The Impact of Mobile Money on Long-Term Poverty: Evidence from Bangladesh

A.T.M. Hasibul, Islam and Syed Abul, Basher and A.K. Enamul, Haque

9 December 2019

The Impact of Mobile Money on Long-Term Poverty:

Evidence from Bangladesh[1]

A.T.M. Hasibul Islam[2], **Syed Abul Basher**[3], and **A.K. Enamul Haque**[4]

December 8, 2019

[1] We thank the seminar participants at East West University and Economic Research Group for their helpful comments. We also thank Megan Foster for assistance with proofreading.
[2] Department of Economics, University of Victoria, Victoria, BC V8P 5C2, Canada. E-mail: hasib2335@uvic.ca
[3] **Corresponding author:** Department of Economics, East West University, Plot No-A/2, Aftabnagar Main Road, Dhaka 1219, Bangladesh. Phone: +8801972226676. E-mail: syed.basher@ewubd.edu
[4] Department of Economics, East West University, Plot No-A/2, Aftabnagar Main Road, Dhaka 1219, Bangladesh. E-mail: akehaque@ewubd.edu

Abstract

Mobile money has become a lifeline for millions of poor people who have limited access to a formal banking system. It encompasses a wide range of benefits such as women's empowerment, risk sharing, improved labor market outcomes and reductions in poverty. In this paper, we ask whether mobile money can help lift people out of poverty. Previous studies have addressed this question by using microanalyses of field experiments or longitudinal data on rural households, whereas we use district-level data to reevaluate the mobile money–poverty nexus. In particular, we study the impact of mobile money on district-level poverty in Bangladesh over the period 2010–2016. Our study finds that every 1 billion Taka (approximately US$ 11.76 million) increase in mobile money transactions via the bKash system leads to a 0.48% reduction in the poverty rate in Bangladesh. The marginal impact ranges from 0.27 to 0.48 percentage points across five poverty quintiles, implying a reduction of poverty rates between 0.9 and 1.5 percentage points compared with the base poverty rate of 31.5% in 2010. The findings suggest that mobile money has been successful in fostering various poverty reduction initiatives and that targeted policy prescriptions can be devised to lift up poorer societies that are still outside the purview of mobile financial services. To further increase mobile money use, the government could use its own infrastructure to enhance mobile agent density in the poorest sectors of society.

JEL Codes: G20, I32, L96, O16.

Keywords: Mobile money, poverty, bKash.

1. Introduction

Since its inception in the Philippines in 2001, mobile money has become a lifeline for millions of poor people who have limited access to a formal banking system. However, the rapid growth of mobile money services in developing countries results from the successful implementation of M-PESA, a mobile money transfer service in Kenya. Incorporated in 2011, Bangladesh's equivalent of M-PESA is called bKash.[5]

Mobile money services have revolutionized the lives of the poor in several ways. Starting from simply sending and receiving money, mobile money is used to "buy" free mobile airtime and saves precious time for women in rural areas that would otherwise be spent traveling. As we elaborate in the next section, the economics of mobile money services encompasses benefits like women empowerment, risk sharing, improved labor market outcomes and reductions in poverty.

The academic interest in mobile financial services (MFS) stems largely from its potential to address a number of market failures (e.g., banking the unbanked, transaction costs) and the resulting impact on poverty, among other outcomes. By now, a burgeoning branch of literature empirically analyzes the economic impact of mobile money. In reviewing the literature, Aron (2018) developed an analytical typology table that summarized the findings of nearly 20 empirical studies, whereas Aron (2017) offered a more in-depth analysis of micro-empirical studies. One conclusion arising from these reviews is the underlying data and the methodological challenge of ensure that appropriate data are used to separate the broader effect of mobile money on rural livelihoods.

How does mobile money help reduce poverty? To reduce poverty, mobile money must address the problems that the poor so often encounter. One such problem concerns the capability of surviving unexpected expenses such as purchasing livestock or buying farming equipment at the right times. In such situations, reliance on cash is tricky because it is easy to lose or spend. Having access to a bank or mobile money helps people take control of their money and financial lives (Klapper, 2018). Moreover, it also

[5] "b" stands for Brac, an international NGO based in Bangladesh; "Kash" is "Cash". Besides bKash, there are 17 operational MFS providers in Bangladesh as of 2018. However, within six years of its launch, bKash had accumulated 30 million registered users and an 80% share of the mobile money market in Bangladesh.

softens the impact of sudden health-related expenses and thus prevents people from falling into poverty. Jack and Suri (2014) found that households without access to mobile money account suffered a 7% drop in consumption compared with households with access to mobile money. Mobile money may not be the solution to extreme poverty, but mobile money and bank accounts enable poor people to effectively confront the problems that keep them stuck in poverty.

The main goal of this paper is to develop an empirical framework for quantifying the impact of the bKash mobile money service on poverty in the 64 districts of Bangladesh. Identifying the causality from mobile money to poverty reduction is not without problems. Some challenges include potential reverse causality from poverty (the lack of it) to greater use of mobile money services, and omitted variables, as many observed and unobserved factors affect poverty. We address this potential endogeneity bias through the use of an instrumental variable regression model, where, following earlier approaches in the literature, a suitable instrument (i.e., “agent density") was chosen.

Overall, our main results that for every 1 billion Taka (approximately US$ 11.76 million) increase in bKash transactions, the poverty rate declines by 0.48%. The effect is statistically significant at the 10% level. Districts in different quintiles have different effects. The largest impact of bKash mobile money on poverty is found for quintile 2, which comprises 14 districts that are largely industrial in nature. A byproduct of our analysis shows a rather persistent effect of the previous poverty level on today's poverty in Bangladesh. The estimated coefficient on lagged poverty suggest a half-life of poverty of six years. Taken together, our results complement the existing literature which suggests that mobile money promotes the welfare and wellbeing of the poor.

The rest of the paper is organized as follows. Section 2 presents the legal and economic environment of MFS. Section 3 briefly reviews empirical studies on the connection between mobile money and poverty reduction. Section 4 discusses the data and offers some summary statistics of the variables of interest. Section 5 outlines the econometric methodology and the model specification. Section 6 presents some graphical analyses as well as the main empirical results. Section 7 concludes the paper.

2. The Legal Structure and the Economics of MFS

2.1 Regulatory Framework of Mobile Money in Bangladesh

Buttressed by rapid expansion of mobile phone users and modernization of payments and financial infrastructure, MFS have become a new, and often the only, medium of doing banking, particularly "for the undeserved, un-banked/under-banked and low income group of population" (Bangladesh Bank, 2018). MFS were first introduced in Kenya (M-PESA) and the concept was adopted in Bangladesh in 2011. In 2011, Bangladesh Bank, the country's central bank, issued guidelines for banks for conducting MFS in Bangladesh (Bangladesh Bank, 2011). Although Bangladesh Bank has allowed 28 banks to offer MFS, to date, 17 banks have gone operational with MFS.

In an interesting study, Evans and Pirchio (2015) explored the factors that led to the success or failure of MFS in 22 developing countries. A rather surprising result was that among the eight countries that had experienced growth in MFS, Bangladesh had the heaviest restrictions on mobile network operators (MNOs). For instance, unlike Kenya's light regulatory requirements, only banks are mandated to offer MFS in Bangladesh. Furthermore, customers must meet stringent know-your-customer (KYC) requirements to open an MFS account. Consequently, all customer accounts, called "mobile accounts", are held by a bank and they must be accessible through customers' mobile devices (Parvez et al., 2015).

Until recently, MFS providers had a revenue sharing agreement with MNOs at agreed rates. Extensive negotiations have taken place between MFS providers and MNOs on the business side, and Bangladesh Bank and Bangladesh Telecommunication Regulatory Commission on the regulatory side for the introduction of unstructured supplementary service data (USSD) session-based pricing and the pricing of the SMS messages sent for the purposes of MFS. Since September 2018, a newly approved USSD-based pricing model has been adopted, where MNOs will get BDT 0.85 for a 90-second revenue-generating USSD session and BDT 0.40 for 90-second non-revenue-generating USSD session. Needless to say, these changes will increase the cost of mobile banking and may deter low-income people from accessing MFS.

2.2 The Economics of Mobile Money

Barely heard of a decade ago, mobile money "has transformed the landscape of financial inclusion in developing and emerging market countries, leapfrogging the provision of formal banking services" (Aron and Muellbauer, 2019). Today, two-thirds of low- to middle-income countries use mobile money for a variety of purposes. Mobile money addresses a number of market failures that would not be addressed by traditional bricks-and-mortar financial services.

Though well-known for its primary function of transferring money (the so-called cash in–cash-out model), mobile money has the potential to become a lending platform for the collateral-less poor. For instance, the real-time history of financial transactions can be used to generate individual credit scores to judge whether the applicant deserves credit (Karlan et al. 2016). In fact, two celebrated tech companies in China have devised an algorithm that allows mobile banks to offer 1-second loan decisions in rural areas (Cho and Hinata, 2019). Mobile money therefore has the potential to materially change the banking landscape in developing and emerging market countries. Below, we briefly discuss the various microeconomic impacts of mobile money.

Transaction costs are the first problem that mobile money solves. Transaction costs include the transport costs of travel, the time value, waiting time, co-ordination costs, delays and leakages. These costs occur when individual-to-individual or institution-to-individual (or vice versa) transactions take place. In Kenya, where families and social networks are widely dispersed through internal migration, remittances travel more than 200 km on average (Jack and Suri, 2014). Let us consider the situation of a worker who works in a garment factory in Dhaka and must travel to the local village in Rajshahi to send money to his/her family (a journey involving over 250 km). A garment worker in Bangladesh gets a minimum monthly wage of BDT 8,000 ($95) a month (Reuters, 2018). The direct transaction costs compared with bKash's cash-out cost is shown in Figure 1. It is evident that for low-earning workers, mobile money is an efficient channel for sending money home compared with direct travel costs.[6]

[6] In a survey, Rahman (2014) found that 47% of Bangladeshi rickshaw operators sent money home weekly and 21% did so fortnightly. All (100%) of the survey respondents believed that mobile money was safe and 85% agreed that it was cost-effective.

— (Insert Figure 1 here) —

The informal economy or, put differently, cash that was previously kept under the pillow and used for day-to-day business is now increasingly relying on a system of recorded cash transactions. This helps lessen the problem of asymmetric information and improves transparency. The user can see their financial transaction history, businesses can create efficient and reliable credit rating histories and the regulators can monitor the financial system better.

Empowerment of women is another important aspect that mobile money brings to the economy. A powerful side-effect of MFS is that women can independently conduct their financial transactions without interference from anyone. Another obvious benefit of MFS is the time savings associated with mobile transfers, giving women more time for other endeavors. For example, such time savings allowed women in Niger to improve household diet diversity by 9–16% compared with households who did not receive mobile transfers (Aker et al. 2016). Mobile money transfers address other important logistical challenges such as buying or transferring mobile airtime instantly and for free, which can be used to access the internet to access valuable information. All in all, MFS create a sense of independence and a feeling of empowerment, especially among women, which can alter the gender gap within the family.

Better savings mechanisms for the poor are another important innovation of mobile money. Here, two opposing forces are present. The storage mechanism reduces the cost of saving and creates an incentive to save, whereas the money transfer mechanism reduces the incentive to save. The net effect is theoretically ambiguous, but Gürbüz (2017) found that rural Kenyan households using M-PESA are 16–22% more likely to save. The saving impact is higher for unbanked households than for those with an existing bank account.

Risk and insurance can be facilitated by mobile money. In the face of a negative shock, cashing-out activities through mobile money significantly increases, as poor households are more likely to receive

---

The remitted money is generally spent as follows: 75% on food and family maintenance, 31% on education for children, 35% is invested, 32% on small business expenses and 9% on repaying loans.

transfers. Jack and Suri (2014) documented that households are 13% more likely to receive remittances during bad times. Similarly, Blumenstock et al. (2016) observe that in response to the Lake Kivu earthquake of 2008, airtime transfers to individuals in the affected region increased immediately and substantially. The resulting increase in velocity (rate of cash use) and the volume of currency in circulation are the affected low-income societies is likely to facilitate risk-spreading. Indeed, families without mobile money transfers experienced a 7% fall in consumption after a major shock (Jack and Suri, 2014). Likewise, mobile insurance and micro-insurance are seeing high growth in sub-Saharan Africa. Payments via mobile money transfer services are helping farms in Ghana, Kenya and Uganda to have access to simple and affordable crop insurance via their smartphones (Bird, 2018).

In summary, the available empirical evidence shows that mobile money has been effective in addressing several areas of market failure in developing countries. In addition to the areas listed above, Aron and Muellbauer (2019) highlighted a number of additional channels through which mobile money can impact the nature of social networks, facilitating trade and increasing labor market opportunities. Encouragingly, the aggregate (or system-wide) benefits of mobile money are far greater than those documented by static microdata-based studies (Aron and Muellbauer, 2019).

3. Literature Review

There is, by now, a large amount of literature on the nature and economic implications of mobile money. The two surveys by Aron (2017, 2018) and the summary by Aron and Muellbauer (2019) contain extensive discussions of empirical evidence on the impact of mobile money. Our goal here is not to provide another survey of the empirical evidence. Instead, we selectively review recent literature on the impact of mobile money on poverty.

Blumenstock et al. (2015) asked a different question that was overlooked in the prior literature. They examined whether an individual's past history of mobile phone use can be used to accurately predict that same individual's socioeconomic characteristics. Their results demonstrate that it is possible to predict poverty and wealth from mobile phone metadata. Although the authors did not focus on mobile money transfer data, one can surely imagine the huge potential of accurately constructing the distribution of wealth of an entire nation when of cash-in and cash-out transaction histories are analyzed.

When the transaction costs of transferring resources between two spatially separated individuals are high, risk sharing is low. Jack and Suri (2014) tested the importance of transaction costs as a barrier to full insurance in the context of cost-reducing mobile money transfers via M-PESA in Kenya. They found that non-M-PESA households suffered a 7% drop in consumption in the face of a negative income shock. The effect was more pronounced for the bottom three quintiles of income distribution. Their results highlighted the vital role of mobile money in facilitating the effective size and number of active participants in risk sharing networks.

In a follow-up study on the M-PESA system, Suri and Jack (2016) examine whether transformative MFS have the capability to lift people out of poverty over the longer term. By using several rounds of a household panel survey between 2008 and 2014, they found that the M-PESA system increased per-capita consumption levels and lifted 194,000 households (representing 2% of Kenyan households) out of poverty. The effects were stronger for female-headed households because of improved labor market outcomes and increased financial resilience.

Until recently, the effectiveness of cash transfers compared with other anti-poverty programs was lower because of hidden costs to program recipients. Possibly, the introduction of mobile money made cash transfers a more potent tool of anti-poverty programs? In a randomized controlled trial (RCT) among 96 villages in Niger, Aker et al. (2016) found that cash transfers via the mobile phone not only reduced costs for both program recipients and implementing agencies but also that households who used mobile money to receive their transfers experienced greater diet diversity and an increased number of meals for children per day.

Many rural households in Bangladesh have access to mobile phones, but English language proficiency can be a barrier when signing up for mobile money services. In a RCT, Lee et al. (2018) provided training to a treatment group in a northwest district in Bangladesh. The intervention led to a sharp increase in mobile money usage from 20% to 70% among the sample rural households.

Consequently, among other positive effects, extreme poverty fell and consumption increased by 7% on average among households receiving the intervention. What is more, the poverty level of the migrant (sender) workers in the capital also fell, as they tended to work longer hours, though at the cost of physical and mental health.

Our contribution in this paper differs from previous studies in several ways. First, rather than microanalyses of field experiments or longitudinal data on rural households, our analysis is based on district-level poverty rates and mobile money transactions. Aron and Muellbauer (2019) pointed out that microanalyses are likely to understate the system-wide benefits of mobile money as they tend to neglect the positive externalities that arise from network growth, increased transparency and formalization of the economy. For instance, because large-scale interventions are costly and logistically difficult, many micro-based field studies on mobile money tend to take place in a limited set of location(s) within a country where the necessary research infrastructure[7] has been already established. Researchers then are forced to scale up their finding for the entire country or replicate them elsewhere. Third, the use of observational data, as opposed to field observations, do not require an in-depth knowledge of the local context. Nunn (forthcoming) questions the meaningfulness of RCT-based studies that neglect a deep understanding of the local context, including the lack use of local scholars in research studies. Third, from an econometric point of view, observational studies often make better predictions, even when they are biased, than RCTs, which make poor predictions even when unbiased (Young, 2018). Fourth, unlike several earlier studies that have relied on static analysis, our analysis covers longer period (2010–2016), which is likely to capture the long-term benefits from mobile money that have accumulated over time.

4. Data and Summary Statistics

The data used in this study has been collected from both primary and secondary sources. The transactions (cash in and cash out) and agent data have been collected from bKash Limited[8], whereas the poverty and

[7] Infrastructure existing in the location ranges from survey companies to finding suitable hotels and offices, reliable internet etc.
[8] www.bkash.com (accessed 26 November 2019).

district level characteristics have been collected from various reports published by the Government of Bangladesh. The mobile money data have been collected for all 64 districts over the period 2015–2017. The data on active bKash agents by district have been collected for 2011 and 2013. With the exception of Munshiganj District, the bKash agent data have been collected for 63 districts. The majority of the district-level socio-economic indicators have been collected from the Household Income and Expenditure Survey (HIES) in 2010 and 2016, and the 2011 Census of Population and Housing. The exact definition of the variables and their sources are described in Table 1.

— (Insert Tables 1 and 2 here) —

Table 2 shows the summary statistics for the data series used in our analysis. The summary statistics are equally weighted. For a representative year (2015), the average cash-in (outflow of physical money[9]) is higher than the average cash-out (inflow of physical money), implying that the districts received more mobile money than they sent. It is not surprising to see that cash-in (outflow) transfers were comparably more volatile than cash-out (inflow) transfers, largely reflecting the variations in transfers during recurrent festivals like Eid. Between 2011 and 2013, the average density of bKash agents increased dramatically, reflecting the increasing popularity of mobile money services in Bangladesh. The poverty headcount ratio declined by nearly 5 percentage points from 2010 to 2016, which will be explored in more detail below. Agriculture remains the primary source of employment across districts in Bangladesh. Its standard deviation is nearly a quarter of its mean, suggesting a very slow transition from agriculture to other sectors in the economy. Nearly one in three households has completed primary school in Bangladesh (the average is 33%), whereas less than one in eight has completed secondary education. The comparatively larger standard deviation of primary versus secondary education is surprising, given that the former has a lower student dropout ratio than the latter (19.2% versus 38.3%). By 2011, nearly half of Bangladeshi adults were literate in the sense that they could write a simple letter. This notion of literacy is different that of the UNESCO, which defines literacy as a person who can read, write and do simple

[9] It is worth noting that when a district performs, say, a cash-out transaction, it actually converts electronic money into physical money, which increases money circulation in that jurisdiction

arithmetic.[10] At 1165 people per km^2, Bangladesh is among the top 10 most densely populated countries in the world.

Table 3 shows the trends in national poverty rates around two poverty lines. These poverty lines are measured in relation to the minimum food and non-food allowances necessary per day per person (Ministry of Finance, 2015). As can be seen, despite many cases of institutional incompetency, Bangladesh has been surprisingly good at improving the lives of its poor. Notably, the poverty rate has persistently fallen despite an annual population growth of 1.36% during the period 2000–2016. The comparably large decline in the number of people living below the poverty line is especially impressive. However, poverty is still high in Bangladesh and despite accelerating economic growth since 2010, the pace of poverty reduction has slowed (World Bank, 2017).

— (Insert Tables 3 and 4 here) —

Table 4 shows the poverty rates in 2010 and 2016 across five quintiles, ranging from the least poor (Quintile 1) to poorest (Quintile 5). Except for Quintile 1, poverty rates have fallen in all remaining quintiles from 2010 to 2016. Surprisingly, poverty in the top quintile, representing districts such as Dhaka (the capital of Bangladesh), has increased. This is consistent with the extreme poverty data in urban areas, which did not change between 2010 and 2016 (World Bank, 2017). Considering the rapid urbanization of Bangladesh, tackling urban poverty is likely to be a major item in the country's poverty reduction agenda.

Past studies have identified several factors that have contributed to the pace of poverty reduction in Bangladesh. For instance, Imam et al. (2018) found that the education level of heads of household and higher landholding reduce the likelihood of being in extremely poor families. Hossain (1995) found that agricultural wage laborers are typically the poorest occupational group. Both internal and external migration play important roles in poverty reduction (Sharma, 2007; World Bank, 2008). Micro-finance has also played and still plays a crucially important role in reducing poverty by increasing employment opportunities for the poor. For example, Khandker (2005) found that the rates of both poverty and

[10] As of 2016, the adult literacy rate jumped to 72.3%

extreme poverty dropped faster among micro-credit borrowers than among non-borrowers. In this paper, we contribute to this strand of literature by examining the extent to which mobile-based money transfer facilities have contributed to reducing poverty within Bangladeshi districts.

5. Model Specification and Econometric Methodology

Our baseline model of the poverty–mobile money regression is specified as follows:

$$poverty16_i = \alpha + \beta_1 poverty10_i + \beta_2 bKash_i + \delta_i (bKash_i \times quintile_i) + \gamma_i X_i + \varepsilon_i, \quad (1)$$

where the outcome variable $poverty16_i$ is the poverty headcount rate in district i, whereas $poverty10_i$ is the poverty headcount rate in 2010, which is included to capture the persistence of poverty, particularly in lagging districts. The main independent variable of interest, $bKash_i$, is cash-in and cash-out transactions via the bKash mobile money platform in district i. To examine the different effects of mobile money transfers on various poverty quintiles, the interaction of bKash and poverty quintile (the quintile have been defined previously).[11] X_i consists of a set of district-level control variables such as population density, literacy, primary and secondary education, and agricultural employment. Equation (1) is estimated via ordinary least squares (OLS) estimation with robust standard errors.

The district control variables (barring population density) are transformed into dummy variables to simplify their interpretation. Thus, instead of using the level of literacy by district, low-literacy districts take the value of 1 if their literacy level is lower than the median district and zero otherwise. Districts with low primary and secondary education are defined in the same manner. In contrast, districts where households' primary employment in agriculture exceeds the median level take the value of 1 and zero otherwise. Because mobile money transfers (bKash) reflect individual behavior, categorizing the districts

[11] We compute the first derivative for δ_i individually and for each of the five quintiles separately. This gives us the marginal impact of change in exogenous bKash on the poverty of a district. We interpret this as a percentage point change in poverty nationally or in a certain quintile resulting from a unit of change in bKash. We also plot these coefficients in a graph to see the relative impact along the quintiles.

according to low literacy or high dependency on agriculture would retain the meaningfulness of the control variables.

However, because the transaction data are mostly demand-driven and are part of the monetary system, it is possible that bKash responds endogenously to poverty rates. For example, an increase in poverty rates in some districts may trigger more bKash inflows and vice versa, leading to reverse causality. To address the potential endogeneity of the bKash transactions with respect to the poverty rate, we exploit the exogenous variation in the agent density of mobile phone operators from 2011 to 2013 and use it as an instrument for bKash transactions. bKash started its operations in 2011. Back then, the bKash mobile money business was just starting and probably did not expand its agent network strategically in selected areas. Instead, agents were assigned randomly[12] in the early years. After 2013, when investors like the Bill & Melinda Gates Foundation came onboard, bKash developed specific targets to increase its visibility in selected poor *zilas* (districts) and *upazilas* (sub-districts). Moreover, after 2013, the mobile money market in Bangladesh began to get competitive and the Bangladesh Financial Intelligence Unit published more detailed guidelines on MFS.[13] Therefore, it is highly likely that after 2013, agent expansion was correlated with demand for mobile money and the subsequent development of legal and administrative institutions.

Once we can address the endogeneity issue, we are able to demonstrate that an economically meaningful reduction in poverty can be attributed to the growth of bKash mobile money. To this end, we estimate an instrumental variable (IV) regression version of Equation (1), which is specified as follows:

$$\begin{gathered} poverty16_i = \alpha + \beta_1 poverty10_i + \beta_2 (bKash_i = agentdensity_i) \\ + \delta_i (bKash_i \times quintile_i) + \gamma_i X_i + \varepsilon_i, \end{gathered} \tag{2}$$

[12] To test the validity of the instrument, we regressed the change in agent density from 2011 to 2013 on various district-level control variables. The estimated coefficients on most of the district-level control variables (e.g., primary education, secondary education and literacy) turned out to be statistically insignificant. Nonetheless, as pointed out by Aron (2018), it is possible that agent density may still be correlated with unobserved or poorly measured observables such as wealth.
[13] Although the first MFS guideline was published by the Bangladesh Bank (the country's central bank), it did not elaborate on several issues that were covered by the Bangladesh Financial Intelligence Unit directive.

where *bKash* is instrumented with *agentdensity* to overcome the endogeneity bias caused by reverse causality (or omitted variables). Equation (2) is estimated via the IV estimator, also commonly called the two-stage least squares estimator. However, the conventional IV estimator is consistent but is inefficient in the presence of heteroskedasticity, and the Generalized Method of Moments (GMM) of Hansen (1982) is thus recommended. In empirical work, GMM has become a very popular estimator in that both OLS and IV can be seen as special cases of GMM estimators (Baum et al. 2003). The GMM is a more consistent estimator than the OLS when the condition of orthogonality between the error term and the regressors is not satisfied (i.e., the explanatory variables are not uncorrelated with the error). The GMM uses not only the mean and variances, but also other moments of the distribution to find better parameters. As a result, the parameters estimated via GMM are closer to the true values of the distribution parameters. Additional tests of overidentification and weak instruments are also reported to check the goodness of fit of the IV model.

6. Empirical results

6.1 Graphical analysis

We begin our empirical analysis with some figures that show the transaction patterns of mobile money use and the poverty headcount rate in connection with money transfers in 2016 for all districts. Figure 2 shows the mobile transaction trends of all districts over the period 2015–2017. The transaction data reveal an M-shaped pattern over all districts. There are two peaks and two troughs with the peaks appearing in May and September. These represent the seasonality effect of the two Eid festivals, during which an unusual seasonal demand for currency in circulation arises to make financial transactions. The magnitude of this effect in a particular month depends on which day of the month Eid falls. Normally, more transactions take place in the days before Eid and falls drastically as the Eid holiday begins.

— (Insert Figure 2 here) —

The top panel of Figure (3) shows the poverty maps of Bangladesh in 2010 and 2016 across the 64 districts. The bottom panel of Figure (3) displays the same data as bar charts. These tools are helpful for visualizing and comparing poverty across geographic areas. They also help us to learn how poverty is distributed within a country, which may be masked in the aggregate data. For instance, the national poverty rate in Bangladesh fell from 31.5% in 2010 to 24.3% in 2016 (World Bank, 2017). To put it differently, almost 1 in 4 Bangladeshis (24.3% of the population) live in poverty, as of 2016. Furthermore, the bulk of the reductions in poverty from 2010 to 2016 originated in rural areas, accounting for 90% of overall poverty reduction. However, a look at the district-level poverty rate (Figure 3) suggests that between 2010 and 2016, the poverty rate has increased in 23 districts, decreased in 40 districts and remained unchanged in one district (Sunamganj). Several districts in the north belonging to the Rangpur division,[14] as well as two hilly districts (Bandarban and Khagrachhari) in the south-east region of the Chittagong division, became poorer, with poverty rates well above 50%. However, the poverty rate has fallen rapidly in Barisal, Dhaka and Sylhet Divisions.

— (Insert Figures 3 and 4 here) —

Finally, in trying to discern the underlying patterns of mobile money and poverty, in Figure (4) we plot the net flows of mobile transactions in 2016 (left panel) together with the poverty rate in 2016 (right panel). In the left panel of Figure (4), the white color represents "sending" districts (where outflows exceed inflows), whereas the dark blue color depicts "receiving" districts (where inflows exceed outflows).[15] The right-hand panel of Figure (4) is the same as before, displaying the poverty rates in 2016. The clear pattern that emerges is a negative relationship between poverty and net cash flows. The sending districts are among the least poor ones in the 2016 poverty map and the receivers are among the poorest districts in the country. This suggests that mobile money is likely to be endogenously driven by the economic health of the districts in the country. The pattern of Khagrachari and Rangamati in the south-

[14] A division consists of several districts. There are eight divisions comprising the 64 districts of Bangladesh.

[15] Dhaka and Chittagong alone contribute to around 33% of total transactions and seem to be the major local remittance senders to other parts of the country. Twelve districts are identified as senders: Bandarban, Chittagong, Dhaka, Feni, Gazipur, Khagrachari, Manikganj, Narayanganj, Narshingdi, Rangamati and Sylhet. Four districts (Brahmanbaria, Comilla, Manikganj and Moulovibazar) have changed position from senders to receivers or vice versa over the period 2015–2017.

east Chittagong division seems to be an oddity that is inconsistent with the pattern seen across the country.

6.2 Main results

Table (5) shows the main results of the paper. Two sets of empirical results are presented: the baseline result is obtained from the OLS (column 2) and the more efficient IV estimator (column 3). As already noted, the main reason for using the IV estimator is to address the potential endogeneity bias caused either by omitted variables or reverse causality between poverty and mobile money transfers. In both the OLS and IV regressions, the dependent variable is the district-level poverty rate in 2016. The main independent variable of interest is bKash. Both models use a set of control variables to account for the heterogeneity in districts' institutional and geographic characteristics.

Previous poverty level has quite a persistent effect on today's poverty landscape in Bangladesh. There is a strongly positive and significant relationship between increases in poverty in 2010 and increases in poverty in 2016. The large values of the lagged poverty rate coefficients (0.50–0.53) suggest that the underlying determinants of district poverty rates have a half-life of six years.[16] The high persistence in regional poverty is consistent with the spatial patterns identified in south Asia (Baulch, 2011). Among other explanations, the persistence in district poverty rates is probably caused by the slower and unequal household consumption growth seen over the period 2010–2016.[17] For instance, the average annual consumption growth fell from 1.8% to 1.4% and most measures of inequality also increased between 2010 and 2016 (World Bank, 2017).

[16] Most worryingly, despite accelerating growth, the pace of poverty reduction has slowed. For instance, GDP grew at a rate of 6.5% on average per year between 2010 and 2016, whereas the poverty rate fell by a tiny 1.2% annually from 2010 to 2016 compared with 1.7% from 2005 to 2010 (World Bank, 2017).

[17] For the first time, the 2016–2017 HIES data provide consumption estimates at the district level. Unfortunately, at the time of writing, these data have not been released to the public.

The IV estimate of bKash indicates that for every 1 billion Taka increase in bKash transactions, the poverty rate declines by 0.48%.[18] The effect is statistically significant at the 10% level. In contrast, the OLS estimate on bKash shows a reduction in poverty of 0.31%, but the effect is not statistically significant. The negative effect of bKash on poverty in both the OLS and IV estimates emphasizes the potential for mobile money technology in improving the lives of the poor. Many poor households in Bangladesh do not have access to formal banking, so they rely on informal social networks, including mobile-based money transfer services, as a form of insurance in the event of emergencies or other economic shocks. Our results reinforce previous evidence on the positive impact of mobile money on consumption smoothing (Jack and Suri, 2014) and lifting households out of poverty (Suri and Jack, 2016).

In order to get a sense of how mobile money affects different population strata regarding the income distribution, we explored the interaction of bKash and five poverty quintiles. Quintile 1 represents the least poor district (i.e., Dhaka), whereas Quintile 5 refers to the poorest district (Kurigram). Both the OLS and IV estimates are in agreement in terms of the direction of the impact of bKash mobile money across poverty quintiles. According to these results, for every 1 billion Taka increase in bKash transactions, the poverty rate of the poorest group (Quintile 5) decreases by roughly half a percentage point. The largest impact of bKash on poverty is found for Quintile 2, which comprises 14 districts. Some of the districts[19] in Quintile 2 are the thriving manufacturing hubs of the country, providing better infrastructure and employment opportunities for the poor. However, the estimates are not significant statistically at the 10% confidence level. In a one-tailed test, these estimates would be statistically significant for Quintiles 2, 4 and 5.

— (Insert Table 5 here) —

[18] The first-stage F-statistic is 129.03 with a *p*-value of 0.00, implying that the instrument is not weak. Since our model is exactly identified (i.e., a single instrument for a single included endogenous regressor), we are unable to test the exogeneity of the instrument.

[19] For example, Habiganj, Narayanganj and Narshingdi.

Next, by using estimates from the IV model, we compute the marginal effects for each quintile to see their relative impact on districts with different levels of poverty. An easy way to look at the marginal impacts is to use a scatter plot, as shown in Figure 5. The coefficients for Quintiles 1 and 3 are not statistically significant. An interpretation of the coefficients for each of the quintiles is given as follows:

— (Insert Figure 5 here) —

Quintile 1: The marginal impact of a 1% change in agent density for districts in Quintile 1 (the least poor group) is a 0.06 percentage point reduction in poverty. This result is not surprising, since the districts in Quintile 1 are the economically richest in the country. Therefore, there is very little scope for mobile money to add value in terms of bringing economic efficiency, development and reduction of poverty.

Quintile 2: The marginal impact of a 1% change in agent density for districts in Quintile 2 (the second least poor group) is a 0.22 percentage point reduction in poverty, which is statistically significant at the 5% level with a *p*-value of 0.030.

Quintile 3: The marginal impact of a 1% change in agent density for districts in Quintile 3 is a 0.23 percentage point reduction in poverty but the effect is not statistically significant.

Quintiles 4 and 5: The marginal effects of a 1% change in agent density for districts in Quintiles 4 and 5 are 0.43 and 0.35 percentage point reductions in poverty, respectively. These effects are statistically significant at the conventional level of significance. These result makes sense, as these districts are the poorest in the country with limited access to finance and thus they depend heavily on remittance inflows from family members and relatives working in other districts. Between these quintiles, the comparatively lower impact in Quintile 5 is probably because these poorest districts are often hit by droughts, depend heavily on agriculture and lack social infrastructure. In summary, higher agent density can lower the poverty level through a number of ways, such as (i) generating employment for the agents, (ii) facilitating of money transfers and (iii) formalizing of rural banking into the overall economy. As can be seen, the direction of the coefficients on bKash is negative across all model specifications, implying that increased mobile money transactions contribute to the reduction of poverty. The IV coefficient is comparatively higher than the OLS estimate and is statistically significant at the 10% level. We also find that in each quintile, bKash helps reduce poverty; however, the estimates lose statistical significance.

7. Conclusion

The main contribution of this paper has been to quantify the effect of mobile money on district-level poverty rates in Bangladesh. Unlike the bulk of the previous studies, which use survey data at the household level, our analysis is based on district-level poverty and mobile money transaction data. The loss of variation and observations caused by aggregation is likely to be more than offset by the system-wide benefits of mobile money (e.g., the positive externalities that arise from network growth) that can be seen in aggregate data. The relatively longer period (2010–2016) in our study is also able to capture the long-term benefits from mobile money that have accumulated over time.

We find that increased mobile money transactions foster poverty reduction. For example, a 1 billion Taka (approximately US$ 11.76 million) increase in bKash transactions leads to a 0.48% reduction in poverty rates among the 64 districts of Bangladesh. Districts that are more manufacturing-oriented saw the greatest reductions in poverty as a result of mobile money transactions. Nevertheless, poorer districts also benefit significantly from mobile money transfers. Our results complement the findings of Jack and Suri (2016) who studied the long-term impact of mobile money on poverty in Kenya.

Our analysis is not without caveats. First, district-level consumption expenditure would be an appropriate control variable for isolating the impact of mobile money on poverty. As already mentioned, such data have not yet been made publicly available. Second, the distribution of mobile money agents, which we used as an instrument, may not be fully random if it correlates with household or village characteristics such as wealth.

Taken together, our results present useful information for policymakers to help them understand mobile money and help them craft policies to combat poverty by using this innovative payment mode. For instance, historical mobile money usage patterns can be analyzed to design nano-loans and grants, especially for small businesses in poorer districts. As agents play a critical role in fostering mobile money use, the government can use its own infrastructure (e.g., post offices) to enhance density. Finally, the government can play a critical role in increasing phone ownership among women so that they are not afraid of their husbands or guardians when using mobile money.

References

Aker, J. C., Boumnijel, R., McClelland, A., & Tierney, A. N. (2016). Payment mechanisms and anti-poverty programs: evidence from a mobile money cash transfer experiment in Niger. *Economic Development and Cultural Change, 65*(1), 1–37.

Aron, J. (2017). *'Leapfrogging': A Survey of the Nature and Economic Implications of Mobile Money.* CSAE Working Paper 2017-2. Centre for the Study of African Economies, University of Oxford, Oxford, UK.

Aron, J. (2018). Mobile money and the economy: a review of the evidence. *World Bank Research Observer 33* (2):135–188.

Aron, J and J Muellbauer (2019). *The Economics of Mobile Money: harnessing the transformative power of technology to benefit the global poor.* Oxford Martin School Policy Paper.

Bangladesh Bank (2011). Guidelines on mobile financial services (MFS) for the Banks. *Bangladesh Bank.* Bangladesh Bank, Dhaka.

Bangladesh Bank (2018). Bangladesh Mobile Financial Services (MFS) Regulations, 2018. Bangladesh Bank, Dhaka.

Baulch, B. (2011). Why Poverty Persists: Poverty Dynamics in Asia and Africa. Edited. Cheltenham: Edward Elgar, Pp. 296

Baum, C.F., Schaffer, M.E. and Stillman, S. (2003). Instrumental variables and GMM: Estimation and testing. *Stata Journal, 3*(1), 1-31.

Bird, J. (2018, December 4). 'Smart' insurance helps poor farmers to cut risk. *Financial Times*. https://www.ft.com/content/3a8c7746-d886-11e8-aa22-36538487e3d0 (accessed 26 November 2019).

Blumenstock, J.E., Cadamuro, G. and On, R. (2015). Predicting poverty and wealth from mobile phone metadata. *Science 350*(6264), 1073–1076.

Blumenstock, J.E., Eagle, N. and Fafchamps, M. (2016). Airtime transfers and mobile communications: Evidence in the aftermath of natural disasters. *Journal of Development Economics, 120*, 157–181.

Cho, Y. and Hinata, Y. (2019). China's mobile banks offer 1-second loan decisions in farmland. *Nikkei Asian Review*. https://kr-asia.com/chinas-mobile-banks-offer-1-second-loan-decisions-in-farmland (accessed 26 November 2019).

Evans, S.D. Pirchio, A. (2015). An empirical examination of why mobile money schemes ignite in some developing countries but flounder in most. University of Chicago Coase-Sandor Institute for Law & Economics Research Paper No. 723. http://dx.doi.org/10.2139/ssrn.2578312 (accessed 26 November 2019).

Gürbüz, A. (2019). *The Economics of Rural Populations in Sub-Saharan Africa: Financial Inclusion and Agriculture*. (Doctoral Dissertation), Georgetown University. http://hdl.handle.net/10822/1054923 (accessed 26 November 2019).

Hansen, L. (1982). Large sample properties of generalized method of moments estimators. *Econometrica 50*(3): 1029‐1054.

Hossain, M. (1995). Socio-economic characteristics of the poor. Rethinking rural poverty. Dhaka: UPL, Bangladesh.

Imam, M. F., Islam, M. A., & Hossain, M. J. (2018). Factors affecting poverty in rural Bangladesh: An analysis using multilevel modelling. Journal of Bangladesh Agricultural University, 123–130.

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

Karlan, D., Kendall, J., Mann, R., Pande, R., Suri, T., & Zinman, J. (2016). Research and impacts of digital financial services. NBER Working Paper No. 22633, Cambridge, Massachusetts.

Khandker, S.R. (2005). Microfinance and poverty: Evidence using panel data from Bangladesh. Work Bank Economic Review 19, 263-286.

Klapper, L. (2018). How mobile money can help reduce poverty. ITU News, August 9, 2018. https://news.itu.int/mobile-money-poverty/ (accessed 26 November 2019).

Ministry of Finance (2015). *Poverty and Inequality in Bangladesh: Journey Towards Progress (2014-15).* Macroeconomic Wing, Ministry of Finance, Government of the People's Republic of Bangladesh.

Lee, J., Morduch, J., Ravindran, S., Shonchoy, A., & Zaman, H. (2018). *Poverty and Migration in the Digital Age: Experimental Evidence on Mobile Banking in Bangladesh*. IGC Working Paper C-89233-BGD-1.

Nunn, N. (forthcoming). Rethinking economic development. Canadian Journal of Economics.

Parvez, J., Islam, A. and Woodard, J. (2015). *Mobile Financial Services in Bangladesh: A Survey of Current Services, Regulations, and Usage in Select USAID Projects.* USAID, Dhaka.

Rahman, M. F. (2014). Most rickshaw-pullers in Dhaka use mobile to send money home: study. *The Daily Star.* https://www.thedailystar.net/most-rickshaw-pullers-in-dhaka-use-mobile-to-send-money-home-study-52223 (accessed 26 November 2019).

Reuters (2018). Bangladesh raises wages for garment workers. *Reuters*. September 13, 2018. https://www.reuters.com/article/us-bangladesh-garments/bangladesh-raises-wages-for-garment-workers-idUSKCN1LT2UR (accessed 26 November 2019).

Sharma, M. (2007). International migration, remittance, and household well-being: A study of twenty communities in Bangladesh. The World Bank: Washington DC

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

World Bank. (2008). Poverty Assessment for Bangladesh: Creating Opportunities and Bridging the East-West Divide. Dhaka: The World Bank.

World Bank. (2017). Bangladesh continues to reduce poverty but at slower pace. World Bank. https://www.worldbank.org/en/news/feature/2017/10/24/bangladesh-continues-to-reduce-poverty-but-at-slower-pace (accessed 26 November 2019).

Young, A. (2018). Channeling Fisher: randomization tests and the statistical insignificance of seemingly significant experimental results. *Quarterly Journal of Economics*, *134*(2), 557–598

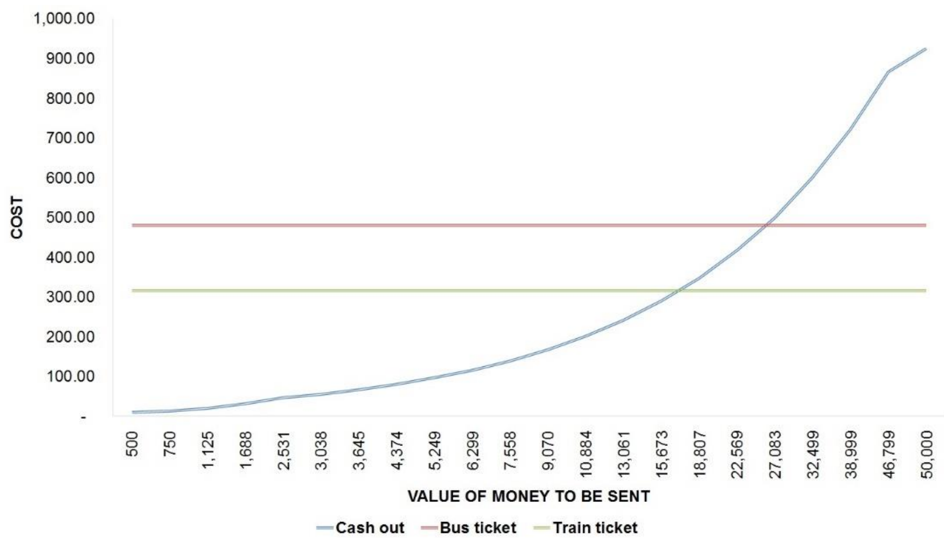


Figure 1: Travel Cost to Rajshahi vs bKash Cash Out Charge

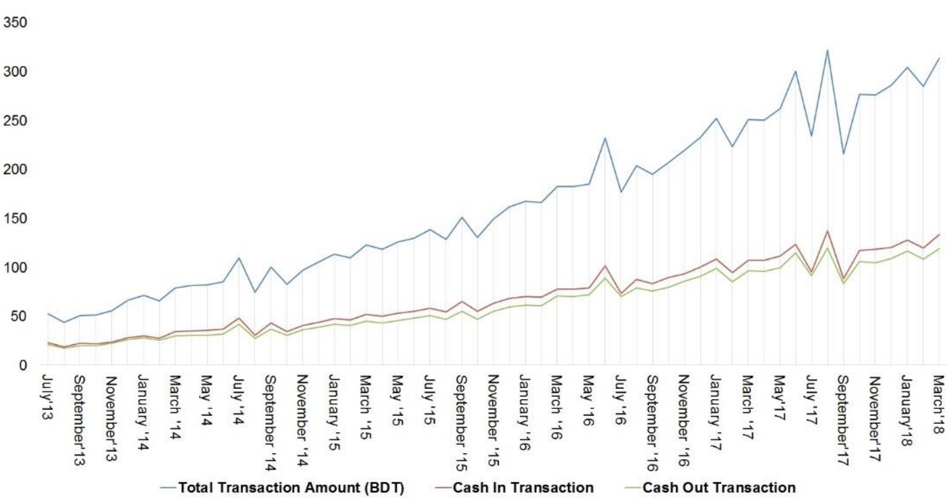
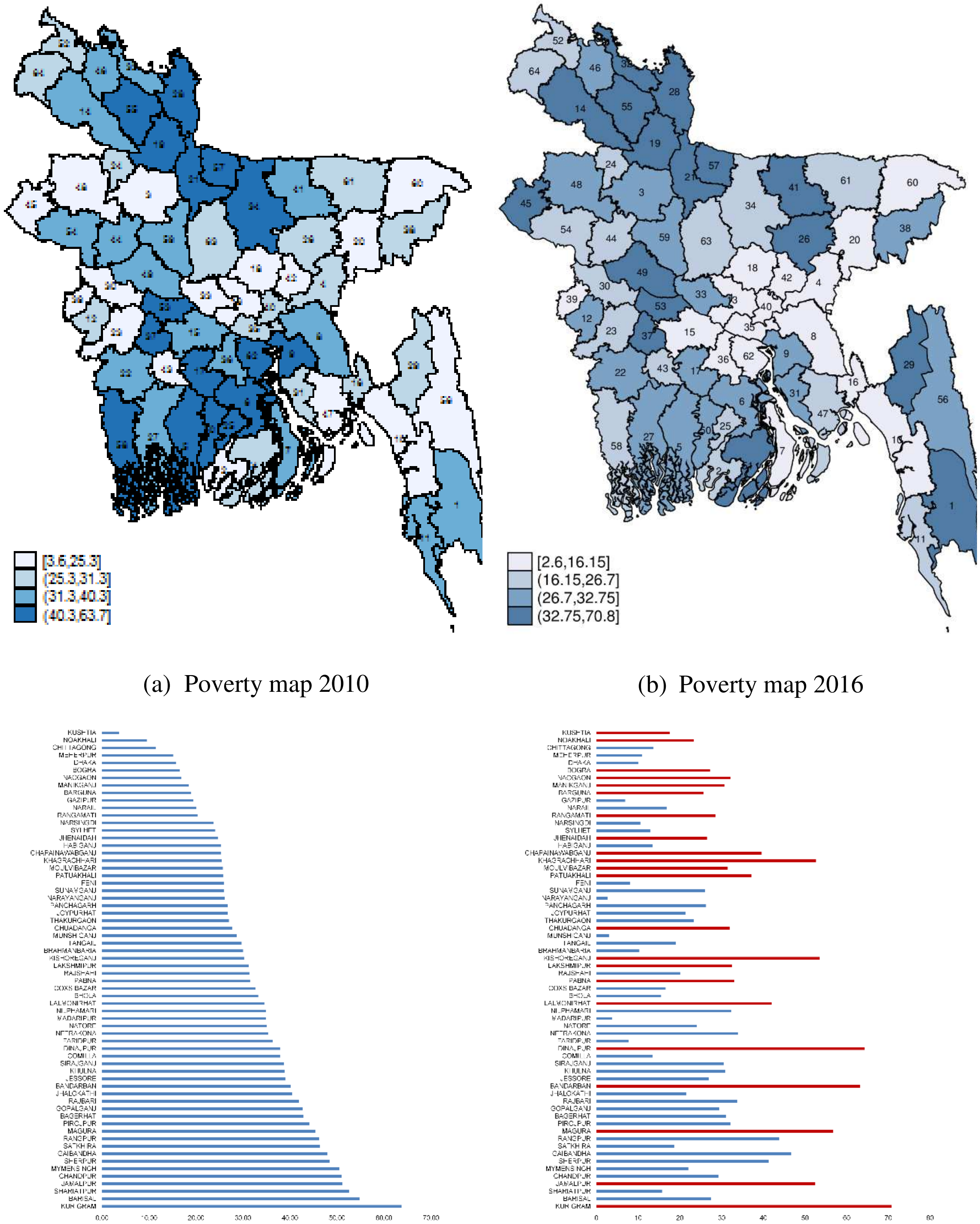


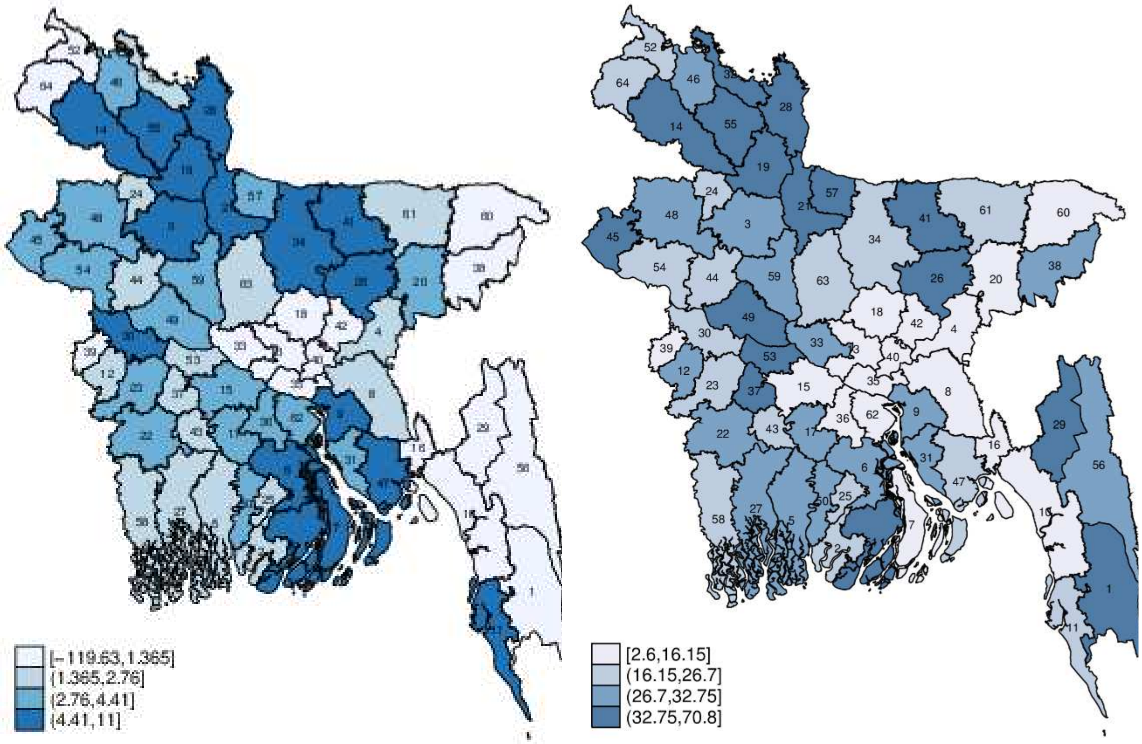
Figure 2: Mobile Money Transactions (BDT billion)



(a) Poverty map 2010 (b) Poverty map 2016

(c) Poverty distribution 2010 (d) Poverty distribution 2016

Figure 3: Poverty map and poverty distribution for Bangladesh



(a) Net flows (inflow – outflow) 2016

(b) Poverty rate in 2016

Figure 4: Mobile money flows and poverty map for Bangladesh

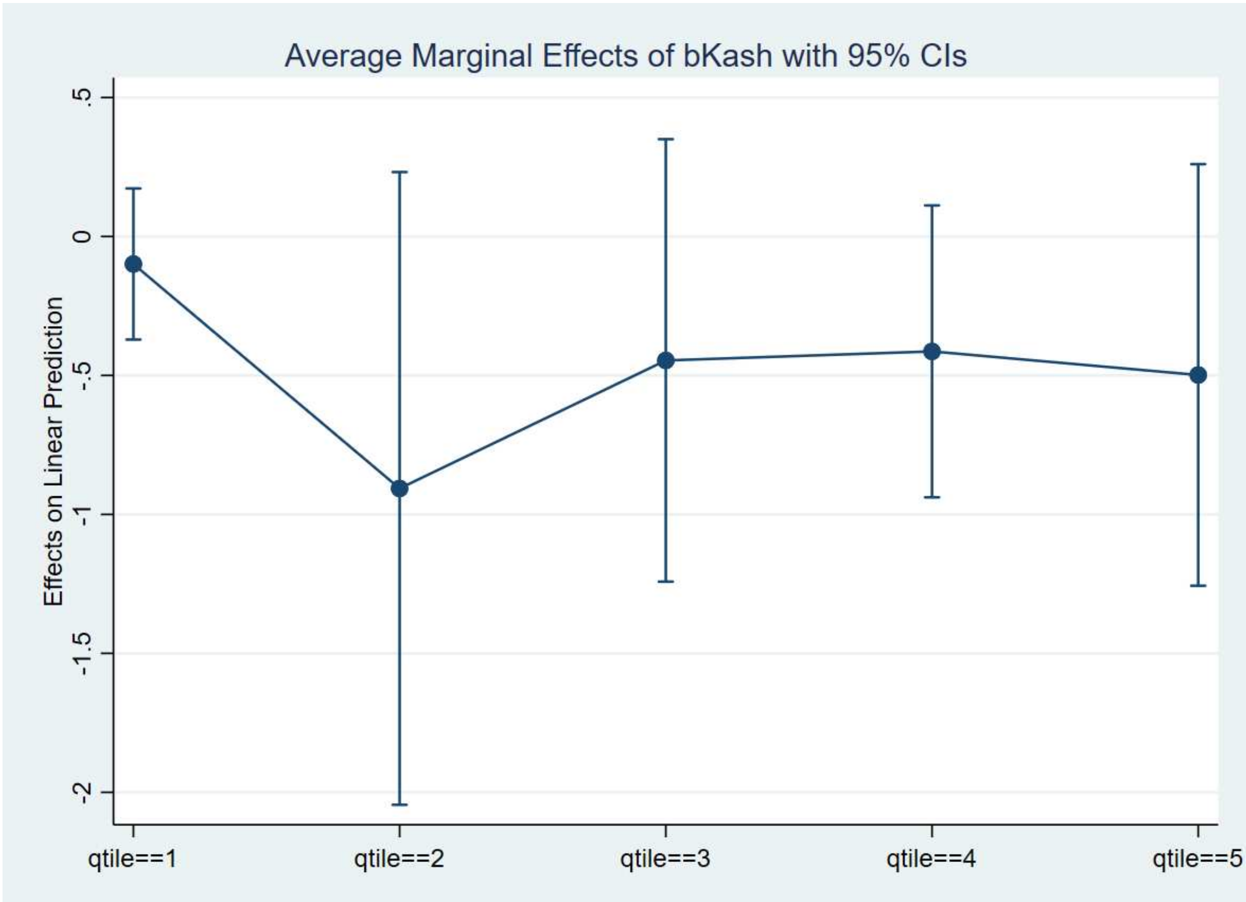


Figure 5: Measuring the marginal effect of mobile money (bKash) on poverty quintiles

Table 1: Data – definition and sources

bKash inflow	Cash-out transaction amounts via the bKash platform, 2015–2017	bKash Limited
bKash outflow	Cash-in transaction amounts via the bKash platform, 2015–2017	-,,-
bKash agent	Number of active bKash agents in each district in 2011 and 2013	-,,-
Poverty	Poverty headcount ratio at $1.90 a day (% of population), 2010 and 2016	HIES 2010 and 2016[a]
Literacy	Percent of adults who can write a letter	World Bank[b]
Density	Population density per km^2, 2011	BBS[c]
Agriculture	Percent of employment in agriculture, 2011	-,,-
Primary	Percent of adults with primary education, 2011	-,,-
Secondary	Percent of adults with secondary education, 2011	-,,-

Notes:
a) HIES (Household Income and Expenditure Survey), 2016 data are preliminary;
b) Bangladesh Interactive Poverty Map, World Bank
c) Census of Population and Housing, BBS (Bangladesh Bureau of Statistics).

Table 2: Summary statistics

Variable	Mean	Std. Dev.
Inflows (2015, BDT billion)	7.63	10.09
Outflows (2015, BDT billion)	8.09	23.37
Agent density (2011, %)	3.16	6.67
Agent density (2013, %)	61.56	122.36
Poverty (2010, %)	32.26	12.06
Poverty (2016, %)	27.45	15.31
Primary employment in agriculture (%)	57.02	15.46
Primary education (%)	32.86	5.70
Secondary education (%)	11.31	3.11
Literacy rate (2011)	48.08	8.94
Population density	1164.63	1082.37

Table 3: Poverty headcount rate, 2000–2016

Poverty line	2000	2005	2010	2016
Upper poverty line	48.9	40	31.5	24.3
Lower poverty line	34.3	25.1	17.6	12.9

Table 4: Average poverty by quintile

Quintiles	Poverty (2010)	Poverty (2016)
1	14.57	16.49
2	25.42	20.46
3	31.20	25.57
4	38.26	28.09
5	50.54	36.53

Table 5: Impact of bKash mobile money on poverty

Dependent variable: Poverty rate in 2016	**OLS**	**IV**
Poverty rate 2010	0.538***	0.500***
	(0.24)	(0.20)
bKash mobile money	**-0.319**	**-0.484***
	(0.26)	(0.29)
bKash × Quintile 1	0.010	-0.099
	(0.11)	(0.14)
bKash × Quintile 2	-0.534	-0.906
	(0.50)	(0.58)
bKash × Quintile 3	-0.318	-0.445
	(0.44)	(0.41)
bKash × Quintile 4	-0.308	-0.413
	(0.28)	(0.27)
bKash × Quintile 5	-0.410	-0.498
	(0.42)	(0.39)
Population density	-0.001	0.001
	(0.00)	(0.00)
Literacy rate	2.180	1.618
	(4.53)	(4.12)
Primary education (%)	10.558	11.178
	(10.38)	(10.10)
Secondary education (%)	-0.979	-1.042
	(3.91)	(3.51)
Employment in agriculture (%)	8.409*	8.844**
	(4.33)	(4.10)

Note: Standard errors are in parentheses. ***, p<0.01; **, p<0.05; *, p<0.1.