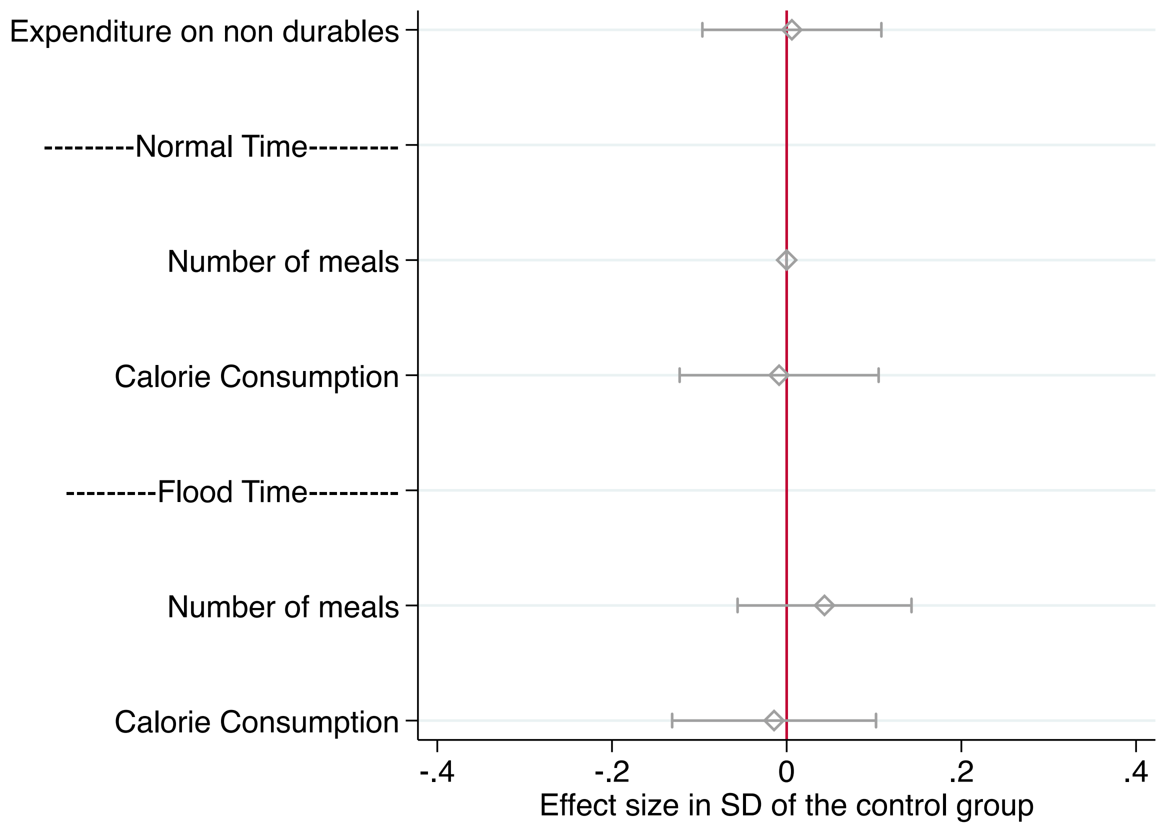


Figure 9 presents treatment effects on consumption of rural households. Despite the relatively tight standard error bars, we do not see any significant treatment impacts on consumption. We asked households about their annual expenditure on non-durables, and monthly consumption of eggs, meat, fish, fruits, and milk, separately for normal periods and flood periods. We then calculated the calorie consumption from these various food groups using calorie conversion factors provided by the Food and Agriculture Organization. Although there was no variation in the number of meals during normal periods (all households consumed 3 meals), households in the treatment group consumed more meals than households in the control group during flood periods, though this result is not statistically different from 0. We explore the treatment impact when households are faced with shocks in greater detail in Section 5.8.

Table 12 presents results for a consumption index, constructed with equal weights on the variables in Figure 9. We see that though the point estimates are positive, overall the treatment did not have a significant impact on consumption.

Table 12: Results for Consumption Index

	(1) Consumption Index (OLS)	(2) Consumption Index (OLS)	(3) Consumption Index (IV)	(4) Consumption Index (IV)
bKash Treatment	0.00625	0.0129		
	(0.0678)	(0.0652)		
Active bKash Account			0.0129	0.0266
			(0.140)	(0.134)
R^2	0.038	0.120	0.038	0.119
Baseline Controls	No	Yes	No	Yes
Baseline Dep. Var. Control	Yes	Yes	Yes	Yes
Observations	815	815	815	815
Endline Control Group Mean	0	0	0	0

Standard errors in parentheses

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

5.8 Rural Households: Risk and Insurance

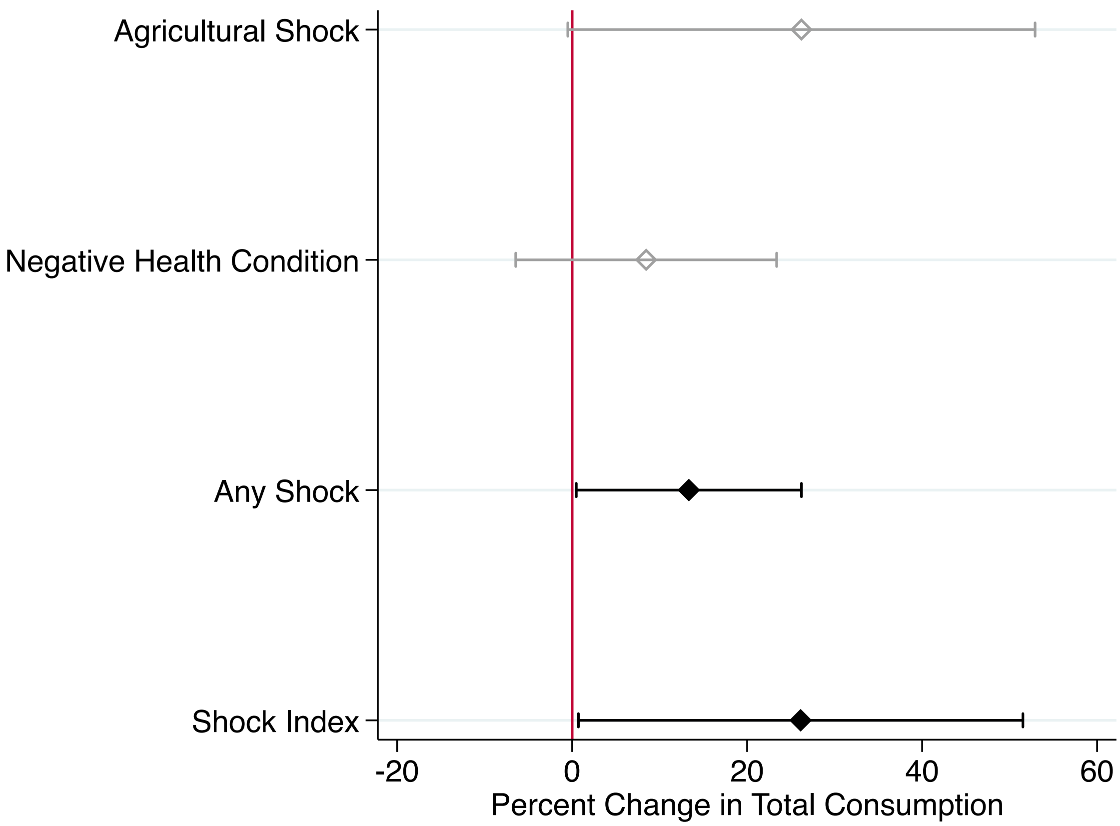
5.8.1 Negative Households Shocks

Though we do not see significant treatment impacts on consumption, remittances sent using bKash in times of negative shocks might help households better smooth their consumption. To test this hypothesis, we study the impact of the treatment on consumption when households are exposed to negative agricultural shock or health condition. Agricultural shocks are defined on agricultural productivity as defined in Section 5.6. A household is said to be hit by a negative agricultural shock if agricultural productivity for the household was in the bottom 30th percentile of the distribution of productivity. We say that a household was hit by a negative health condition if the head of the household was sick in bed or unable to perform normal activities for a week or more due to disability or illness, over the past 12 months.

We also aggregate the negative agricultural shocks and negative health conditions faced by households in two ways. First, we create a variable that captures whether the household was exposed to either type of shock. Second, we create a "shock index" variable in the spirit of Batista and Vicente (2016), by taking the average of the binary indicators for negative agricultural shocks and negative health conditions. In doing so, this index places equal weight on each type of shock.

We estimate Equation (3) and report β_1, the coefficient on the treatment assignment, in Figure 10. These coefficients compare the consumption of households in the treatment group hit by negative shocks with households in the control group hit by negative shocks. Here we use log(total consumption) as the dependent variable, and present the coefficients for negative agricultural shocks, negative health conditions, any shocks, and the shock index variable:

Figure 10: Impact on Log(Total Consumption)



Although the treatment did not have a significant impact on consumption overall, consumption of households in the treatment group hit by negative shocks was significantly higher than consumption of households in the control group hit by negative shocks. The cofficient obtained for agricultural shocks suggests that households in the treatment group hit by negative agricultural shocks consumed 26% more than households in the control group hit by negative agricultural shocks (p-value = 0.106). The point estimate is positive when we use negative health conditions, though not statistically significant at conventional levels. As such, sending remittances digitally during times of hardship is an important channel by which mobile money can help provide insurance and smooth consumption of households. The result lines up with Jack and Suri (2014), who also show that consumption of mobile money user households is unaffected during times of (self-reported) shocks while consumption falls by 7% for nonusers in Kenya.

Figure 11: Impact on Log(Food Consumption)

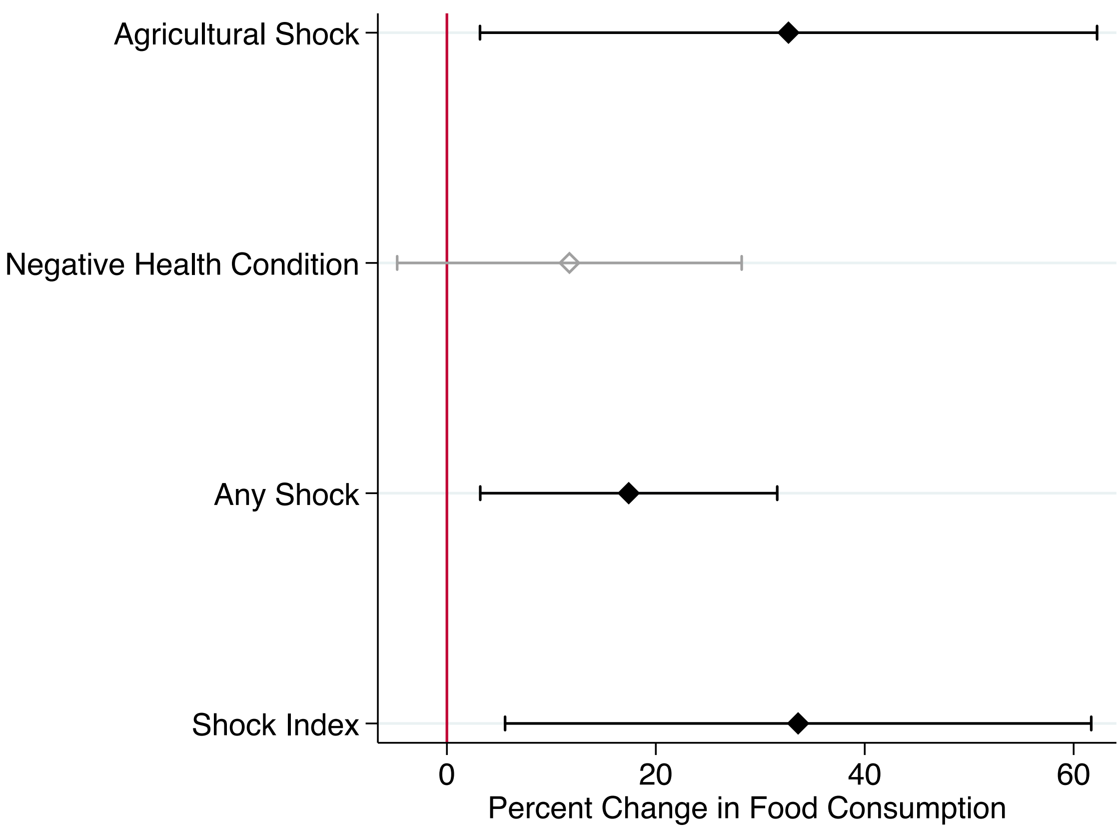
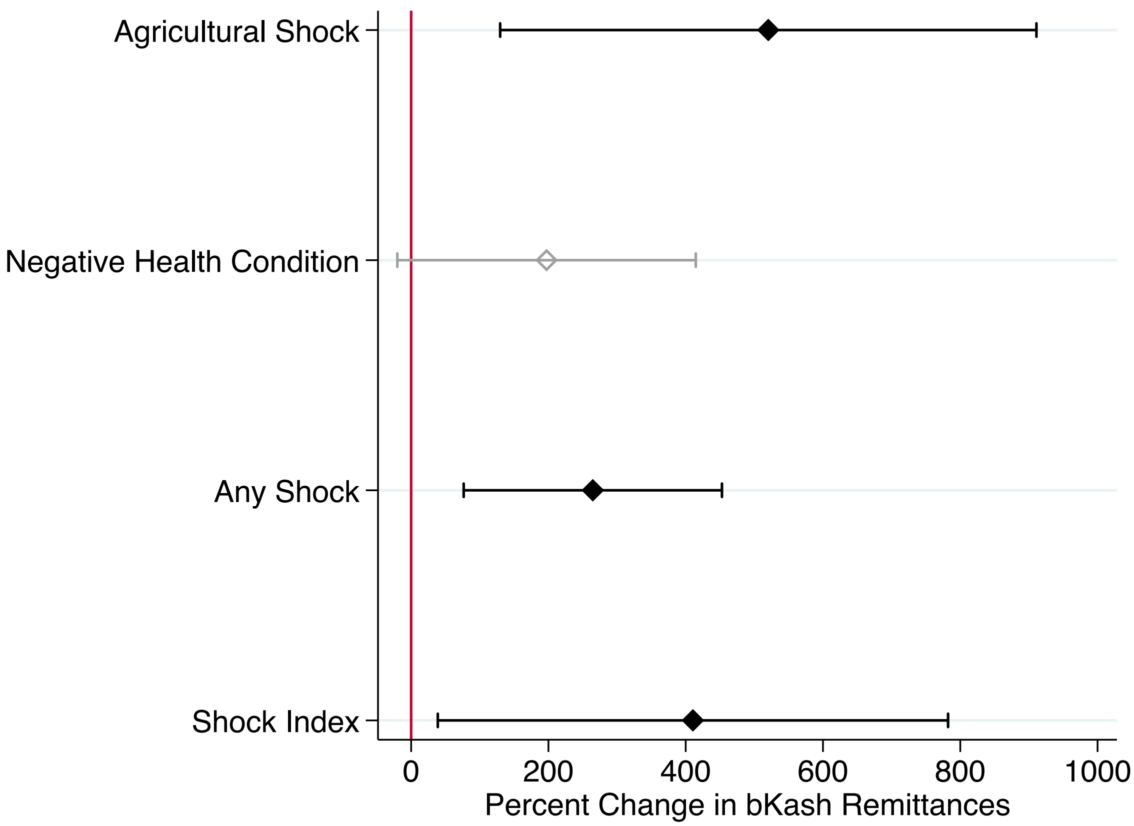


Figure 11 presents results on food consumption in the face of negative shocks. Results are stronger when log(food consumption) is used as the dependent variable, showing the insurance value of remittances against shocks that threaten basic nutrition.

Figure 12: Impact on Log(bKash Remittances + 1)



Next, we turn to the mechanisms underlying the positive impact on consumption when households in the treatment group are faced with negative shocks. Figure 12 shows that urban migrants paired to the rural households in the treatment group send significantly more remittances when the rural household was hit by negative shocks (the point estimate for negative health condition is estimated with p-value 0.13). Again, we estimate Equation (3) and report β_1, the coefficient on treatment assignment, where the dependent variable used is log(bKash remittances + 1). We see a pattern of remittances flows very consistent with the increases in consumption. The magnitudes of the point estimates suggest that migrants in the treatment group whose rural households are hit by negative shocks send

197 - 520% more remittances using bKash than migrants in the control group whose rural households are hit by negative shocks. These magnitudes are large, given that on average, migrants in the treatment group send 105% more remittances using bKash than migrants in the control group. This pattern of bKash remittance flows that matches the pattern of impacts on consumption highlights one key mechanism by which mobile money helps provide insurance to rural households in times of distress.

5.8.2 Negative Households Shocks, Negative Migrant Health Condition

Given that a key channel by which mobile money helps rural households smooth consumption is through remittances sent by the urban migrants, we next investigate the extent to which this consumption smoothing occurs when the paired migrants are hit with negative shocks as well. We hypothesize that consumption of rural households in the treatment group who face negative health conditions will be no different from that of rural households in the control group who face negative health conditions if additionally, the paired migrant is hit by a negative health condition as well. This is because the migant will be less able to smooth consumption by sending more remittances[10]. Again, the unique rural household - urban migrant matched pair design of the experimental setup enables us to study this.

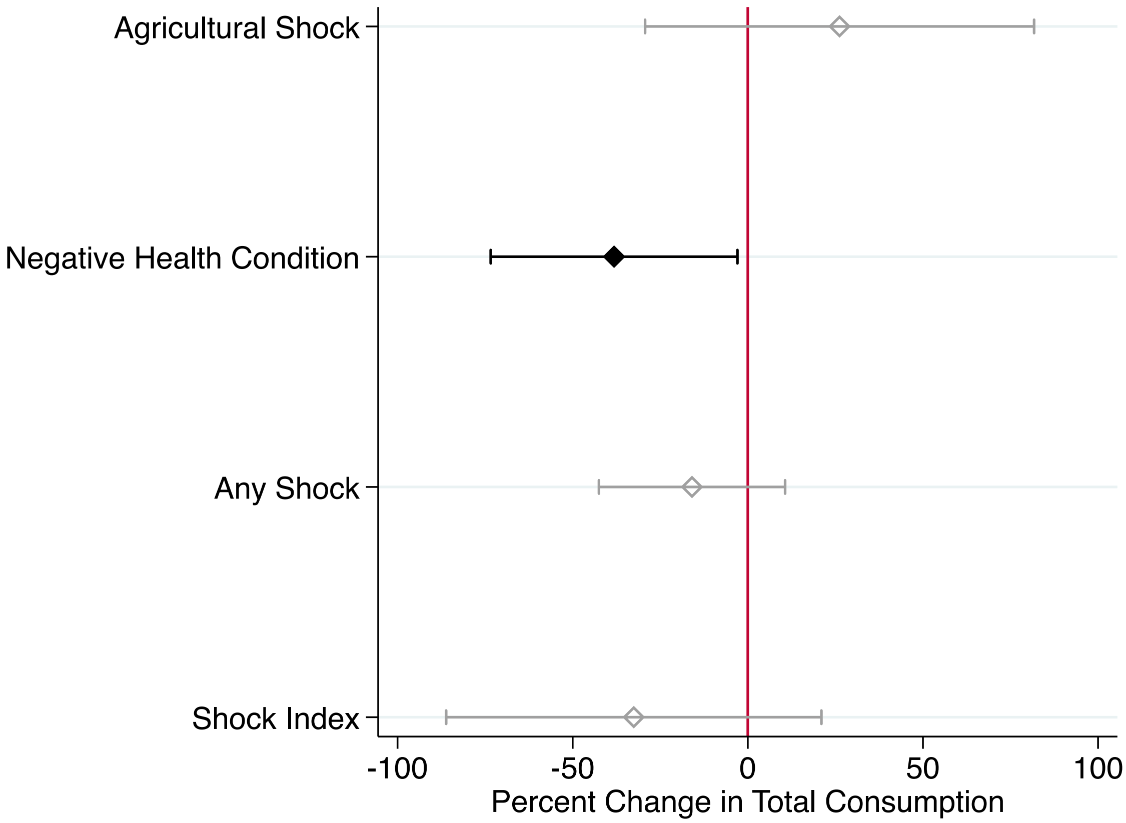
We estimate Equation (4) and report β_1, the coefficient on treatment assignment, in Figures 13 and 14, for total consumption and food consumption, respectively. The coefficients compare the consumption of households in the treatment group hit by negative shocks and whose paired migrant is also hit by a negative health condition, with households in the control group hit by negative shocks whose paired migrant is also hit by a negative health condition. Here, migrants are defined as hit by a negative health condition if their responses to any of the questions in the health questionnaire were in the worst two categories (i.e. severe and bad)[11]. With this definition, 31% of migrants were exposed to negative health

[10]We did not explicitly plan to investigate this hypothesis in the initial project proposal.

[11]Due to constraints of survey length in the urban sample, the urban health questionnaire presented responses in an ordered list of categories such as severe, bad, moderate, etc.

conditions, consistent with the 30th percentile cutoff used in the definition of agricultural shocks.

Figure 13: Impact on Log(Total Consumption) - Negative Migrant Health Condition



Indeed, when the paired migrant is hit by a negative health condition and hence unable to provide insurance in times of distress, the consumption of rural households in the treatment group is overall not statistically different from consumption of rural households in the control group. We obtain very similar results for food consumption, and bKash remittances, presented in Figures 14 and 15, respectively:

Figure 14: Impact on Log(Food Consumption) - Negative Migrant Health Condition

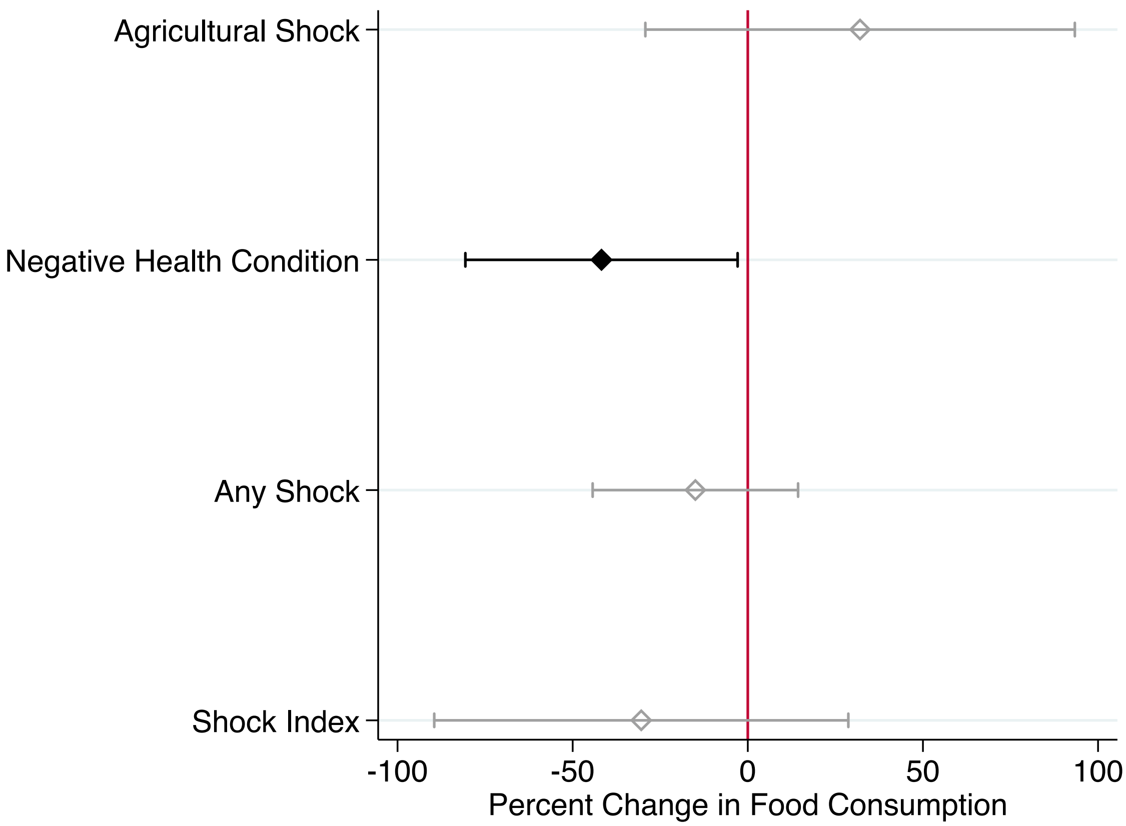
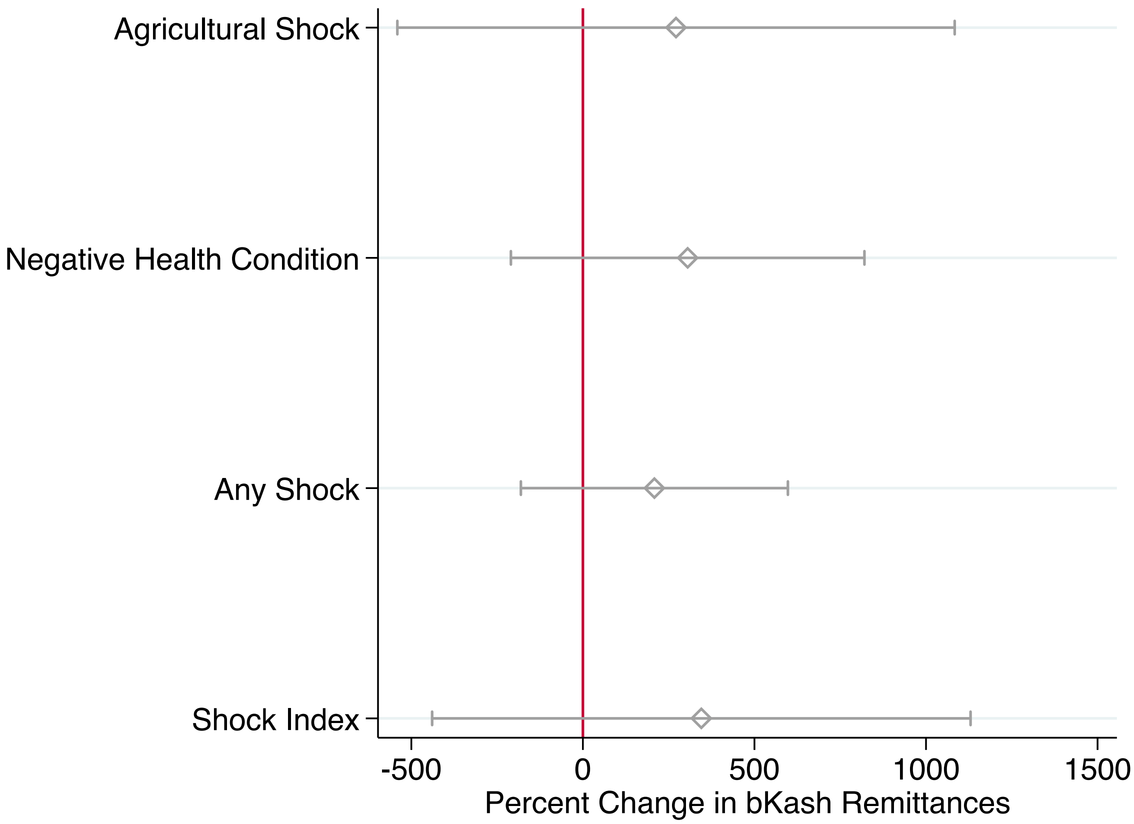


Figure 15: Impact on Log(bKash Remittances+1) - Negative Migrant Health Condition

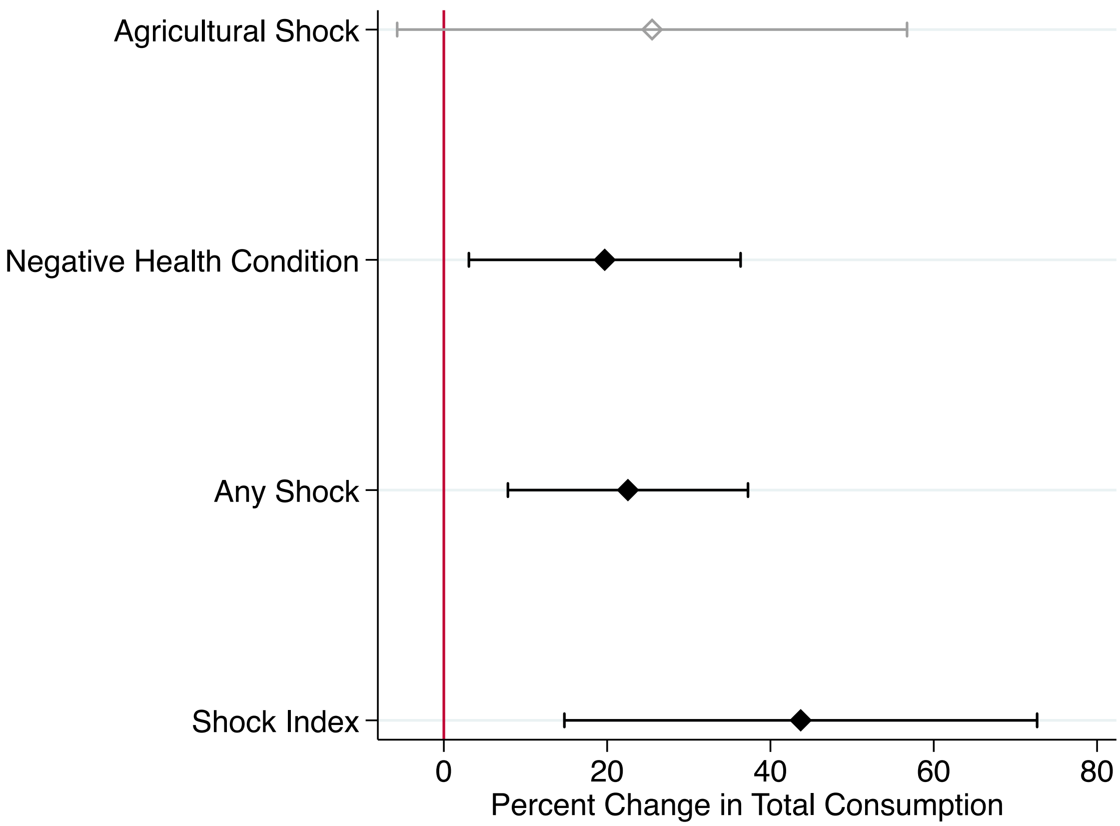


5.8.3 Negative Household Shocks, No Negative Migrant Health Condition

We also show the converse result that consumption of rural households in the treatment group who face negative health conditions is signficantly higher than that of rural households in the control group who face negative health conditions if additionally, the paired migrant is *not* hit by a negative health condition as well. This is because the migant will be better able to smooth consumption by sending more remittances when he/she is healthy[12]. We estimate Equation (5) and report β_1, the coefficient on treatment assignment, for each of the shock variables.

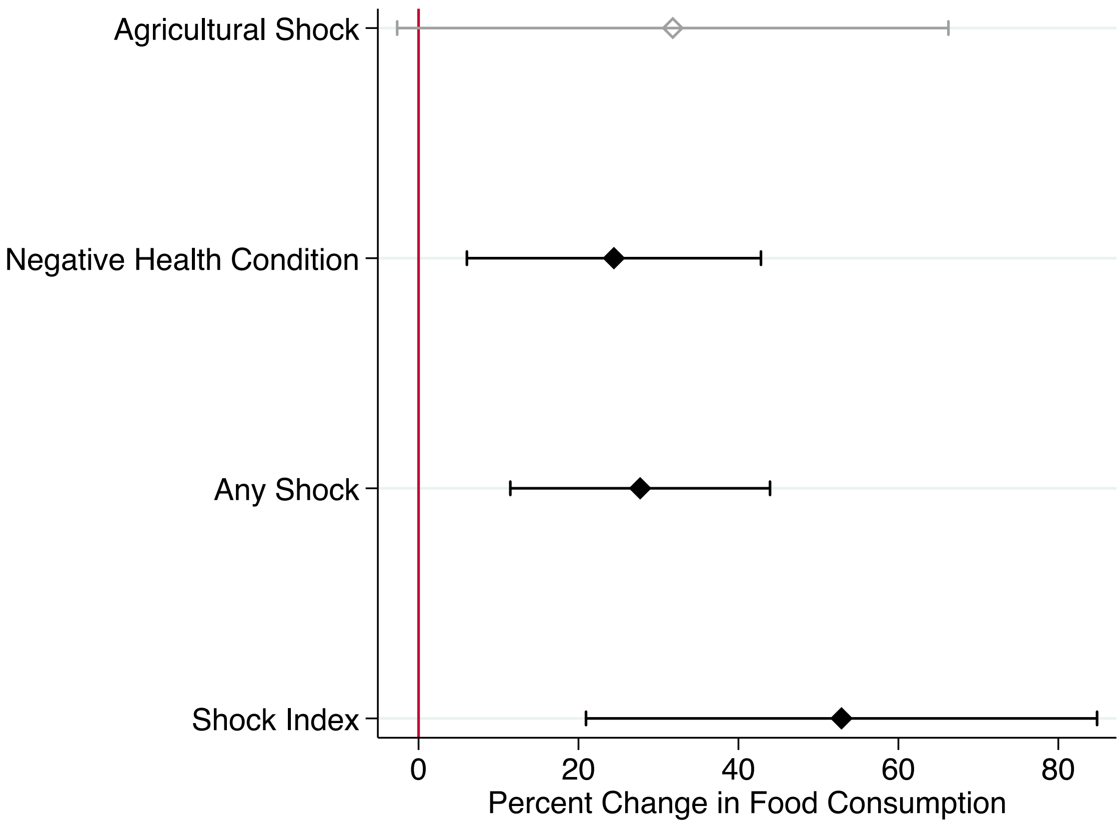
[12]We did not explicitly plan to investigate this hypothesis in the initial project proposal.

Figure 16: Impact on Log(Total Consumption) - No Negative Migrant Health Condition



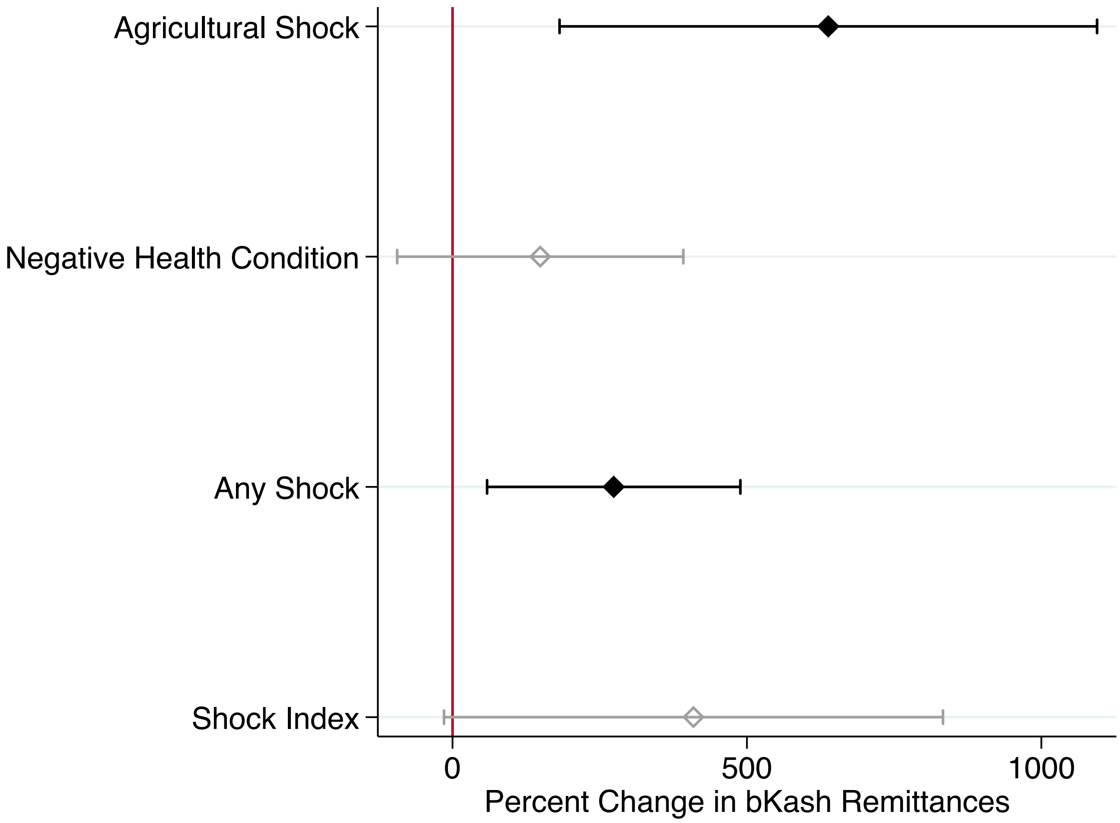
We now obtain stronger results on total consumption, than when we studied negative shocks to households in general in Figure 10. We present these results in Figure 16. In fact, the point estimate when studying negative health conditions is positive and now significant with a p-value of 0.051. The results are even stronger when we look at food consumption in Figure 17:

Figure 17: Impact on Log(Food Consumption) - No Negative Migrant Health Condition



Remittances sent using bKash follows a similar pattern to the increases in consumption, and are larger in magnitude relative to the point estimates in Figure 12. For example, migrants in the treatment group whose rural households are hit by a negative agricultural shock and whose migrant is not hit by a negative health condition send 638% more remittances using bKash than migrants in the control group whose rural households are hit by a negative agricultural shock and whose migrant is not hit by a negative health condition. The corresponding point estimate is Figure 12 was 520%. The point estimate on the shock index is positive and significant at a p-value of 0.11.

Figure 18: Impact on Log(bKash Remittances+1) - No Negative Migrant Health Condition



5.8.4 Positive Household Shocks

In this section, we study the impact of mobile money on savings when rural households are faced with positive agricultural shocks. A household is said to be hit by a positive agricultural shock if agricultural productivity for the household was in the top 30th percentile of the distribution of productivity. Table 13 presents results estimating Equation (3):

Table 13: Results for Savings with Positive Shocks

	(1) Any Savings	(2) Log(Savings+1)
bKash Treatment	0.434***	1.218***
	(0.0303)	(0.247)
No Positive Shock$_h$	-0.130	-0.549
	(0.0981)	(0.797)
No Positive Shock$_{h,baseline}$	0.0630	0.296
	(0.0424)	(0.345)
bKash Treatment $*$ No Positive Shock$_h$	0.0865	0.784
	(0.143)	(1.159)
R^2	0.225	0.042
Baseline Controls	Yes	Yes
Baseline Dep. Var. Control	Yes	Yes
Observations	815	815
Endline Control Group Mean	0.43	2.58

Standard errors in parentheses

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

The coefficient on bKash treatment implies that households in the treatment group who face positive shocks are 43% more likely to save, compared to households in the control group who face positive shocks. Furthermore, they save 122% more than households in the control group who face positive shocks. This is because bKash offers an additional way in which households can save, simply by leaving money in their accounts. Given that such savings can help households in times of need, the treatment impact on the extensive margin of savings highlights that in addition to remittances, mobile money can also help households smooth their consumption and mitigate risk through savings.

5.9 Urban Households: Poverty

In this section, we turn attention from rural households to the urban migrants. Before a detailed analysis of treatment impacts on remittances, savings, employment, and health of migrants, we present results on measures of poverty that capture treatment impacts on expenditure and income of migrants. Table 14 presents these results:

Table 14: Results for Poverty

	(1) BPL (OLS)	(2) BPL (IV)
bKash Treatment	-0.0514*	
	(0.0272)	
Active bKash Account		-0.108*
		(0.0571)
R^2	0.140	0.141
Baseline Controls	Yes	Yes
Baseline Dep. Var. Control	Yes	Yes
Observations	811	811
Endline Control Group Mean	0.242	0.242

Standard errors in parentheses

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

Table 14 presents results for treatment impacts on migrants who are Below Poverty Line (BPL) using the expenditure method. The poverty line was constructed using the national poverty line for Bangladesh. Urban poverty line data was obtained from the World Bank, and adjusted to 2016 prices using the urban Consumer Price Index from the Bangladesh Bureau of Statistics. Migrants were defined as BPL if their per capita daily expenditures were below the poverty line.

Migrants in the treatment group were 5.1 percentage points significantly less likely to be below the poverty line, on a control mean base of 24.2% (p-value = 0.059)[13]. Furthermore, the TOT estimate in column (2) shows that treated migrants were 10.8 percentage points less likely to be below the poverty line. These large points estimates suggest that bKash can serve as an effective poverty reduction tool for the poor[14].

[13] 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.

[14] As a robustness check, we repeated the BPL exercise using per capita income instead of expenditures, and obtained qualitatively similar estimates.

5.10 Urban Households: Savings

We next turn to results on savings by migrants in Table 15:

Table 15: Results for Savings

	(1) Any Savings	(2) Any Savings	(3) Log(Savings+1)	(4) Log(Savings+1)
bKash Treatment	0.180***		0.384	
	(0.0243)		(0.249)	
Active bKash Account		0.380***		0.811
		(0.0515)		(0.523)
R^2	0.090	0.074	0.036	0.037
Baseline Controls	Yes	Yes	Yes	Yes
Baseline Dep. Var. Control	Yes	Yes	Yes	Yes
Observations	811	811	811	811
Endline Control Group Mean	0.756	0.756	5.682	5.682

Standard errors in parentheses

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

Columns (1) and (2) present results for the extensive margin on savings. We see that migrants in the treatment group are 18 percentage points more likely to save, on a control mean base of 75.6%. 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 (3) suggests that migrants in the treatment group save 38.4% more than migrants in the control group (p-value = 0.09 without baseline controls, p-value = 0.12 with baseline controls). This result is not conditioned on having saved, and hence combines the extensive and intensive margins of savings.

5.11 Urban Households: Employment and Health

Table 16: Results for Work in Garments Industry

	(1) Garments Worker (OLS)	(2) Garments Worker (OLS)	(3) Garments Worker (IV)	(4) Garments Worker (IV)
bKash Treatment	0.0596*	0.0541		
	(0.0347)	(0.0344)		
Active bKash Account			0.125*	0.114
			(0.0728)	(0.0723)
R^2	0.004	0.031	0.000	0.029
Baseline Controls	No	Yes	No	Yes
Baseline Dep. Var. Control	No	No	No	No
Observations	811	811	811	811
Endline Control Group Mean	0.549	0.549	0.549	0.549

Standard errors in parentheses

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

Table 16 presents treatment effects on employment in the garments and textiles industry. Migrants in the treatment group were 6 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 54.9% (p-value = 0.086 without controls, p-value = 0.116 with controls)[15].

There are two possible reasons for the above result: it could either be the case that more migrants decided to move into garments work (higher entry), or more migrants decided to stay on in their current jobs in the garments 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[16].

Next, we turn to the health impacts of the treatment on migrants:

[15]Unfortunately, we did not collect occupation data at baseline and thus did not run these regressions with control for the baseline value of the dependent variable.

[16]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.

Figure 19: Impact on Health

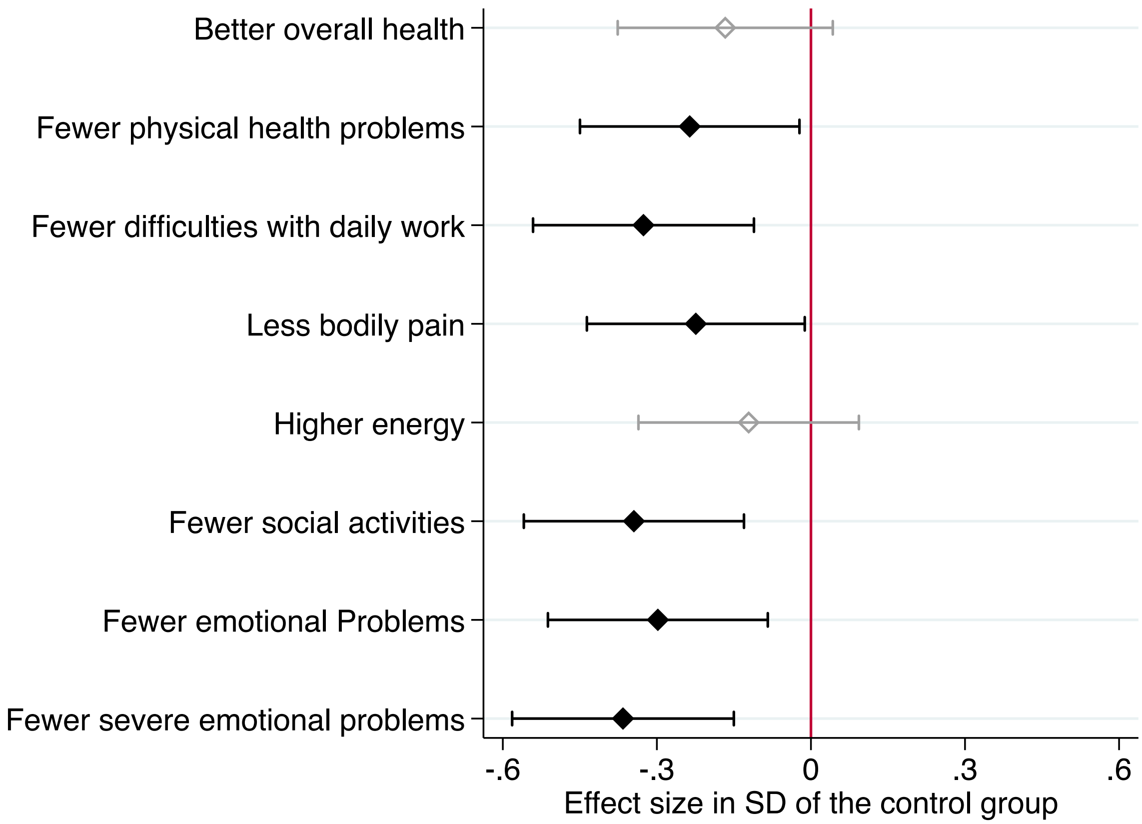


Figure 19 presents these treatment effects. For this section of the questionnaire, migrants were presented with an ordered list of responses. For example, the options to the first question on overall health were Poor, Fair, Good, Very Good, and Excellent. As such, the regressions were run using an ordered logit specification. The point estimates and standard error bars in Figure 19 are obtained from these regressions[17].

The treatment had several negative impacts on the health of migrants. For example, migrants in the treatment group have more difficulties with daily work and emotional problems. The negative health impact overall is shown in Table 17 below, which presents results for the health index variable, constructed with equal weight on each of the variables in Figure 19:

Table 17: Results for Health Index

	(1) Health Index (OLS)	(2) Health Index (OLS)	(3) Health Index (IV)	(4) Health Index (IV)
bKash Treatment	-0.125*	-0.128*		
	(0.0690)	(0.0686)		
Active bKash Account			-0.263*	-0.271*
			(0.145)	(0.145)
R^2	0.072	0.093	0.064	0.091
Baseline Controls	No	Yes	No	Yes
Baseline Dep. Var. Control	Yes	Yes	Yes	Yes
Observations	811	811	811	811
Endline Control Group Mean	0	0	0	0

Standard errors in parentheses

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

Columns (1) and (2) of Table 17 show that the treatment decreased the health index of households in the treatment group by 0.125 standard deviation units, significant at the 10% level. Columns (3) and (4) show that the treatment decreased the health index of treated households by 0.26 standard deviation units.

[17] 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.

One potential channel for this negative health impact could arise from the increased stress of having to remit money back home, for migrants in the treatment group, as we saw in the impacts on the fraction of income remitted. We saw that migrants in the treatment group remitted 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%, which could arise from greater pressure to remit money back home in the treatment group. Such stress could be a contributing factor for the negative health impacts we see for migrants.

To further study the reasons for this negative health impact, we investigate the link between migrants' employment and health. We note that while garment workers earn more and work longer, they do so at the expense of their health. Table 18 illustrates this:

Table 18: 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	1.369***	3.216***	1.791***	-0.160**
	(0.158)	(0.302)	(0.166)	(0.0701)
R^2	0.143	0.314	0.163	0.095
Baseline Controls	Yes	Yes	Yes	Yes
Baseline Dep. Var. Control	Yes	Yes	Yes	Yes
Observations	811	811	811	811
Endline Control Group Mean	10.969	4.744	9.753	0

Standard errors in parentheses

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

Columns (1), (2), and (3) show that while garments workers earn more income, they also work longer. This is also reflected in the higher overtime income of garments workers. These results are large and significant at the 1% level. In particular, migrants in the garments sector receive 320% more overtime pay than migrants in other sectors. 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. Controlling for either overtime income or hours worked in column (4) yields an insignificant relationship between garments work and health, suggesting that the longer hours in garments work is a plausible explanation for worse health.

This, combined with the result from Table 16, which shows that migrants in the treatment group are more likely to be employed in the garments sector at endline, offers one possible explanation for why migrants in the treatment group have worse health. In fact, we do not observe the negative health impacts of the treatment once we drop migrants who are employed in the garments sector at endline[18]. These results are in line with results by Blattman and Dercon (2016), who 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.

5.12 Robustness Checks: Spillovers

One potential concern with the study design is spillovers to the control group, given that the randomization was done at the individual level. In this section, we check for potential spillovers in the rural and urban samples using treatment density. 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.

[18]We do note, however, that the number of observations falls from 811 to 341 when we exclude migrants in the garments sector, so this null result on health could also be due to a decrease in power.

Table 19: Spillover Analysis - Rural Households

	(1) Adopted bKash (OLS)	(2) Adopted bKash (OLS)	(3) Active bKash Account (OLS)	(4) Active bKash Account (OLS)
Treatment Density	-0.0455	-0.0377	-0.0413	-0.0279
	(0.0975)	(0.0978)	(0.0877)	(0.0874)
R^2	0.001	0.009	0.001	0.022
Baseline Controls	No	Yes	No	Yes
Baseline Dep. Var. Control	No	No	No	No
Observations	402	402	402	402
Endline Control Group Mean	0.303	0.303	0.219	0.219

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 19 presents results for the spillover analysis for rural households. Here treatment density was defined at the village level[19]. Columns (1) and (2) present results for bKash adoption, while columns (3) and (4) present results for active bKash accounts[20]. We see that 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, 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, there do not seem to be any 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. In fact, Emma Riley (2016) shows that villages with more mobile money users in Tanzania saw consumption of non-users in the villages increase as well, owing to sharing of remittances throughout the village. We can directly test for this in the data:

[19]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.

[20]Unfortunately, we were only able to obtain bKash administrative data for the one-year peroid 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 20: Spillover Analysis - Rural Households (Consumption)

	(1) Daily Per Capita Expenditure (OLS)	(2) Daily Per Capita Expenditure (OLS)	(3) Consumption Index (OLS)	(4) Consumption Index (OLS)
Treatment Density	-3.996	-6.385	-1.067	-0.691
	(9.419)	(8.888)	(0.728)	(0.700)
R^2	0.052	0.186	0.029	0.133
Baseline Controls	No	Yes	No	Yes
Baseline Dep. Var. Control	Yes	Yes	Yes	Yes
Observations	402	402	402	402
Endline Control Group Mean	36.085	36.085	0	0

Standard errors in parentheses

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

Table 20 shows no evidence of consumption spillovers. In fact, the point estimates are consistently negative when we consider potential spillovers to daily per capita expenditures and the consumption index.

We turn to the spillover analysis for urban migrants in Table 21:

Table 21: Spillover Analysis - Urban Migrants

	(1) Adopted bKash (OLS)	(2) Adopted bKash (OLS)	(3) Active bKash Account (OLS)	(4) Active bKash Account (OLS)
Treatment Density	-0.0309	0.0125	0.0517	0.0889
	(0.172)	(0.167)	(0.165)	(0.162)
R^2	0.000	0.073	0.000	0.049
Baseline Controls	No	Yes	No	Yes
Baseline Dep. Var. Control	No	No	No	No
Observations	397	397	397	397
Endline Control Group Mean	0.232	0.232	0.207	0.207

Standard errors in parentheses

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

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. (The result is robust to using logit and probit specifications.) Taken together with the results on the rural sample, the analysis shows no evidence of spillovers to the control group.

6 Conclusion

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 may require revisiting.

The movement of people and money also suggests the possibility of broadening ways to improve rural conditions (Bryan et al 2014). We show that rural conditions can also be improved by facilitating engagement with urban jobs and opportunities – and with 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, 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. 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 Englsh-language 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.

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.

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, we find that rural households in the treatment group reduced borrowing levels, increased savings, and saw improvements in health, education and agricultural productivity. We also find stronger ability to protect consumption in the face of negative health and agricultural shocks. In this setting, mobile money services facilitate the transfer of substantial net resources to rural Gaibandha and improves insurance mechanisms. The migrants to Dhaka, though, have mixed experiences. We find increases in garment work, and reductions in poverty, but declines in self-reported health status (a finding parallel to work on 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.

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