CIRJE-F- 1219

Shocks and Brave Farmers: Evidence from a Randomized Agricultural Microfinance Experiment in Bangladesh

Md Amzad Hossain
University of Arkansas
Mohammad Abdul Malek
University of Tsukuba
Yasuyuki Sawada
The University of Tokyo

August 2023

Shocks and Brave Farmers: Evidence from a Randomized Agricultural Microfinance Experiment in Bangladesh*

Md Amzad Hossain, Mohammad Abdul Malek, and Yasuyuki Sawada

Abstract

In developing countries, insurance products against various climate and non-climate-related shocks targeting farmers are still largely unavailable. We implement a large-scale randomized experiment of a customized microcredit program for small farmers in Bangladesh to explore the role of credit as an insurance mechanism. We show that the program enhanced the resilience of tenant farmers to adverse shocks by facilitating greater credit utilization. This enabled farmers to be more independent in crop-farming activities, encouraged technology adoption, and increased income from crop-farming activities. These results highlight the effectiveness of expanding credit as a tool for institutions to support households susceptible to shocks.

Keywords: Agricultural micro-credit, idiosyncratic and covariate shocks, insurance
JEL codes: G21, J43, C93, D13, O14

*Hossain: University of Arkansas, USA. Malek: University of Tsukuba (e-mail: malekr25@gmail.com). Sawada: The University of Tokyo, Japan. Acknowledgments: We benefitted from comments and suggestions from Shahe Emran, Takahashi Kazushi, Jonathon Bauchet, and numerous seminar and conference participants at the Tokyo International Development Workshop February 2016, Hayami Conference Dec 2016, 6th Winter Conference on Economics Research December 2016, 9th Asian Society for Agricultural Economists (ASAE) International Conference January 2017, Agricultural Economics Society of Japan Annual Meeting March 2017, Regional Environmental Economics Seminar at Kyoto University April 2017, Midwest International Economic Development Conference (Wisconsin-Madision) April 2018 and Development Economics Research Seminar at Sophia University May 2017. We would like to thank the late Mahabub Hossain, Atiur Rahman, and other collaborators at BRAC for their support. We acknowledge the following financial support: Bangladesh Bank for sponsoring the BCUP program, the International Initiative for Impact Evaluation (3ie) for sponsoring the impact evaluation, the financial support from Grants in aid for Japan Society for the Promotion of Science Fellow (Tokubetsu Kenkyuin Shrei-hi) and Scientific Research Fund (Kakenhi) from the Ministry of Education, Culture, Sports, Science and Technology (MEXT). This experiment was registered into AEA RCT Registry by Palmen Nikolov (RCT ID: AEARCTR-0004460). The study protocol for this study was approved by the Ethical Review of the BRAC University Ethical Review Committee (ERC). The usual disclaimer applies. Correspondence: malekr25@gmail.com

1 Introduction

In developing countries, farmers face a variety of shocks that negatively impact agricultural production and overall prosperity. These shocks come from various factors such as price and other market fluctuations (Bellemare, Lee and Just, 2020; Burke, Bergquist and Miguel, 2019), seasonality in rainfalls, and agricultural harvests (Paxson, 1993; Pitt and Khandker, 2002; Khandker, 2012; Basu and Wong, 2015; Fisher et al., 2012), and floods, droughts, and other extreme weather events (Brooks and Donovan, 2020; Kubik and Maurel, 2016; Dell, Jones and Olken, 2012; Felkner, Tazhibayeva and Townsend, 2009). Against these shocks, especially aggregate ones, various microinsurance programs, such as index-based risk transfer products, have been developed (Carter et al., 2017). While the literature to date suggests that insurance encourages a shift to more profitable but riskier crops (Mobarak and Rosenzweig, 2013; Cai, Janvry and Sadoulet, 2015) and leads to higher investment (Karlan, Knight and Udry, 2015; Cole and Xiong, 2017), the problem of persistently low uptake remains a significant challenge in these insurance systems (Dercon et al., 2014; Cole et al., 2013; Giné and Yang, 2009; Giné, Townsend and Vickery, 2008; Mobarak and Rosenzweig, 2012, 2013, 2014). In this regard, access to formal credit arrangements could provide an alternative insurance mechanism (Burke, Bergquist and Miguel, 2019; Stephens and Barrett, 2011; Basu and Wong, 2015; Beaman et al., 2014; Shoji, 2010; Giné and Yang, 2009). Nevertheless, a rigorous evaluation of formal agricultural credit programs in terms of their insurance function is missing, especially in the context of landless, marginal, and small tenant farmers, who are typically known as resource-poor tenants in developing countries (Dimble and Mobarak, 2019; Maîtrot and Niño-Zarazúa, 2017; González, 2014).

This paper fills this critical gap in the existing literature by conducting a randomized controlled trial (RCT) to investigate the impact of an innovative microcredit program in Bangladesh. The program, known as Borgachashi Unnayan Prakalpa (BCUP) or "Credit Program to the Tenant Farmers," was specifically designed to support resource-poor tenant farmers in adopting technology and coping with risks to enhance their livelihoods. Developed by BRAC, the world's largest NGO, and financially supported by Bangladesh Bank, BCUP received a loan of approximately USD 75 million to provide lower-interest loans to tenant farmers compared to traditional microfinance institutions. Since its inception in 2009, BCUP has successfully provided credit to about 400,000 borrowers across 46 districts in Bangladesh, supporting various activities such as crop cultivation, livestock rearing, land leasing, and agro-machinery loans.[1] Thus, the BCUP loan, which offers loans at a subsidized interest rate, is tailored to the needs of tenants and improves the technology adoption and agricultural productivity of borrowers. Like prominent BRAC innovations such as the experimental Targeting Ultra-Poor (TUP) program, which has received wide international acclaim (Banerjee et al., 2015; Balboni et al., 2022), BCUP is an innovative program and the first tailored agricultural microcredit initiative aimed primarily at alleviating financial constraints among resource-poor tenant farmers who are otherwise bypassed by traditional MFIs and the formal banking sector.

This paper uses data from a randomized experiment to answer two primary research questions: first, whether shocks increase borrowing in treatment groups, and second, how shock-induced borrowing affects various farmer outcomes, such as attitudes toward riskier but higher-yielding production, technology adaptation, and income. The experiment was conducted in 40 sub-districts of Bangladesh where the BCUP program had not started by 2012. We randomly chose 20 of these 40 sub-districts for treatment; the remaining sub-districts served as control. The baseline survey was conducted in 2012, and the follow-up survey for the same group of households was conducted two years later, in 2014. The final panel includes 4,141 households.[2] We use survey data collected at baseline and endline

[1] BRAC Microfinance MIS data, June 2017.

[2] This panel data have been used in some other recent studies to examine the causal relationship between the intervention and various outcomes (e.g., yield, varietal adoption, income, expenditure, child labor, etc.) (Malek et al., 2015; Hossain et al., 2019; Hossain, 2023); test the theory of sharecropping under the credit and land contracting framework (Das, de Janvry and Sadoulet, 2019); assess the effects of access to credit on productivity by separating technological changes from changes in technical efficiency (Jimi et al., 2019). However, none of these papers explores the impact of idiosyncratic and covariate shocks that these farmers have faced during the intervention period. In this paper, we bridge this gap in evidence of the role of agricultural microcredit programs.

in 2012 and 2014, respectively. A particular focus is on risk coping strategies and thus on prosperity during shocks. Therefore, we collected idiosyncratic household-level shocks and village-level covariates for three years, including 2012, 2013, and 2014. To check the effectiveness of randomization, we perform the standard balancing tests of covariates between the treatment group and control group by comparing means and test the exogeneity of price shocks and crop losses by comparing the covariates among households with and without shocks and conclude that the treatment assignment and shocks are both exogenous, and, thus, our regression results can be interpreted as causal relationships.

We extend the theoretical models developed by Eswaran and Kotwal (1989), Morduch (1994), and Giné and Yang (2009) to construct a simple two-period model of technology adoption that shows consumer credit as an insurance mechanism.[3] In our model, we include a transitory shock in the first period to study the ex-post response of a household to the realization of an unexpected transitory shock and to explain the view that random factors in output are not correlated across periods. A credit system is a good alternative because it at least allows risk to be pooled over time. To preview our results, our intent-to-treat (ITT) estimates of the BCUP program show that the average uptake of the program is 19.8 percent, which is not necessarily high but is comparable to other recent microfinance experiments (Banerjee, Karlan and Zinman, 2015). More importantly, we find that covariate shocks at the village level significantly increase borrowing in treatment groups. While a companion study by Hossain et al. (2019) is silent about the underlying reasoning for the low uptake of the BCUP program, this paper helps us understand possible implicit insurance mechanisms in the limited liability clause of the credit product. Thus, we confirm the findings of previous studies (e.g., Karlan, Knight and Udry, 2015; Giné and Yang, 2009) by combining microfinance data with shock data to show a strong insurance motive behind microfinance participation in an unexplored context of agricultural credit programs. We also document that treated households choose riskier investment options in the presence of

[3]While BCUP is a production credit, money is fungible within each household. Hence, BCUP can play the role of a consumption credit effectively.

covariate shocks, such as leasing more land under fixed leases and increasing the adoption of high-yielding varieties. These results are broadly consistent with the theoretical implications of a standard model of technology adoption by Eswaran and Kotwal (1989), Morduch (1994), and Giné and Yang (2009), who show that consumption credit is an insurance substitute.

Finally, we find that microcredit helps farm households facing village-level covariate shocks earn higher income from self-employed farm activities. However, this gain is offset by a decline in income from wage-dependent activities, leaving total income unchanged. This result is consistent with other microfinance experiments (Meager, 2019; Banerjee, Karlan and Zinman, 2015). We also observe a positive but insignificant effect on independent consumption and subjective well-being.[4]

We believe we make unique contributions to several strands of the existing literature. First, our research contributes to the literature on interventions that improve household resilience and adaptive capacity to climate change risks. Previous literature highlights the role of building physical infrastructure such as bridges (Brooks and Donovan, 2020) and deploying risk-reducing technologies such as irrigation and flood-resistant seed (Jones et al., 2022). Nevertheless, various market failures, which are more salient in developing countries, pose obstacles to effectively adapting these measures to respond to environmental shocks. For example, investments in flood protection infrastructure are costly and difficult to implement, especially in rural areas (Brooks and Donovan, 2020), and adoption of climate-resilient technologies such as drought- or flood-resistant seeds is often hampered by their unpredictable outcomes (Emerick et al., 2016). The BCUP loan is a valuable addition to this literature because it is a cost-effective tool that financially mitigates the negative impacts of climate shocks and overcomes the barriers that hinder the widespread adoption of these other adaptation measures. For example, unlike large infrastructure projects, the BCUP loan is relatively inexpensive and relies on existing institutions. Moreover, unlike climate-resilient technologies, it does not require costly behavioral adjustments to realize

[4] In the local economic context, the estimated impact on these indicators might be underestimated compared to the true impact to be explained later.

the benefits.

Second, we contribute to the already large literature on the effectiveness of financial services that low-income households can use to withstand shocks and stressors (Rosenzweig and Binswanger, 1993; Conning and Udry, 2007). This literature has predominantly examined insurance products to decrease households' vulnerability to risks. However, these insurance products are largely underdeveloped in developing countries, especially among low-income people, due to various elements, including weak institutions and a lack of demand (Fafchamps and Lund, 2003; Mobarak and Rosenzweig, 2013; Casaburi and Willis, 2018). Some of the literature suggests that access to formal credit arrangements may provide an alternative insurance mechanism in the absence of a well-functioning insurance market (Burke, Bergquist and Miguel, 2019; Stephens and Barrett, 2011; Basu and Wong, 2015; Beaman et al., 2014; Giné and Yang, 2009) . However, most of these studies are observational and often suggestive. To the best of our knowledge, this is the first study to use a RCT design to examine the impact of microcredit on farmers' risk-taking capacity and improving farmers' technology adoption and welfare. Also, our findings on BCUP's role in making the resource-poor tenant farm households independent and eliminating the downside risk of falling into a poverty trap can be seen as consistent with the recent poverty trap literature (Bandiera et al., 2020; Parekh and Bandiera, 2020; Banerjee, Niehaus and Suri, 2019).

Third, our work also contributes to the second wave of microfinance studies that focus on improving microfinance through innovative product design (Duflo, 2020; Dimble and Mobarak, 2019). Examples include a grace period before repayment begins (Field et al., 2013), changes in repayment frequency (Kono, Takahashi and Shonchoy, 2021; Field and Pande, 2008), relaxation of group structure (Maitra et al., 2017; Giné and Karlan, 2014), identifying the most entrepreneurial customers based on community information (Hussam, Rigol and Roth, 2022), allowing lump-sum repayments after harvest (Beaman et al., 2014), offering credit during the lean agricultural season (Fink, Jack and Masiye, 2020), and using the credit line as insurance against floods (Lane, 2022). Evidence suggests that such innovative product design has the potential to reduce borrower transaction costs, encourage investment, and increase borrower profitability (Field and Pande, 2008; Field et al., 2013; Beaman et al., 2014). The BCUP loan builds on this movement toward more innovative loan design by offering a customized microloan program for tenant farmers that helps mitigate shocks and encourages more investment in riskier but more profitable self-employment activities.

The remainder of the paper is organized as follows: Section 2 describes the BCUP credit program. We describe the experimental design and data in Section 3. Section 4 provides a detailed discussion of the theoretical and empirical models. We present the main results in Section 5. Finally, Section 6 discusses the results and concludes the paper.

2 The BCUP Loan

BCUP is a customized agricultural microcredit program for the economic emancipation of marginalized tenant farmers who are not served by traditional microcredit and formal banks in Bangladesh. To be eligible for the BCUP loan program, the following criteria apply: The farmer must (a) hold a national identity card; (b) be between 18 and 60 years of age; (c) have no more than 10 years of schooling; (d) have resided in a designated area for at least three years; (e) have land ownership of less than 200 decimals; (f) not be a member of another MFI; and (g) be willing to take out a BCUP credit.

Under BCUP, a village organization (VO) is formed in a branch (roughly equivalent to a sub-district in Bangladesh) as a platform for service delivery. VOs are composed of four to eight teams, each consisting of five members drawn from the informal association of tenants at the village level. A BCUP program organizer attends the monthly meetings of the VO to discuss and offer credit, address the collection of due installments and deposit of savings, provide information on the productive use of agricultural credit, and so on.

BCUP offers a variety of financial products. The most common is a loan to secure the necessary working capital for crop production, especially for introducing technologies (e.g., improved seed varieties, fertilizers, pesticides, irrigation, mechanization, etc.). The loan amount ranges from a minimum of BDT 20,000 to a maximum of BDT 70,000, depending on the size of the farm or crop enterprise.[5] Additionally, BCUP offers credit for purchasing machinery up to a maximum of BDT 120,000. Leasing lands up to a maximum of BDT 60,000 and rearing livestock. The usual loan repayment period is one year. However, for leasing machinery and land, the BCUP allows an extended loan repayment period of up to three years. Farmers initially received loans at a flat annual interest rate of 10 percent, highly subsidized and much lower than any other microcredit provider. Later the flat interest was changed into the declining balance form, where the effective interest rate is about 19 percent.[6]

Under the same intervention, BCUP offers different financial products as introduced above. Among the disbursements to date, the crop share, livestock (including fish culture), and land lease (including agro-machineries) loans are 71%, 22%, and 7%, respectively, and these figures do not vary significantly across the branches. Our previous report shows that BCUP also provided some complementary enhancement support that was very small and insignificant (Malek et al., 2015). Further examination of the BCUP dataset confirms that BCUP ceased its extension support when we considered the BCUP program for this assessment. Thus, when we use the BCUP program in this study, it primarily indicates the BCUP credit intervention.

The BCUP has undergone several other changes since its inception. One of these significant changes was to shift the target group or clientele from male to female borrowers, recognizing that female borrowers are more disciplined than their male counterparts when it comes to managing credit use for household economic activities and adhering to the repayment cycle that BCUP requires. This was started in 2012 to encourage women to become more involved in agricultural production. Another important change was the redesign of the

[5] We use \$1=BDT78 in this article.

[6] BRAC micro-finance MIS data, June 2017.

loan repayment method from unequal periodic installments to equal monthly installments, introduced in 2012 at the request of farmers based on feedback from field staff.[7] Initially, farmers had the right to pay their debts according to the seasonal agricultural calendar, which was also practiced to some extent in India (Field et al., 2013). Gradually, however, BCUP staff realized that most borrower households were multi-person households (i.e., they used diversified livelihood options, which primarily included agricultural self-sufficiency, non-farm activities, and day labor). Although BCUP loan officers target farm households and provide loans for various farm purposes, they recognize the fungibility of money. Therefore, the program emphasizes the productive use of credit by household members and the potential management of risk, even when faced with shocks to.

Thus, it is expected that the flexibility of the loan will help borrowers to ease their overall household management and to repay comfortably in equal monthly installments. Therefore, the main distinction between BCUP credit with conventional micro-credit is that: whereas conventional microcredit promotes non-farm IGAs, BCUP credit is customized to the needs of farming and livelihoods of a marginalized farming community (tenant farmers) at a lower interest rate which aims at contributing to tenant farmers‘ technology adoption and farm productivity more efficiently.

3 Experimental Design and Data

3.1 Experimental Design

The study was conducted in a large geographic area in rural Bangladesh and covered 40 subdistricts (branches) in 22 districts (Appendix Figure A.1). The impact evaluation study used a three-stage cluster randomization procedure, with the first stage of randomization conducted at the branch level (each representing a specific sub-district). In the first stage of

[7] One-third of the loan had to be repaid before harvesting and two-thirds had to be repaid after harvesting in a three-periodic installment scheme (10 months, eight months, and six months).

randomization, 40 branches were randomly selected from the predetermined list of branches where the BRAC-BCUP program had not yet been implemented but were scheduled to be implemented in 2012. A total of 20 branches were then randomly selected as treated areas and the remaining 20 branches were taken as control areas. Note that the problem of potential contamination of the control areas was also considered. Since randomization was conducted at the branch level, each representing a separate sub-district, and BCUP typically implements the program within an 8-kilometer radius of the branch, there should be a sufficient geographic distance between the control and treatment areas. To verify this, information on the distance between the peripheries of each control branch office and the nearby intervention branch offices were collected to identify the actual difference between the control areas and nearby intervention areas. Once the branches were mapped, it was found that most of the control areas were sufficiently distant from the treatment areas, except for the branch areas in the southern region. Therefore, GIS mapping was conducted for the branches in the southern region (Appendix Figure A.2), and the map was distributed among program participants to maintain the extent of intervention branches only within intervention areas and not in control areas. Once the branches were selected, the second phase involved randomly selecting six villages within 8 km of the BRAC program branches from each branch. In this phase, a census was conducted in these 240 villages. About 61,322 households were interviewed during the census. Based on the census data, it was determined that only 7,563 of these households met the criterion for participation in the program (mentioned above).

In the final phase of randomization, a total of 4,141 households were randomly selected from 7,563 eligible households. The calculation yielded a power that ensured at least 80 percent power to detect the assumed different effect sizes of the program on the outcomes of interest at the five percent significance level (Malek et al., 2015). However, eligible households were not evenly distributed across branches and villages. Therefore, a population-proportional random sampling method was used based on the concentration of eligible households. This gave more weight (i.e., more households were selected) to areas where the concentration of eligible households was higher. Thus, 2,072 households were selected from the treatment area and 2,069 households were selected from the control area, for a sample size of 4,141 households.

3.2 Data Description

We use a unique panel data set that emerged from our experiment. Following a standard survey and experiment procedure of the study and the intervention (Appendix Figure 3), we use two rounds of surveys conducted in 2012 (baseline) and 2014 (endline) for a wide range of variables (i.e., household demographics, borrowing, and credit use, land use and cropping intensity/diversification, household members' engagement in agricultural and non-agricultural activities, income from various sources, consumption patterns, asset ownership, etc. for all 4,141 sample households). For a detailed data description, see Malek et al. (2015). The definitions of the variables can be found in Appendix Table A.1. In addition, we collected data on whether the household faced any price shock or crop loss shock in those years. This form the basis of idiosyncratic shocks in our analysis. The average of the total number of idiosyncratic shocks in 2012 was 0.93, while the corresponding number for 2014 was 0.49.

Later, our anthropological (qualitative) research suggested that credit played a role in mitigating various covariate shocks. Therefore, we were motivated to retrospectively collect data on village-level covariate shocks (crop losses and price shocks) for three years (2012, 2013, 2014) in 2014. To this end, we collected crop loss data which were caused mainly by flood/heavy rain, drought, insects, lack of technical knowledge, and so forth across the crop calendar (Annex Figure A.4). We also collected data on price shock, which is caused by higher production costs, insufficient market demand/bad market prices, poor quality of products, lack of transportation and storage facilities, and so on. From these data, we calculated the total number of covariate shocks each village faced. The average of the total number of covariate shocks in 2012 was 1.34, whereas the corresponding numbers for 2013 and 2014 were 1.55 and 1.82, respectively.

In our primary empirical regression model, we use the aggregate number of shocks – both idiosyncratic and covariate shocks (A list of these two types of shocks can be found in Table I). In addition, we show the effect of idiosyncratic and covariate shocks separately to shed light on heterogeneity.[8]

4 Theoretical and Empirical Frameworks

We are interested in the special role of credit as insurance against exogenous shocks. A farmer exposed to a negative shock increases the demand for insurance, which in turn encourages risk-taking in production. BCUP is designed to reinforce such decisions.

4.1 Theoretical Framework

To illustrate these mechanisms theoretically, we follow Eswaran and Kotwal (1989), Morduch (1994), and Giné and Yang (2009) to construct a simple two-period model of technology choice in which an individual may take out a loan rather than receive an insurance payment, smoothing out income shocks. Suppose that a representative farmer maximizes the expected utility of the time separable concave utility function as follows: $E[u(c_1) + u(c_2)]$, where c_1 and c_2 denote period 1 and 2 consumption, respectively, under an assumption of $u''' = 0$. The subjective discount rate and the interest rate on assets are assumed to be zero for simplicity. The farmer determines consumption and investment allocations to maximize expected utility. There are two investment options available: new technologies and traditional technologies. The former offers high risk and high return, while the latter entails no risk but yields lower returns. At the beginning of the first period, the farmer determines the allocation between these two types of investments, which can be considered a standard portfolio

[8] Given the high correlation between the covariate and idiosyncratic shocks, we also show how treatment effects vary with covariate shocks alone. These results are reported in Appendix Tables B.1-B.5.

selection problem. We denote the investment allocations for new and old investments by p and $1-p$, respectively.

With traditional technology, the first- and second-period returns are deterministic and constant across time, denoted by x. On the other hand, with new technology, the income in the first period is stochastic with two states. The high return, $z+\sigma$, and the low return, $z-\sigma$, are realized with equal probability where σ is a mean zero stochastic variable with $z > \sigma > 0$. We assume that, in the second period, the return from new technology is z with probability one.[9] Since the expected return of new technology should be higher than that of the old technology, and there should be room for investing in the old technology, we assume that $z - x > 0 > z - x - \sigma$. Additionally, we consider (positive) transitory income shock (y^T) hitting in the first period. Our focus here is to explore the response of a farmer to the realization of a transitory shock (y^T) in technological investment decisions, and we can incorporate the shock into the budget constraint as a non-stochastic variable.

Let us consider the case of the good state first. In the second period, the farmer's income is $pz + (1-p)x$, which is non-stochastic, and in the first period, the farmer's income over two periods is $p(z+\sigma) + (1-p)x + y^T$. Accordingly, assuming a zero interest rate, the total lifetime income in the good state becomes $2[pz+(1-p)x]+p\sigma+y^T$. With an expected utility of the form, $E[u(c_1)+u(c_2)]$, the farmer will optimally consume an equal amount in each of the two periods, $c_H = c_{1H} = c_{2H} = [pz + (1-p)x] + (p\sigma + y^T)/2$. Accordingly, in this good state, the farmer saves half of the positive income shock $(p\sigma + y^T)/2$, in the first period to finance the gap between consumption and income in the second period. In the bad state, a farmer's total income becomes $2[pz + (1-p)x]–p\sigma + y^T$. Such a farmer will try to consume the level, $c_{1L} = c_{2L} = [pz + (1-p)x]–(p\sigma - y^T)/2$, in each of two periods by borrowing $D = (p\sigma - y^T)/2$ in the first period.

First, in the case of binding credit constraints, i.e., $(p\sigma - y^T)/2 > B$ where B is the credit ceiling, the farmer consumption in period one and period two under the bad state

[9] Here, we implicitly assume the existence of a strong learning effect in using the new technology.

becomes $c_{1L} = [pz + (1-p)x] - p\sigma + y^T + B$ and $c_{2L} = [pz + (1-p)x] - B$, respectively. Accordingly, the credit-constrained farmer's investment decision problem becomes the following maximization problem of expected utility: $(1/2)[u(c_{1L}) + u(c_{2L})] + u(c_H)$ subject to $c_{1L} = [pz+(1-p)x]-p\sigma+y^T+B$, $c_{2L} = [pz+(1-p)x]-B$, and $c_H = [pz+(1-p)x]+(p\sigma+y^T)/2$. From the first-order condition, we can easily show that:

$$dp*/dB > 0, \tag{1}$$

where the asterisk indicates the optimal level and the inequality (1) corresponds to Proposition 1 of Eswaran and Kotwal (1989). The intuition behind these two inequalities should be clear. The credit constraint is binding only if a bad condition occurs. Thus, the consumption credit B available to a farmer with a credit constraint is relevant only in the bad state. When B is increased, the farmer's marginal utility decreases in the first period and increases in the second period. To smooth marginal utility over time, the farmer has the incentive to invest in the new technology.

On the other hand, the impact of a realized transitory income shock on the technology adoption, $dp*/dy^T$, is indeterminate because of the two opposing effects (Appendix A): while a positive transitory income can induce technology adoption by providing downside insurance in the bad state, it can also disincentivize adoption because a positive shock can decrease the importance of a positive return in the good state.

Denoting the expected value of aggregate yield or farm income of each farm household by q where $q \equiv pz + (1-p)x$. Since $z > x$, it is straightforward to show that $dq/dB > 0$. As to the transitory shocks, their impacts on yields and farm income are not necessarily clear because the direction of $dq/dy^T < 0$ is ambiguous.

Second, suppose that the BCUP program given to a farmer relaxes his or her credit constraints perfectly. Such a case can be formalized by a situation where the credit constraint does not bind. In the bad state, a farmer will borrow $D = (p\sigma - y^T)/2$ in the first period.

Combining the expected utility with the optimality conditions, $c_L = c_{1L} = c_{1L}$ and $c_H = c_{1H} = c_{2H}$, the farmer's investment decision problem becomes to maximize $u(c_L) + u(c_H)$ subject to $c_L = [pz + (1-p)x] - (p\sigma - y^T)/2$ and $c_H = [pz + (1-p)x] + (p\sigma + y^T)/2$. From the first-order condition, we obtain (Appendix A):

$$dp*/dy^T < 0. \tag{2}$$

In this case, we can also verify that the aggregate yield and farm income of each farm household, q, will satisfy a condition, $dq/dy^T < 0$. In this case, it is straightforward to show that the optimal amount of borrowing, $D \equiv (p\sigma - y^T)/2$, is negatively (positively) affected by the realized positive (negative) transitory shock:

$$dD/dy^T < 0 \tag{3}$$

This is true because a positive transitory shock provide additional liquidity to the household and thus mitigates the need for borrowing to smooth consumption. In contrast, when transitory income is negative, a farmer must borrow more to smooth consumption. Inequalities (1), (2), and (3) as well as the associated results can be summarized in the following proposition, which will provide us with testable theoretical implications:

Proposition: If the consumer credit available to a credit-constrained farmer is increased, he or she will adopt a larger share of the new technology, resulting in a higher yield and income. Yet, the impact of a transitory income on technology adoption is ambiguous. If the credit constraint is not binding due to the BCUP program, the amount of borrowing will be negatively (positively) affected by a positive (negative) transitory shock. Without credit constraints, a positive (negative) transitory shock will clearly reduce (increase) new technology adoption and total revenue.

Proof: See Section A of the Appendix.

4.2 Empirical Framework

To test these hypotheses, we estimate treatment effects by running least squares (OLS) regressions and comparing average outcomes between treated and control households. Such an approach yields intent-to-treat (ITT) estimates. This approach exploits randomization of treatment assignment to estimate causal effects. More specifically, to estimate the ITT effect of treatment assignment on the different outcomes, we run a regression in the following form of analysis of covariance (ANCOVA):

$$Y_{i,2014} = a_0 + a_1 T_i + a_2 Y_{i,2012} + \epsilon_i \tag{4}$$

where i denotes a household; 2014 and 2012 are the end-line year and the baseline year, respectively; Y_i is the outcome of interests; T_i is an indicator variable that takes a value of 1 if the household i belongs to the treated sub-districts and zero otherwise. We are mainly interested in the coefficient of the treatment variable, T_i, which shows the average difference in means between the treatment group and the control group. We included the baseline version of the outcome as an additional covariate to account for random differences between treatment and control groups in variables that may be important determinants of outcomes. Although the baseline variable is not required for the causal estimation of a_1 because it is unrelated to treatment status, it can improve the precision of the estimates (Taubman et al., 2014). In all of our analyzes, we cluster standard errors at the village level; this allows us to control for any variance-covariance matrix for households within the same village.

4.3 Shocks and Heterogeneity in the Effect of Credit

In this paper, we are mainly interested in exploring how shocks affect the decision to take credit. To this end, we run the following regression:

$$BCUP_{i,2014} = b_0 + b_1 T_i + b_2 T_i * S_i + b_3 S_i + u_i \tag{5}$$

where $BCUP$ is a binary indicator variable taking a value of 1 if at least one member in the household received credit from the BCUP program at any point during the study period and 0 otherwise; S_i is the total number of shocks – both idiosyncratic and covariate shocks (See Table 1 for the definition of this variable). We particularly focus on the parameter b_2, which shows how the treatment effect on credit uptake varies with the shocks. We are also interested in the subsequent effect of shocks on the treatment effects on other outcomes, W_i. More specifically, we are interested in estimating the following model:

$$W_{i,2014} = d_0 + d_1 T_i + d_2 T_i * S_i + d_3 S_i + v_i \tag{6}$$

where W_i is an outcome variable of interest, including land use, adoption of modern varieties, and income. We are primarily interested in parameter d_2, which shows how the treatment effects vary with the shocks.

5 Main Results

To test the efficacy of randomization, we performed the standard balancing tests of the covariates between the treatment and control groups by comparing the means of the baseline variables. Test results are presented in Table II for household-level treatment assignments. They show no systematic differences in the means of the baseline variables between these two groups, except for a few variables (i.e., the total income of the households and borrowing from NGOs other than BRAC). We also test the similarity at village level BCUP program assignment (Appendix Table A.2) and the exogeneity of price shocks and crop losses by comparing average covariates between households with and without shocks (Appendix Tables A.3-A.4). All these results indicate that the two groups are very similar. Therefore, we believe that both the treatments and the shocks are exogenous and that our regression results can be interpreted as causal relationships. We also distinguish between two different types of shocks: (a) idiosyncratic shocks, which are specific to a particular household, and (b) covariate shocks, which are specific to all households in a village. We see that the average number of covariate shocks and idiosyncratic shocks were also balanced at baseline (Table III).

We first show the impact of the intervention on the probability of taking a loan from the BCUP program. The results are reported in Table IV. Column 1 shows the ITT estimate for the homogeneous model. The probability of taking a loan from the BCUP program is 19.8 percentage points higher among treated households. In column 2, we include the number of shocks and their interaction with treatment assignment to see how treatment effects vary with the number of shocks. The coefficient on the interaction between the number of shocks and treatment assignment is significant at the 5 percent level. Each shock is associated with a 2.19 percentage point increase in the probability of claiming a BCUP credit for the households from treated areas. This suggests that treated households use credit as a coping strategy when faced with various idiosyncratic and covariate shocks.

In Column 3 of Table IV, we show how the treatment effects vary across idiosyncratic and covariate shocks and find that the treatment effects vary more with covariate shocks. Each additional increase in the number of covariate shocks increases the likelihood of borrowing from BCUP by 2.81 percentage points for the treated households. In contrast, the interaction between treatment assignment and idiosyncratic shocks is small and not statistically significant. Thus, the individual household-specific shocks do not appear to increase the propensity to borrow under the program. This result should not come as a surprise because when faced with idiosyncratic shocks, a rural household might prefer to borrow from friends, relatives, or neighbors rather than NGOs, and such idiosyncratic shocks can be diversified if individuals have effective informal insurance networks (Srinivas, 2016). For the remainder of our empirical analysis, we mainly focus on the effect of aggregate shocks in our empirical analyses.

We then show the impact of the shock on the amount of credit used for various purposes. Panel A of Table V show the average ITT effects of the program on credit use for different purposes from the homogeneous model. The estimates are positive and significant. Panel B shows that these effects are not uniform across households, and are driven by shocks. The treatment effects for households not exposed to shocks are positive but not statistically significant. However, the more shocks households experience, the larger the treatment effect for using credit for various purposes. Again, this suggests that credit is a coping strategy to deal with the shocks. Panel C of Table V shows how the treatment effect varies by idiosyncratic and covariate shocks. We observe a similar pattern as in Table IV – the treatment effect on credit use for different self-reported purposes is significantly higher for households facing covariate shocks. In contrast, idiosyncratic shocks have no discernible effect.

Next, we examine the effect of the program on land use. The average ITT effect is insignificant for own-cultivated land or land leased under share-cropping contracts and significant for land leased under fixed-rental contact (Columns 1, 3, and 5 of Table VI). However, the average ITT effects hide substantial heterogeneity across households facing different types of shocks. The results are reported in Table VI. The ITT estimates from the homogeneous models show that treated households are more inclined to rent land with fixed leases (Column 5). However, this effect is mainly driven by covariate shocks (Column 6). Treated households without shocks cultivate significantly lower amounts of land under share-cropping contracts (Column 4). However, as covariate shocks increase, treated households lease more land under sharecropping contracts. This is consistent with the literature, which argues that renting land through sharecropping contracts is relatively efficient because they make the best of an inherently uncertain and risky situation for both parties ((Newbery, 1977)).

The effects of the intervention on the adoption of modern varieties (MV) are shown in Table VII. The average treatment effects indicate that treated households are more likely to adopt modern varieties for rice production: Treated households are 6.3 and 7.6 percentage points more likely to adopt high-yielding and hybrid varieties, respectively (columns 1 and 3). However, columns 2 and 4 suggest that these effects are mainly driven by households exposed to higher shocks. For example, each additional shock is associated with a 1.1 percentage point higher probability of treatment households adopting hybrid varieties than control households. We also show heterogeneity in the treatment effect of the intervention on the adoption of MV across different types of shocks but find no discernible difference in idiosyncratic and covariate shocks (Annex Table A.6).

Finally, in Table VIII, we show the effects of the program on income from various sources. The average ITT effects in the models without heterogeneity indicate that treated households experienced a significant increase in crop production (column 5) but a significant decrease in wage income (column 7), with no discernible effect on total income. The models with shocks and their interaction with the program reveal important heterogeneity. The treatment effect on farm income increases as the household is exposed to more shocks. This is not surprising, as we have previously seen that treated households were more likely to take a loan from the BCUP program as the number of shocks increased. We also showed that the treatment effect on the amount of credit used for crop production increased with the number of shocks, increasing income from crop production for households facing a higher number of shocks. However, this increase in farm income was offset by a substantial decrease in wage income.

We then report the program's impact on two other important indicators of household well-being: households' consumption smoothing strategies and subjective well-being. In the homogeneous model, the treated households reduced skipping days without meals and increased credit use slightly to purchase food compared to the control groups (odd-numbered

Columns in Appendix Table A.8); thus, the BCUP credit helped the borrowers achieve household consumption independence. Again these treatment effects are mainly driven by shocks although the effects are not statistically significant (even-numbered columns in Appendix Table A.8). Similar evidence exists for households' self-reported subjective well-being (Appendix Table A.9). Finally, we do not observe any significant heterogeneity in the effects of credit on consumption independence strategies and subjective well-being across idiosyncratic and covariate shocks.[10]

Thus, we can summarize and interpret our empirical findings as follows: to weather transitory shocks faced during the immediately preceding crop season, farmers take BCUP credit that helps the tenant farm households to engage in rice farming activities and gain income from self-employment farming activities. In the face of shocks, tenant households lease more land through sharecropping agreements, adopt modern technologies, and pursue agricultural self-sufficiency opportunities. We also observe that households facing covariate shocks, compared to idiosyncratic shocks, participate more in the BCUP program, take more credit for cropping, expand cropping under sharecropping contracts, and earn more income from rice cultivation but earn less from agricultural wage labor. Finally, we observe a positive but insignificant effect on total household income, consumption smoothing, and subjective well-being.

6 Discussion & Conclusion

This study examined the role of an innovative, customized credit program for resource-poor tenant farmers in facilitating tenant farmers' risk-management strategies in the face of various production shocks. Using unique panel survey data with shock information generated from a carefully designed RCT study, we estimated the causal impact of BCUP on various outcome indicators, such as credit uptake for different purposes, adoption of new farm technologies, and itemized as well as aggregated income. Our empirical estimates show that

[10] Results are not reported here for brevity but are available upon request.

shocks increase credit uptake considerably among the treatment groups. While a companion study by (Hossain et al., 2019) was silent about the underlying reasoning for the low uptake of the BCUP credit program, this paper uncovered a possible mechanism at least partly: Farmers find implicit insurance in the limited liability clause of an uninsured loan when they face various shocks. This implicit insurance motivates farmers to increase their use of the loan product. Since the rural financial market in developing countries does not offer innovative insurance products such as rainfall insurance, as shown by Karlan, Knight and Udry (2015), microcredit programs can serve as an alternative insurance tool (Giné and Yang, 2009). Therefore, when designing microcredit for agriculture, it is essential that microfinance institutions consider the various shocks that farmers are exposed to.

We also find that to cope with temporary shocks in the immediately preceding harvest season, farmers use BCUP credit to grow their own crop and generate income. In the face of shocks, resource-poor tenant households can acquire more land under sharecropping and fixed-rental tenancy agreements, adopt modern technologies in rice cultivation, and practice self-sufficiency farming. We also distinguish between a household's response to covariate and idiosyncratic shocks. We find that faced with covariate shocks compared to idiosyncratic shocks, treatment households participate more in the BCUP program, use credit more for crop farming activities, increase cultivation under shared-in contact, earn more through rice crop farming, and earn less from farm wage employment. We also observe a positive but insignificant effect on household income, consumption independence, and subjective well-being - results largely consistent with Banerjee, Karlan and Zinman (2015). From a policy perspective, our results suggest that an innovative microcredit program like BCUP can act as a robust insurance policy against impoverishment by eliminating the downside risk of falling into a poverty trap, which is consistent with the poverty trap literature (Bandiera et al., 2020; Parekh and Bandiera, 2020; Banerjee, Niehaus and Suri, 2019). Our results are broadly consistent with the theoretical implications of a simple two-period model of technology adoption that we develop to show consumer credit as an insurance substitute.

Under BCUP credit availability, a credit-constrained farmer adopts a larger share of the new technology to strengthen home cultivation and increase welfare. Even if the credit constraint is not binding due to the BCUP program, the amount of credit taken is positively affected by a negative transitory shock, leading to the adoption of new technology and improving household welfare.

As climate change increases the frequency and severity of weather shocks, it is important to provide households with an easily accessible tool to reduce vulnerability to these risks. In countries with severe market frictions, achieving such cost-effective solutions can be challenging when commonly employed adaptation measures like infrastructure, insurance schemes, and social safety net programs are not readily available (Lane, 2022). Our findings can inform the policymaker to expand access to customize credit to agricultural households as a practical policy adaptation tool in the face of adverse shocks.

References

Balboni, Clare, Oriana Bandiera, Robin Burgess, Maitreesh Ghatak, and Anton Heil. 2022. "Why do people stay poor?" *The Quarterly Journal of Economics*, 137(2): 785–844.

Bandiera, Oriana, Niklas Buehren, Robin Burgess, Markus Goldstein, Selim Gulesci, Imran Rasul, and Munshi Sulaiman. 2020. "Women's empowerment in action: evidence from a randomized control trial in Africa." *American Economic Journal: Applied Economics*, 12(1): 210–259.

Banerjee, Abhijit, Dean Karlan, and Jonathan Zinman. 2015. "Six randomized evaluations of microcredit: Introduction and further steps." *American Economic Journal: Applied Economics*, 7(1): 1–21.

Banerjee, Abhijit, Esther Duflo, Nathanael Goldberg, Dean Karlan, Robert Osei, William Parienté, Jeremy Shapiro, Bram Thuysbaert, and Christopher Udry. 2015. "A multifaceted program causes lasting progress for the very poor: Evidence from six countries." *Science*, 348(6236): 1260799.

Banerjee, Abhijit, Paul Niehaus, and Tavneet Suri. 2019. "Universal basic income in the developing world." *Annual Review of Economics*, 11: 959–983.

Basu, Karna, and Maisy Wong. 2015. "Evaluating seasonal food storage and credit programs in east Indonesia." *Journal of Development Economics*, 115: 200–216.

Beaman, Lori, Dean Karlan, Bram Thuysbaert, and Christopher Udry. 2014. "Selection into Credit Markets: Evidence from Agriculture in Mali." National Bureau of Economic Research Working Paper 20387.

Bellemare, Marc F, Yu Na Lee, and David R Just. 2020. "Producer attitudes toward output price risk: Experimental evidence from the lab and from the field." *American Journal of Agricultural Economics*, 102(3): 806–825.

Brooks, Wyatt, and Kevin Donovan. 2020. "Eliminating uncertainty in market access: The impact of new bridges in rural Nicaragua." *Econometrica*, 88(5): 1965–1997.

Burke, Marshall, Lauren Falcao Bergquist, and Edward Miguel. 2019. "Sell low and buy high: arbitrage and local price effects in Kenyan markets." *The Quarterly Journal of Economics*, 134(2): 785–842.

Cai, Jing, Alain De Janvry, and Elisabeth Sadoulet. 2015. "Social networks and the decision to insure." *American Economic Journal: Applied Economics*, 7(2): 81–108.

Carter, Michael, Alain de Janvry, Elisabeth Sadoulet, and Alexandros Sarris. 2017. "Index insurance for developing country agriculture: a reassessment." *Annual Review of Resource Economics*, 9: 421–438.

Casaburi, Lorenzo, and Jack Willis. 2018. "Time versus state in insurance: Experimental evidence from contract farming in Kenya." *American Economic Review*, 108(12): 3778–3813.

Cole, Shawn A, and Wentao Xiong. 2017. "Agricultural insurance and economic development." *Annual review of Economics*, 9: 235–262.

Cole, Shawn, Xavier Giné, Jeremy Tobacman, Petia Topalova, Robert Townsend, and James Vickery. 2013. "Barriers to household risk management: Evidence from India." *American Economic Journal: Applied Economics*, 5(1): 104–135.

Conning, Jonathan, and Christopher Udry. 2007. "Rural financial markets in developing countries." *Handbook of agricultural economics*, 3: 2857–2908.

Das, Narayan, Alain de Janvry, and Elisabeth Sadoulet. 2019. "Credit and land contracting: A test of the theory of sharecropping." *American Journal of Agricultural Economics*, 101(4): 1098–1114.

Dell, Melissa, Benjamin F Jones, and Benjamin A Olken. 2012. "Temperature shocks and economic growth: Evidence from the last half century." *American Economic Journal: Macroeconomics*, 4(3): 66–95.

Dercon, Stefan, Ruth Vargas Hill, Daniel Clarke, Ingo Outes-Leon, and Alemayehu Seyoum Taffesse. 2014. "Offering rainfall insurance to informal insurance groups: Evidence from a field experiment in Ethiopia." *Journal of Development Economics*, 106: 132–143.

Dimble, V, and AM Mobarak. 2019. "Saving microfinance through innovative lending." *IGC Growth Brief Series*, 17.

Duflo, Esther. 2020. "Field experiments and the practice of policy." *American Economic Review*, 110(7): 1952–73.

Emerick, Kyle, Alain De Janvry, Elisabeth Sadoulet, and Manzoor H Dar. 2016. "Technological innovations, downside risk, and the modernization of agriculture." *American Economic Review*, 106(6): 1537–1561.

Eswaran, Mukesh, and Ashok Kotwal. 1989. "Credit as insurance in agrarian economies." *Journal of development economics*, 31(1): 37–53.

Fafchamps, Marcel, and Susan Lund. 2003. "Risk-sharing networks in rural Philippines." *Journal of development Economics*, 71(2): 261–287.

Felkner, John, Kamilya Tazhibayeva, and Robert Townsend. 2009. "Impact of climate change on rice production in Thailand." *American Economic Review*, 99(2): 205–210.

Field, Erica, and Rohini Pande. 2008. "Repayment frequency and default in microfinance: Evidence from India." *Journal of the European Economic Association*, 6(2-3): 501–509.

Field, Erica, Rohini Pande, John Papp, and Natalia Rigol. 2013. "Does the classic microfinance model discourage entrepreneurship among the poor? Experimental evidence from India." *American Economic Review*, 103(6): 2196–2226.

Fink, Günther, B Kelsey Jack, and Felix Masiye. 2020. "Seasonal liquidity, rural labor markets, and agricultural production." *American Economic Review*, 110(11): 3351–3392.

Fisher, Anthony C, W Michael Hanemann, Michael J Roberts, and Wolfram Schlenker. 2012. "The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather: comment." *American Economic Review*, 102(7): 3749–3760.

Giné, Xavier, and Dean S Karlan. 2014. "Group versus individual liability: Short and long term evidence from Philippine microcredit lending groups." *Journal of development Economics*, 107: 65–83.

Giné, Xavier, and Dean Yang. 2009. "Insurance, credit, and technology adoption: Field experimental evidence from Malawi." *Journal of development Economics*, 89(1): 1–11.

Giné, Xavier, Robert Townsend, and James Vickery. 2008. "Patterns of rainfall insurance participation in rural India." *The World Bank Economic Review*, 22(3): 539–566.

González, Christian R. 2014. "Can micro-finance help small farmers in developing countries improve their livelihoods? A Systematic Review." *Florida International University, Florida.*

Hossain, Marup, Mohammad Abdul Malek, Md Amzad Hossain, Md Hasib Reza, and Md Shakil Ahmed. 2019. "Agricultural microcredit for tenant farmers: Evidence from a field experiment in Bangladesh." *American Journal of Agricultural Economics*, 101(3): 692–709.

Hossain, Md Amzad. 2023. "Unintended Consequences of a Well-Intentioned Policy: Impact of Credit on Child Labor in Bangladesh." *Journal of Human Resources*, 0920–11179R2.

Hussam, Reshmaan, Natalia Rigol, and Benjamin N Roth. 2022. "Targeting high ability entrepreneurs using community information: Mechanism design in the field." *American Economic Review*, 112(3): 861–98.

Jimi, Nusrat Abedin, Plamen V Nikolov, Mohammad Abdul Malek, and Subal Kumbhakar. 2019. "The effects of access to credit on productivity: separating technological changes from changes in technical efficiency." *Journal of Productivity Analysis*, 52: 37–55.

Jones, Maria, Florence Kondylis, John Loeser, and Jeremy Magruder. 2022. "Factor market failures and the adoption of irrigation in rwanda." *American Economic Review*, 112(7): 2316–52.

Karlan, Dean, Ryan Knight, and Christopher Udry. 2015. "Consulting and capital experiments with microenterprise tailors in Ghana." *Journal of Economic Behavior & Organization*, 118: 281–302.

Khandker, Shahidur R. 2012. "Seasonality of income and poverty in Bangladesh." *Journal of Development Economics*, 97(2): 244–256.

Kono, Hisaki, Kazushi Takahashi, and Abu Shonchoy. 2021. "At the Right Time: Modifying Repayment and Disbursement Schedule in Microcredit." mimeo. Retrived from https://confit-sfs.atlas.jp/customer/jea2021s/web/outline/1R601-04-03.pdf.

Kubik, Zaneta, and Mathilde Maurel. 2016. "Weather shocks, agricultural production and migration: Evidence from Tanzania." *The Journal of Development Studies*, 52(5): 665–680.

Lane, Gregory. 2022. "Adapting to Floods with Guaranteed Credit: Evidence from Bangladesh." Retrived from https://www.gregoryvlane.com/pdfs/Lane_Floods.pdf.

Maitra, Pushkar, Sandip Mitra, Dilip Mookherjee, Alberto Motta, and Sujata Visaria. 2017. "Financing smallholder agriculture: An experiment with agent-intermediated microloans in India." *Journal of Development Economics*, 127: 306–337.

Maîtrot, Mathilde, and Miguel Niño-Zarazúa. 2017. "Poverty and wellbeing impacts of microfinance: What do we know?" WIDER Working Paper 190/2017; ISBN 978-92-9256-416-2 , Available at SSRN: https://ssrn.com/abstract=3076781.

Malek, MA, A Ahasan, MA Hossain, MS Ahmed, M Hossain, and MH Reza. 2015. "Impact assessment of credit programme for the tenant farmers in Bangladesh, 3ie grantee final report." *New Delhi: International Initiative for Impact Evaluation (3ie).*

Meager, Rachael. 2019. "Understanding the average impact of microcredit expansions: A bayesian hierarchical analysis of seven randomized experiments." *American Economic Journal: Applied Economics*, 11(1): 57–91.

Mobarak, Ahmed Mushfiq, and Mark Rosenzweig. 2014. "Risk, insurance and wages in general equilibrium." National Bureau of Economic Research.

Mobarak, Ahmed Mushfiq, and Mark R Rosenzweig. 2012. "Selling formal insurance to the informally insured." Yale Economics Department Working Paper No. 97, Available at SSRN: https://ssrn.com/abstract=2009528 or http://dx.doi.org/10.2139/ssrn.2009528.

Mobarak, Ahmed Mushfiq, and Mark R Rosenzweig. 2013. "Informal risk sharing, index insurance, and risk taking in developing countries." *American Economic Review*, 103(3): 375–380.

Morduch, Jonathan. 1994. "Poverty and vulnerability." *The American Economic Review*, 84(2): 221–225.

Newbery, David MG. 1977. "Risk sharing, sharecropping and uncertain labour markets." *The Review of Economic Studies*, 44(3): 585–594.

Parekh, N, and O Bandiera. 2020. "Do social assistance programmes reach the poor? Micro-evidence from 123 countries." IGC Growth Brief Series 023. London: International Growth Centre.

Paxson, Christina H. 1993. "Consumption and income seasonality in Thailand." *Journal of political Economy*, 101(1): 39–72.

Pitt, Mark M, and Shahidur R Khandker. 2002. "Credit programmes for the poor and seasonality in rural Bangladesh." *Journal of Development Studies*, 39(2): 1–24.

Rosenzweig, Mark R, and Hans P Binswanger. 1993. "Wealth, weather risk and the composition and profitability of agricultural investments." *The economic journal*, 103(416): 56–78.

Shoji, Masahiro. 2010. "Does contingent repayment in microfinance help the poor during natural disasters?" *The Journal of Development Studies*, 46(2): 191–210.

Srinivas, Hari. 2016. "Reasons why the informal credit market is used by the poor: Policy implications for microcredit programmes in developing countries." *GDRC research output*.

Stephens, Emma C, and Christopher B Barrett. 2011. "Incomplete credit markets and commodity marketing behaviour." *Journal of agricultural economics*, 62(1): 1–24.

Taubman, Sarah L, Heidi L Allen, Bill J Wright, Katherine Baicker, and Amy N Finkelstein. 2014. "Medicaid increases emergency-department use: evidence from Oregon's Health Insurance Experiment." *Science*, 343(6168): 263–268.

Table I: List of Idiosyncratic & Covariate Shocks

Idiosyncratic Shocks	**Covariate Shocks**
Idiosyncratic price shock in 2012	Covariate price shock in 2012
Idiosyncratic crop loss in 2012	Covariate crop loss in 2012
Idiosyncratic price shock in 2014	Covariate price shock in 2013
Idiosyncratic crop loss in 2014	Covariate crop loss in 2013
	Covariate price shock in 2014
	Covariate crop loss in 2014

Table II: Baseline Summary Statistics and Tests of Balance

	Control		Treatment		Treatment-control	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Error
Household composition						
Household size (No of members)	4.77	1.69	4.94	1.83	0.18	0.18
No of working age members	3.11	1.3	3.11	1.38	0	0.1
HH head is male	0.95	0.22	0.92	0.28	-0.03	0.02
Head with no education	0.75	0.43	0.8	0.4	0.04	0.03
Maximum education of Household Head (in Years)	4.92	4.53	5.08	4.56	0.15	0.51
Age	44.46	11.83	45.24	11.37	0.77	0.71
Amount of Land (in Decimal)						
Owned land	38.71	51.83	37.46	49.6	-1.25	3.22
Rented in land	51.25	78.6	51.53	99.84	0.29	7.28
Total cultivated land	89.95	88.92	88.99	106.08	-0.96	9.16
Tenancy Status (Proportion of Total)						
Pure Owner	0.35	0.48	0.35	0.48	0.002	0.03
Owner-cum-tenant	0.34	0.47	0.32	0.47	-0.026	0.04
Pure Tenant	0.31	0.46	0.33	0.47	0.024	0.03
Asset Holding and electricity connection						
Whether HH has a Cow (Dummy)	0.59	0.49	0.59	0.49	0	0.04
Whether HH has a goat	0.26	0.44	0.18	0.39	-0.08	0.05
Value of Total asset (in BDT)	75648	439373	27610	196869	-48038	45879
Whether HH has electricity connection (Dummy)	0.6	0.49	0.59	0.49	-0.01	0.07
Modern variety adoption						
Whether farm adopts Aman (HYV)	0.3	0.46	0.36	0.48	0.06	0.12
Whether farm adopts Aman (Hybrid)	0.02	0.13	0.01	0.1	-0.01	0.01
Whether farm adopts Boro (HYV)	0.69	0.46	0.7	0.46	0.01	0.12
Whether farm adopts Boro (Hybrid)	0.04	0.19	0.04	0.19	0	0.02
Income (in BDT)						
Agricultural Self-employment	21418	32127	18496	30712	-2,923	2622
Rice farming	8526	10392	8404	10636	-122	1230
Non-rice crop farming	6077	25590	2700	15360	-3,376	2495
Non-crop farming	6067	12915	6527	22456	460	907.7
Total wage	33617	43718	40702	51944	7,085	4258
-Agricultural wage	12246	20573	11408	21618	-839	1628
-Non-agricultural wage	21370	42417	29294	51179	7,924*	4357
Non-agricultural self-employment	11930	38864	16107	46739	4,177	2713
Remittance	17534	129506	25278	97881	7,744	8032
Total Income	91513	149490	107815	121859	16,302**	8008
Consumption independence strategies						
Skipped days without eating (dummy)	0.02	0.14	0.02	0.14	0	0.01
Sold poultry birds to purchase food (dummy)	0.62	0.48	0.45	0.5	-0.173	0.13
Sold farm equipment to purchase food (dummy)	0.58	0.49	0.42	0.49	-0.162	0.14
Used credit to purchase food (dummy)	0.59	0.49	0.43	0.49	-0.158	0.14
Amount of loan from different sources (BDT)						
Bank/Co-operative	1442	11984	1531	20161.83	88.89	652.9
Grameen Bank	573	6826	310	2726.68	-263.1	184.1
Other BRAC Program	342	5848	371	5018.34	28.94	200.2
Other NGOs	532	3693	237	2009.71	-295.2**	120.5
Informal	1756	17944	1686	17343.52	-70.42	937.8

Notes: Data from baseline (2012) survey. The sample size is n = 4,141, of which 2,072 were assigned to treatment and 2,069 were assigned to control. Columns 1 and 2 report statistics for households in the control areas. Columns 3 and 4 report statistics for households in the treated areas. Column 5 shows the difference between the mean for households in the treatment and control areas. Column 6 shows p-values for the test of equality of means, robust to intra-cluster correlation. The number of clusters (sub-districts) is 40. Asterisks denote statistical significance at the 10(*), 5(**) or 1(***) percent level. All figures expressing monetary values are in BDT. Unit of land is in decimal, where 100 decimals=1 acre. Informal lenders include moneylenders, loans from friends or family, and buying goods or services on credit from sellers.

Table III: Exogeneity test of shocks

	Shocks for Baseline (2012)			Shocks for all three years (2012, 2013 and 2014)		
	Number of Idiosyncratic shocks	Number of covariate shocks	Total number of shocks	Number of Idiosyncratic shocks	Number of covariate shocks	Total number of shocks
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Program assignment	-0.0202	-0.336	-0.356	-0.003	-0.483	-0.486
	(0.0666)	(0.312)	(0.263)	(0.129)	(0.63)	(0.595)
Control mean	0.939***	1.505***	2.444***	1.406***	4.950***	6.356***
	(0.0373)	(0.179)	(0.196)	(0.0759)	(0.408)	(0.423)
Observations	4141	4141	4141	4141	4141	4141
R-squared	0	0.037	0.03	0	0.018	0.016

Notes: In each column, different shock variables are regressed on a dummy variable indicating treatment assignment. The dependent variables are the number of different types of shocks. Idiosyncratic shocks refer to the shock where one household's experience is typically unrelated to that of neighboring households. Covariate shocks refer to the shocks where many households in the same geographical location suffer similar shocks. *** p¡0.01, ** p¡0.05, * p¡0.1

Table IV: BCUP participation

VARIABLES	(1) Participates in BCUP	(2) Participates in BCUP	(3) Participates in BCUP
Program assignment	0.198***	0.0696	0.0898
	(0.021)	(0.0558)	(0.0571)
Number of shocks		-0.000332	
		(0.000457)	
Program x Number of shocks		0.0219**	
		(0.00952)	
Number of idiosyncratic shocks			-0.00318*
			(0.00168)
Number of covariate shocks			0.000419
			(0.000501)
Program x Number of idiosyncratic shocks			-0.0119
			(0.0165)
Program x Number of covariate shocks			0.0281***
			(0.0101)
Constant	0.00242*	0.00453	0.00482
	(0.00126)	(0.00352)	(0.00328)
Observations	4141	4141	4141
R-squared	0.108	0.116	0.124

Notes: Data from 2012 and 2014 surveys. Cluster-robust standard errors are in parentheses. The coefficients in columns (1) and (2) are intention-to-treat (ITT) estimates of the models (1) and (2) of the text, respectively. The dependent variables in each column show the probability that a household participates in the BCUP program. The baseline means reported at the bottom of each panel are calculated for the control areas that were randomly assigned not to receive BCUP credit. Number of shocks refers to the total number of idiosyncratic and covariate shocks. Idiosyncratic shocks refer to the particular shock where one household's experience is typically unrelated to that of neighboring households. Covariate shocks refer to the shocks where many households in the same geographical location suffer similar shocks. Asterisks denote statistical significance at the 10(*), 5(**) or 1(***) % level.

Table V: Used amounts of BCUP credit for self-reported purpose

VARIABLES	(1) Crop farming	(2) Non-crop farming	(3) Farming	(4) Others	(5) Total amount
Panel A: No heterogeneity					
Program	2.4860***	0.799***	3.285***	2.499***	5.784***
	(0.3868)	(0.165)	(0.427)	(0.320)	(0.648)
Observations	4,141	4,141	4,141	4,141	4,141
R-squared	0.0272	0.011	0.038	0.039	0.066
Panel B: Heterogeneity by total number of shocks					
Program	0.3325	0.276	0.608	1.000	1.608
	(0.9959)	(0.429)	(1.100)	(0.778)	(1.586)
Number of shocks	-0.0035	0	-0.00348	-0.00465	-0.00813
	(0.0045)	(0)	(0.00451)	(0.00439)	(0.00885)
Program x Number of shocks	0.3666**	0.0892	0.456**	0.255*	0.711***
	(0.1573)	(0.0849)	(0.181)	(0.138)	(0.272)
Observations	4,141	4,141	4,141	4,141	4,141
R-squared	0.0310	0.012	0.042	0.041	0.072
Panel C: Heterogeneity by types of shocks					
Program	0.4493	0.352	0.801	1.472*	2.272
	(1.0853)	(0.440)	(1.188)	(0.790)	(1.633)
Number of idyosyncratic shocks	-0.0313	0**	-0.0313	-0.0220	-0.0533*
	(0.0220)	(0)	(0.0220)	(0.0159)	(0.0294)
Number of covariate shocks	0.0039	-0***	0.00385	-8.53e-05	0.00377
	(0.0061)	(0)	(0.00607)	(0.00400)	(0.00825)
Program x Number of idiosyncratic shocks	0.1806	-0.0466	0.134	-0.573**	-0.439
	(0.3880)	(0.131)	(0.425)	(0.248)	(0.519)
Program x Number of covariate shocks	0.3996***	0.115	0.514***	0.410***	0.924***
	(0.1422)	(0.0895)	(0.172)	(0.151)	(0.283)
Observations	4,141	4,141	4,141	4,141	4,141
R-squared	0.0315	0.013	0.043	0.051	0.079

Notes: Data from 2012 and 2014 surveys. Cluster-robust standard errors are in parentheses. The coefficients in the odd columns and even columns are intention-to-treat (ITT) estimates of the models (1) and (2) of the text, respectively. The dependent variables in columns 1-10 show the amount of BCUP credit used for different purposes (self-reported): crop farming (Columns 1 2), non-crop framing (Columns 3 4), non-farm business activities (Columns 5 6), others including non-farm business use, consumption smoothing, household repairment, etc. (Column 7 8) and the total amount of credit (Column 9 10). All figures expressing monetary values are in BDT ('000) units. The PPP exchange rate, according to the latest World Bank figures, is 25.97 BDT/1 USD (World Bank 2014). Number of shocks refers to the total number of idiosyncratic and covariate shocks. Asterisks denote statistical significance at the 10(*), 5(**) or 1(***)

Table VI: Land Use

	Amount of land (in decimals) cultivated by farm households under different tenurial arrangements					
	Own land	Own land	Share cropped-in	Share cropped-in	Leased-in	Leased-in
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Program	0.033	-12.211***	-2.365	-13.175*	6.675***	-5.029
	(1.704)	(3.705)	(2.013)	(7.242)	(1.790)	(3.733)
Number of shocks		-0.100		-0.533		0.554*
		(0.357)		(0.911)		(0.323)
Program x Number of shocks		2.084***		1.802*		2.051***
		(0.653)		(1.088)		(0.703)
Constant	7.681***	8.474***	11.056***	14.459**	2.242***	-1.264
	(1.596)	(2.669)	(1.781)	(6.608)	(0.734)	(1.824)
Observations	4,080	4,080	4,080	4,080	4,080	4,080
R-squared	0.442	0.445	0.247	0.248	0.341	0.343

Notes: : Data from 2012 and 2014 surveys. Cluster-robust standard errors are in parentheses. The coefficients in the odd columns and even columns are intention-to-treat (ITT) estimates of the models (1) and (2) of the text, respectively. The dependent variables in columns 1-8 show the amount of land cultivated under different tenancy arrangements. The baseline means reported at the bottom of each panel are calculated for the control areas that were randomly assigned not to receive BCUP credit. All land figures are in decimals. (1 acre=100 decimals). Number of shocks refers to the total number of idiosyncratic and covariate shocks. Asterisks denote statistical significance at the 10(*), 5(**) or 1(***) % level.

Table VII: Adoption of Modern Varieties

VARIABLES	Boro HYV (1)	Boro HYV (2)	Boro Hybrid (3)	Boro Hybrid (4)
Program	0.0634**	0.0185	0.0756***	0.0115
	(0.0303)	(0.0760)	(0.0123)	(0.0292)
Number of shocks		-0.0132		0.00125
		(0.00929)		(0.00276)
Program x Number of shocks		0.00655		0.0111**
		(0.0120)		(0.00557)
Constant	0.116***	0.204***	0.0250***	0.0174
	(0.0263)	(0.0647)	(0.00676)	(0.0176)
Observations	4,080	4,080	4,080	4,080
R-squared	0.275	0.277	0.049	0.053

Notes: Data from 2012 and 2014 surveys. Cluster-robust standard errors are in parentheses. The coefficients in the odd columns and even columns are intention-to-treat (ITT) estimates of the models (1) and (2) of the text, respectively. The dependent variables in columns 1-4 show the likelihood of adopting different types of modern varieties, high-yield varieties (HYV), and hybrid varieties in the irrigated Boro season. The baseline means reported at the bottom of each panel are calculated for the control areas that were randomly assigned not to receive BCUP credit. Number of shocks refers to the total number of idiosyncratic and covariate shocks. Asterisks denote statistical significance at the 10(*), 5(**) or 1(***) % level.

Table VIII: Income from different sources

	Household income from different sources (in BDT)					
	Rice farming	Rice farming	Non-rice crop farming	Non-rice crop farming	All crop farming	All crop farming
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Program	3.2060***	-5.1912*	-0.5815	-1.7540	2.7954**	-7.5207**
	(0.8921)	(2.8799)	(1.2049)	(1.8769)	(1.3067)	(2.9170)
Number of shocks		-0.9203***		0.4095*		-0.7596**
		(0.2448)		(0.2409)		(0.3194)
Program x Number of shocks		1.3541***		0.2319		1.6946***
		(0.4210)		(0.3534)		(0.5053)
Observations	4,141	4,141	4,141	4,141	4,141	4,141
R-squared	0.2111	0.2184	0.1130	0.1147	0.1290	0.1320
	Livestock and poultry	Livestock and poultry	Farm wage	Farm wage	Total	Total
VARIABLES	(7)	(8)	(9)	(10)	(11)	(12)
Program	0.2466	-0.2920	-4.2874***	1.1015	6.0045	8.7919
	(0.2130)	(0.7802)	(1.3202)	(3.7278)	(5.8846)	(19.0369)
Number of shocks		-0.1288***		0.6456*		-1.7302
		(0.0478)		(0.3600)		(1.6086)
Program x Number of shocks		0.0806		-0.8647		-0.6166
		(0.1109)		(0.6032)		(2.9417)
Observations	3,822	3,822	4,141	4,141	4,141	4,141
R-squared	0.0010	0.0029	0.1709	0.1723	0.1541	0.1546

Notes: Data from 2012 and 2014 surveys. Cluster-robust standard errors are in parentheses. The coefficients in the odd columns and even columns are intention-to-treat (ITT) estimates of the models (1) and (2) of the text, respectively. The dependent variables in columns 1-12 show the likelihood of household income from major farming and non-farming sources and total income. Income from rice farming: Profit earned from rice production-the difference between the total revenue from rice production and the total cost incurred for rice production. Income from non-rice crop framing: Profit earned from the non-rice production-the difference between total revenue from non-rice crop production and the total cost incurred for non-rice crop production. Income from livestock and poultry production: Profit earned from livestock and poultry production-the difference between the total revenue from livestock and poultry production and the total cost incurred for livestock and poultry production. Income from farm wage: Wage and salaries earned from agricultural labor employment activities. Total income earned by household including all farm, non-farm, remittance, transfers, etc. The baseline means reported at the bottom of each panel are calculated for the control areas that were randomly assigned not to receive BCUP credit. All figures expressing monetary values are in BDT ('000) units. The PPP exchange rate, according to the latest World Bank figures, is 25.97 Taka/1 USD (World Bank 2014). Number of shocks refers to the total number of idiosyncratic and covariate shocks. Asterisks denote statistical significance at the 10(*), 5(**) or 1(***) % level.

A Appendix: Proof of Propositions

A.1 Case of Binding Credit Constraints

By solving the household maximization problem, we can obtain the following first-order condition:

$$(1/2)(z-x-\sigma)u'[p*z+(1-p*)x-p*\sigma+y^T+B]+(1/2)(z-x)u'[p*z+(1-p*)x-B]+(z-x+\sigma/2)u'[p*z+(1-p*)x+(p*\sigma+y^T)/2]=0,$$

where the asterisk shows the optimal level. Total-differentiating this equation with respect to $p*$ and B, we obtain:

$$(1/2)(z-x-\sigma)^2u''[p*z+(1-p*)x-p*\sigma+y^T+B]dp*+(1/2)(z-x)^2u''[p*z+(1-p*)x-B]dp*+(z-x+\sigma/2)^2u''[p*z+(1-p*)x+(p*\sigma+y^T)/2]dp*+(1/2)(z-x-\sigma)u''[p*z+(1-p*)x-p*\sigma+y^T+B]dB-(1/2)(z-x)u''[p*z+(1-p*)x-B]dB=0.$$

Since $u'''=0$ and $z–x>0>z–x–\sigma$, we can verify that $dp*/dB>0$. This corresponds to the proposition 1 of Eswaran and Kotwal (1989). Total-differentiating the first-order condition with respect to $p*$ and y^T, we obtain:

$$(1/2)(z-x-\sigma)^2u''[p*z+(1-p*)x-p*\sigma+y^T+B]dp*+(1/2)(z-x)^2u''[p*z+(1-p*)x-B]dp*+(z-x+\sigma/2)^2u''[p*z+(1-p*)x+(p*\sigma+y^T)/2]dp*+(1/2)(z-x-\sigma)u''[p*z+(1-p*)x-p*\sigma+y^T+B]dy^T+(1/2)(z-x+\sigma/2)u''[p*z+(1-p*)x+(p*\sigma+y^T)/2]dy^T=0.$$

From this equation, we obtain that:

$$\frac{dp*}{dy^T}=\frac{-(1/2)(z-x-\sigma)u''[p*z+(1-p*)x-p*\sigma+y^T+B]-(1/2)(z-x+\sigma/2)u''[p*z+(1-p*)x+(p*\sigma+y^T)/2]}{((1/2)(z-x-\sigma)^2u''[p*z+(1-p*)x-p*\sigma+y^T+B]+(1/2)(z-x)^2u''[p*z+(1-p*)x-B]+(z-x+\sigma/2)^2u''[p*z+(1-p*)x+(p*\sigma+y^T)/2])},$$

where the direction of the derivative is indeterminate.

A.2 Case of Non-Binding Credit Constraints

In the case of non-binding credit constraints, we can obtain the following first-order condition of the household's optimization problem:

$$(z-x-\sigma/2)u'[p*z+(1-p*)x-(p*\sigma-y^T)/2]+(z-x+\sigma/2)u'[p*z+(1-p*)x+(p*\sigma+y^T)/2]=0,$$

Total-differentiating this equation with respect to $p*$ and y^T, we obtain:

$(z-x-\sigma/2)^2u''[p*z+(1-p*)x-(p*\sigma-y^T)/2]dp*+(z-x+\sigma/2)^2u''[p*z+(1-p*)x+(p*\sigma+y^T)/2]dp*+(1/2)(z-x-\sigma/2)u''[p*z+(1-p*)x-(p*\sigma-y^T)/2]dy^T+(1/2)(z-x+\sigma/2)u''[p*z+(1-p*)x+(p*\sigma+y^T)/2]dy^T=0.$

Hence, under an assumption of $u'''=0$, we can verify that:

$$\frac{dp*}{dy^T}=\frac{(-(1/2)(z-x-\sigma/2)u''[p*z+(1-p*)x-(p*\sigma-y^T)/2]-(1/2)(z-x+\sigma/2)u''[p*z+(1-p*)x+(p*\sigma+y^T)/2])}{((z-x-\sigma/2)^2u''[p*z+(1-p*)x-(p*\sigma-y^T)/2]+(z-x+\sigma/2)^2u''[p*z+(1-p*)x+(p*\sigma+y^T)/2])}<0.$$

Q.E.D

B Appendix Figures and Tables

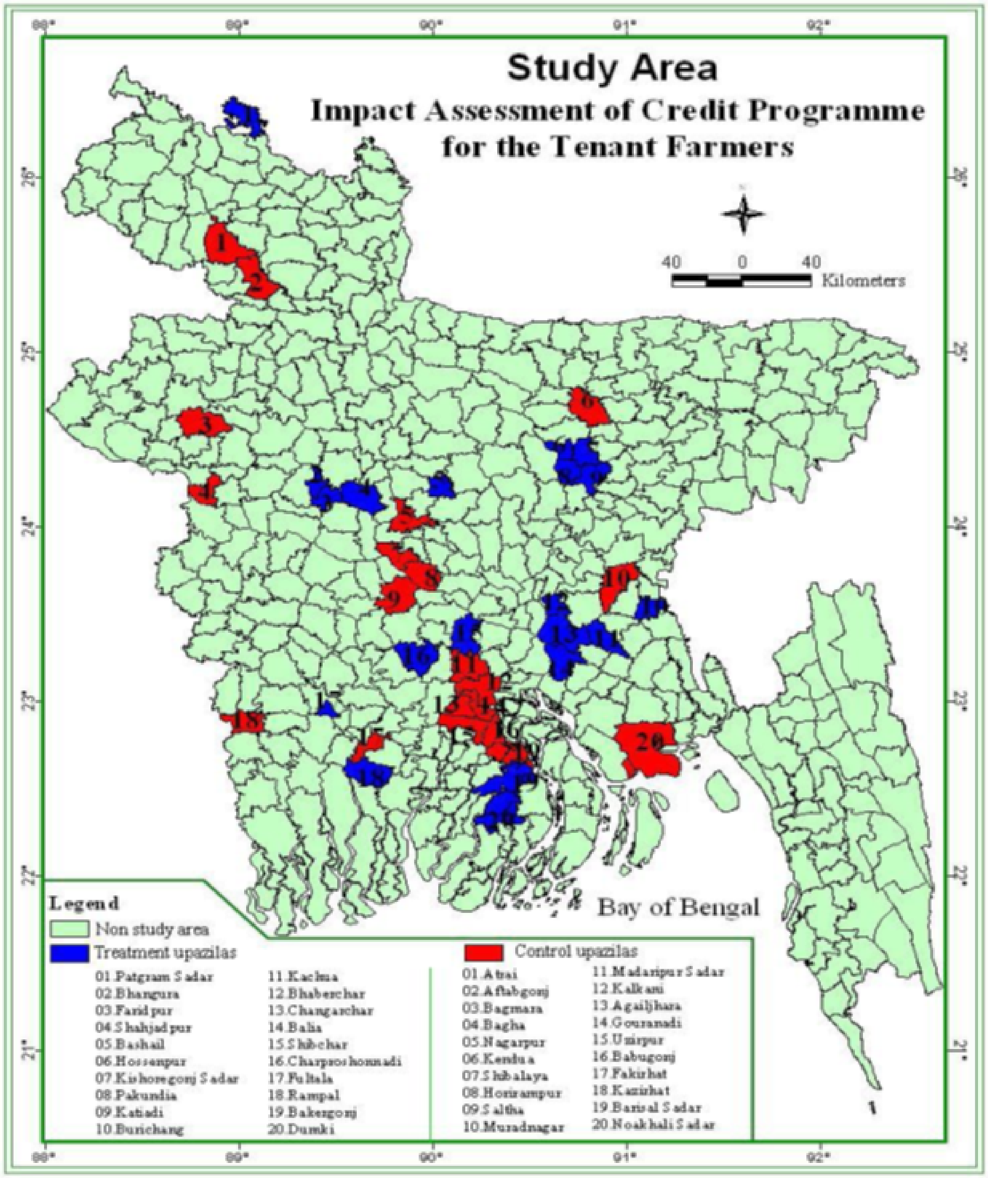

Figure A.1: Study area (Branches)

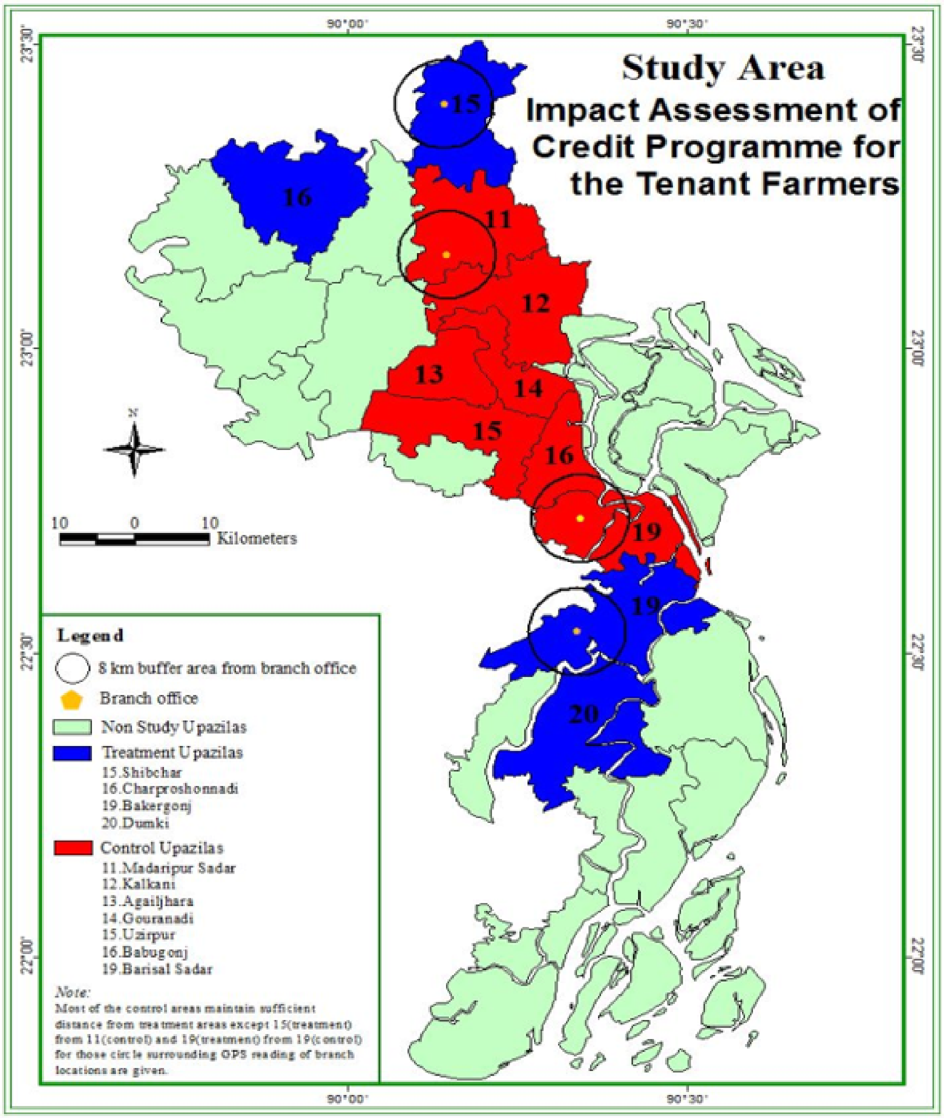

Figure A.2: GIS mapping for the southern region under study areas

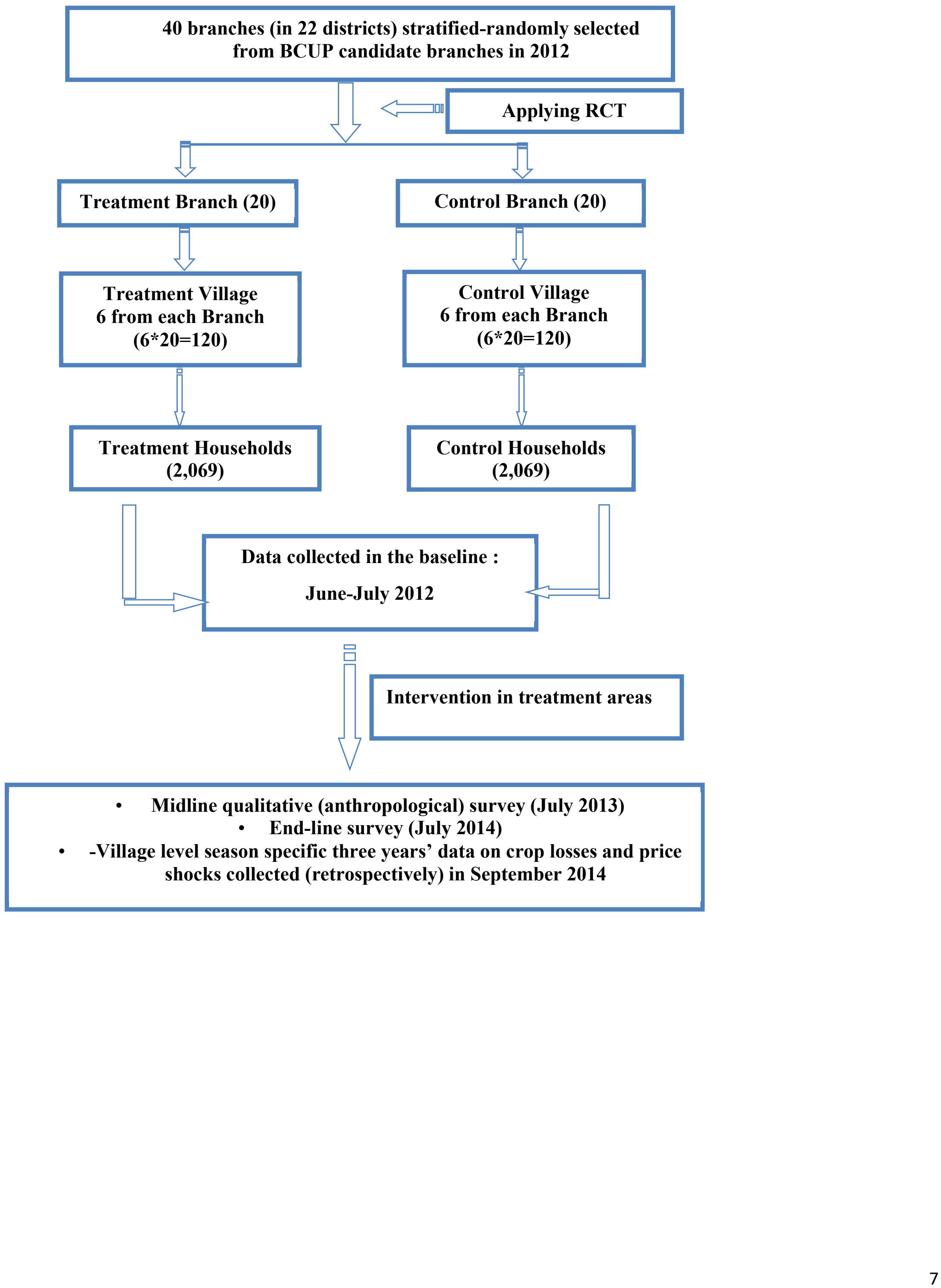

Figure A.3: Survey and Experiment Procedure

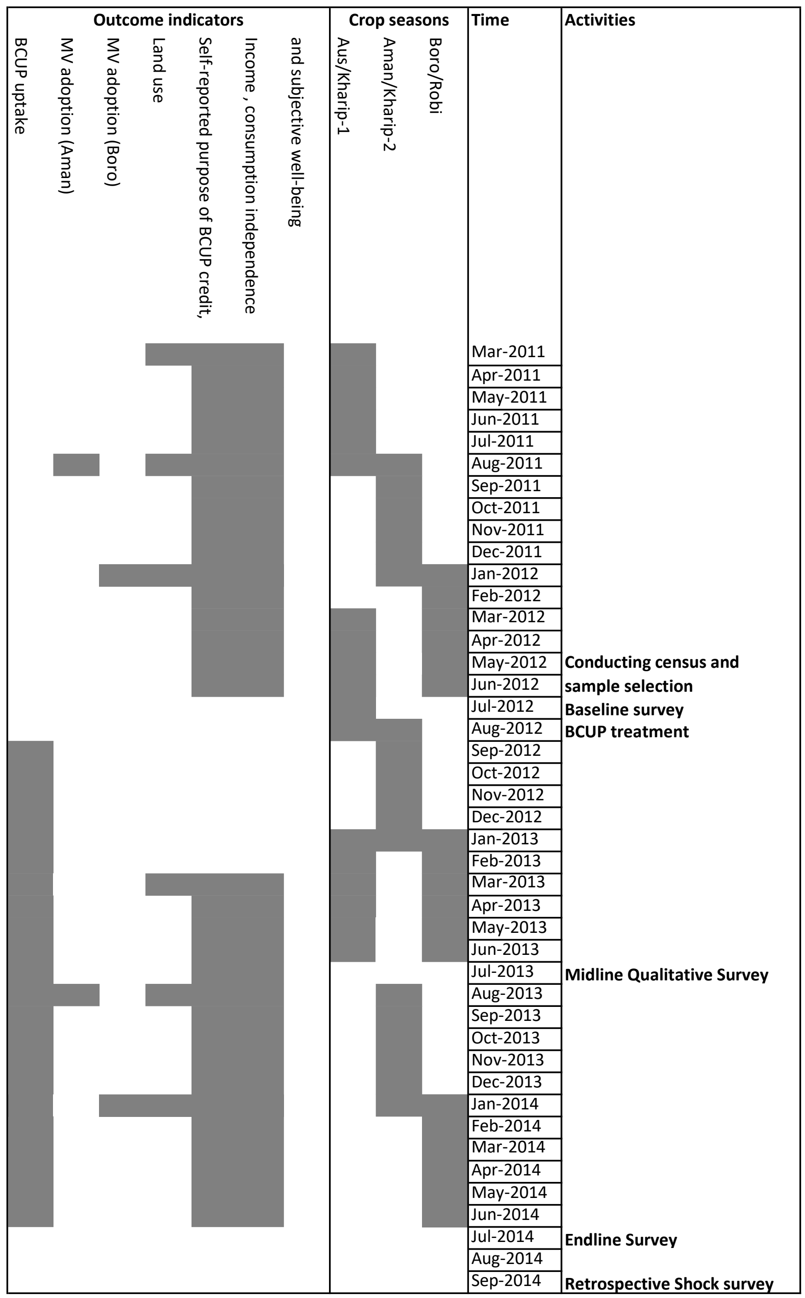

Figure A.4: Timeline of the study activities, intervention, and outcome decisions across crop calendar

Table A.1: Definition of the main variables used in the paper

Variable	Variable Description
Bank/ Co-operative	All formal Banks specialized banks like Bangladesh Krishi (Agricultural) Bank and co-operatives like Bangladesh Samobay Bank.
Grameen Bank	Grameen Bank
Other BRAC Program	Different BRAC microcredit programs other than BCUP
Other NGOs	Different other microcredit programs other than BRAC
Informal	Money lenders or other individuals such as family and friends
Crop farming	Credit used for crop production (both rice and non-rice crop)
Non-crop farming	Credit used for non-crop farm activities. Such activities include poultry farming, livestock rearing, fisheries, and forestry.
Non-farm self-employment activity	Credit used for non-farm self-employment activities. These include micro, small and medium businesses
Credit used for Other purposes	Credit used for other purposes such as repayment of previous loans, expenses for marriage, construction of houses or repairing, purchase of non-productive assets, and so on.
Total credit	Total credit used by the household.
Own cultivation	Amount of owned land (in decimal) used for crop cultivation.
Share-in	Amount of land (in decimal) cultivated under Share-tenancy contact
Mortgage-in	Amount of land (in decimal) cultivated under Mortgage contact, one form of fixed-rent tenancy contact
Leased-in	Amount of land (in decimal) cultivated under Lease contact, one form of fixed-rent tenancy contact
Others	Amount of land (in decimal) cultivated under other forms of tenancy contact
Total rented-in	Total land (in decimal) cultivated under different tenancy arrangements.
Total rented-out	Total amount of land (in decimal) rented out under different tenancy arrangements.
Total cultivated land	Amount of owned cultivated land and land (in decimal) cultivated under different types of tenancy arrangements.
Aman HYV	A binary variable that takes a value of 1 if the household adopts High Yielding Varieties in Aman season and zero otherwise.
Aman Hybrid	A binary variable that takes a value of 1 if the household adopts Hybrid Varieties in Aman season and zero otherwise.
Boro HYV	A binary variable that takes a value of 1 if the household adopts High Yielding Varieties in Boro season and zero otherwise.
Boro Hybrid	A binary variable that takes a value of 1 if the household adopts Hybrid Varieties in Boro season and zero otherwise.
Aman Yield	Yield of rice in Aman season. The unit is Ton per Hectare.
Boro Yield	Yield of rice in Boro season. The unit is Ton per Hectare.
Rice income	Profit earned from rice production. This has been calculated as the difference between the Total revenue from rice production and the total cost incurred for rice production.
Non-rice crop income	Profit earned from non-rice production. This has been calculated as the difference between total revenue from non-rice crop production and the total cost incurred for non-rice crop production.
Livestock and poultry	Profit earned from livestock and poultry production. This has been calculated as the difference between the total revenue from livestock and poultry production and the total cost incurred for livestock and poultry production.
Farm wages	Wages and salaries earned from agricultural labor employment activities.
Total Income	Total income earned by the household including all farm, non-farm, remittance, transfers, etc.

Table A.2: Balancing tests of village-level BCUP program assignment (N=240)

		Treatment-control	
	Mean of control group	Difference	P-value
	(1)	(2)	(3)
Total Population	1636.47	-49.55	0.85
Distance to the nearest (in km)			
Upazilla	6.2	0.1	0.87
BRAC Microfinance Office	3.78	-0.11	0.7
Other NGOs	3.14	-0.31	0.26
Rail Station	13.01	-1.22	0.7
Bus Stoppage	3.02	-0.5	0.13
River/ Launch Station	12.01	2.71	0.35
Bank	3.47	-0.46	0.16
Hospital	5.67	0.1	0.87
Secondary School	1.56	-0.24	0.06
Market	2.52	-0.33	0.29
Primary Health Care	2.16	-0.34	0.2
Mother and Children Health care	4.32	-1.39	0.17
Post office	2.37	-0.04	0.93
Cost to reach Nearest (in BDT)			
Upazilla	21.89	2.26	0.25
BRAC Microfinance Office	16.53	0.3	0.9
other NGOs	15.06	0.75	0.66
Rail Station	32.43	-3.11	0.61
Bus Stoppage	11.59	-2.89	0.1
River/ Launch Station	29.47	-1.67	0.74
Bank	15.32	0.77	0.64
Hospital	21.98	4.13	0.09
Secondary School	5.17	0.29	0.77
Market	9.62	-0.77	0.61
Mother and Children Health care	14.13	-1.64	0.42
Post office	6.87	-1.94	0.12
Other Village Profile			
No of Village Organizations of BRAC Microfinance	1.79	0.03	0.85
Access to Electricity (Dummy)	0.9	0.08	0.08
Household percentage connected with National Greed	66.09	6.07	0.17
Household Percentage Using Solar Power	5.1	-2.63	0.14
No of MBBS Doctors	0.19	0.11	0.08
BRAC health Worker in the village	0.78	0.68	0.65
Boys' Secondary School	0.07	-0.01	0.86
Girls' Secondary School	0.03	-0.05	0.17
Combined Secondary School	0.35	0.03	0.65
BRAC School	0.33	0.07	0.24
Bank Branch	0.03	0.01	0.39
Percentage of Mobile User	75.11	5.02	0.12
Land Elevation Status			
No Water Logging	28.85	6.25	0.11
Knee Height	37.47	3.64	0.31
Chest Height	22.31	-1.99	0.52
Soil Type			
Clay	24.54	-2.46	0.51
Sandy	10.44	0.04	0.99
Loamy	33.31	-0.48	0.91
Silo	31.69	2.88	0.45

Notes: Data from baseline (2012) survey. The unit is Village. Sample size is n = 240, of which 120 are assigned to treatment and the remaining 120 to Control. Columns 2 report statistics for Village in the control area. Column 3 shows the difference between the mean for villages in the treatment area and the means in column 2. Column 4 shows p-values for the test of equality of means, robust to intra- branch correlation. The number of clusters (branches) is 40. Asterisks denote statistical significance at the 10(*), 5(**)or 1(***)% level.

Table A.3: Baseline exogeneity test of household-level price shock

	Without shock		With shock-without shock	
	Mean	Standard error	Difference.	p-value
Household Composition				
Household size (No of members)	4.98	0.106	-0.234	0.01
No of active members	3.19	0.056	-0.137	0.018
HH head is male	0.93	0.013	0.003	0.793
Head with no education	0.78	0.02	-0.01	0.706
Maximum education of Household Head (in Years)	5.15	0.36	-0.276	0.471
Amount of Land (in Decimal)				
Owned land	35.08	2.04	-5.43	0.01
Rented in land	53.34	5.7	-3.53	0.547
Total cultivated land	88.42	6.68	1.9	0.774
Tenancy Status (Proportion of Total)				
Pure Owner	0.35	0.02	0.01	0.07
Owner-cum-tenant	0.53	5.14	-4.03	0.54
Pure Tenant	0.33	0.02	-0.03	0.29
Asset Holding and electricity connection				
Whether HH has a goat	0.22	0.03	0.02	0.495
Value of Total asset (in BDT)	142191.1	6719.86	-1852.24	0.8
Electricity connection (Dummy)	0.59	0.033	-0.009	0.792
Modern variety adoption				
Whether farm adopts Aman (HYV)	0.249	0.063	0.143	0.477
Whether farm adopts Aman (Hybrid)	0.014	0.009	0.002	0.87
Whether farm adopts Boro (HYV)	0.481	0.08	0.387	0
Whether farm adopts Boro (Hybrid)	0.018	0.006	0.034	0.043
Income (in BDT)				
Agricultural Self-employment	19161	1079	1991	0.53
Total wage	35274	3004	6729	0.22
Non-agricultural self-employment	14654.24	1891.71	-937.6	0.616
Remittance	18228.65	4315.79	5747.78	0.093
Total Income	101960.7	4265.29	-4141	0.36
Consumption Independence Strategies				
Skipped days without eating (dummy)	0.0189	0.0037	0	0.977
Sold poultry birds to purchase food (dummy)	0.5276	0.0703	0.0167	0.832
Sold farm equipment to purchase food (dummy)	0.4962	0.0736	0.011	0.889
Used credit to purchase food (dummy)	0.5011	0.073	0.01	0.899
Amount of loan from different sources (BDT)				
Bank/cooperative	1534.59	533.81	-85.66	0.876
Grameen Bank	473.78	139.38	-57.8	0.755
Other BRAC Program	429.73	167.71	-132.04	0.463
Other NGOs	337.3	96.21	85.23	0.463
Informal	1930.81	693.21	-378.37	0.579

Notes: Data from baseline (2012) survey. Sample size is n = 4, 141, of which 2, 072 assigned to treatment and 2, 069 assigned to Control. Columns 1 and 2 report statistics for households not facing any type of price shocks. Column 3 shows the difference between the mean for households facing any kind of price shocks and the means in column 1. Column 4 shows p-values for the test of equality of means, robust to intra- branch correlation. The number of clusters (branches) is 40. Asterisks denote statistical significance at the 10(*), 5(**)or 1(***)

Table A.4: Baseline exogeneity test of village-level crop loss

	Without shock		With shock-Without shock	
	Mean	Standard error	Difference	p-value
Household Composition				
Household size (No of members)	4.83	0.113	-0.292	0.62
No of active members	3.08	0.065	0.493	0.149
HH head is male	0.92	0.012	0.142	0.022
Head with no education	0.76	0.02	0.174	0.17
Maximum education of Household Head (in Years)	4.78	0.29	2.99	0.146
Age (years)	44.58	0.42	3.62	0.223
Amount of Land (in Decimal)				
Owned land	36.71	1.92	18.75	0.151
Rented in land	51.43	4.74	-0.57	0.981
Total cultivated land	88.14	5.94	18.17	0.593
Tenancy Status (Proportion of Total)				
Pure Owner	0.36	0.02	-0.02	0.43
Owner-cum-tenant	0.31	0.02	0.04	0.24
Pure Tenant	0.33	0.02	-0.02	0.53
Asset Holding and electricity connection				
Whether HH has a goat	0.23	0.03	-0.054	0.739
Value of Total asset (in BDT)	138696.8	6478.77	33840.25	0.399
Electricity connection (Dummy)	0.56	0.039	0.422	0.021
Modern variety adoption				
Whether farm adopts Aman (HYV)	0.358	0.07	-0.409	0.278
Whether farm adopts Aman (Hybrid)	0.013	0.006	0.025	0.459
Whether farm adopts Boro (HYV)	0.697	0.079	-0.029	0.938
Whether farm adopts Boro (Hybrid)	0.027	0.01	0.134	0.035
Income (in BDT)				
Agricultural Self-employment	18107	939	4673	0.12
Rice farming	8855.46	751.33	-5346.84	0.119
Agricultural wage	11125.54	770.01	9609.09	0.224
Non-agricultural wage	23515.43	2860.59	24932.56	0.134
Non-agricultural self-employment	14115.24	1942.5	50.3	0.98
Remittance	25234.56	5398.78	-52426.61	0.039
Total Income	98637.4	5936	2608.2	0.69
Consumption Independence Strategies				
Skipped days without eating (dummy)	0.02	0.0037	-0.018	0.359
Sold poultry birds to purchase food (dummy)	0.517	0.085	0.275	0.592
Sold farm equipment to purchase food (dummy)	0.4771	0.088	0.348	0.514
Used credit to purchase food (dummy)	0.4822	0.088	0.3377	0.529
Amount of loan from different sources (BDT)				
Bank/cooperative	1244.51	387.9	613.5	0.3
Grameen Bank	228.92	58.21	538.1	0.01
Other BRAC Program	342.3	116.75	36.12	0.87
Other NGOs	335.99	84.68	122.49	0.35
Informal	1849.24	606.9	-0.32	0.69

Notes: Data from baseline (2012) survey. Sample size is n = 4, 141, of which 2, 072 assigned to treatment and 2, 069 assigned to Control. Columns 1 and 2 report statistics for households from villages not facing any type of crop loss. Column 3 shows the difference between the mean for households from villages facing any kind of price shocks and the means in column 1. Column 4 shows p-values for the test of equality of means, robust to intra- branch correlation. The number of clusters (branches) is 40. Asterisks denote statistical significance at the 10(*), 5(**)or 1(***)% level.

Table A.5: Heterogeneity in land use by types of shocks

VARIABLES	(1) Own land	(2) Own land	(3) Share cropped-in	(4) Share cropped-in	(5) Leased-in	(6) Leased-in
Program	0.033	-12.255***	-2.365	-14.173**	6.675***	-6.202
	(1.704)	(4.119)	(2.013)	(6.435)	(1.790)	(3.784)
Number of idiosyncratic shocks		3.100**		3.833***		0.889
		(1.230)		(1.125)		(0.941)
Number of covariate shocks		-0.942*		-1.685*		0.465
		(0.495)		(0.939)		(0.290)
Program x Number of idiosyncratic shocks		-0.549		-0.069		3.834*
		(1.546)		(1.519)		(1.948)
Program x Number of covariate shocks		2.830***		2.483**		1.739**
		(0.787)		(1.116)		(0.766)
Constant	7.681***	8.253**	11.056***	14.102**	2.242***	-1.298
	(1.596)	(3.213)	(1.781)	(5.749)	(0.734)	(1.784)
Observations	4,080	4,080	4,080	4,080	4,080	4,080
R-squared	0.442	0.447	0.247	0.252	0.341	0.343

Notes: Data from 2012 and 2014 surveys. Cluster-robust standard errors are in parentheses. The coefficients in the odd columns and even columns are intention-to-treat (ITT) estimates of the models (1) and (2) of the text respectively. The dependent variables in columns 1-6 show the amount of land cultivated under different tenancy arrangements. The baseline means reported at the bottom of each panel are calculated for the control areas that were randomly assigned not to receive BCUP credit. All land figures are in decimals. (1 acre=100 decimals).A numb of shocks refers to the total number of idiosyncratic and covariate shocks. Asterisks denote statistical significance at the 10(*), 5(**) or 1(***)

Table A.6: Heterogeneity in the adoption of modern varieties of crops by types of shocks

VARIABLES	(1) Boro HYV	(2) Boro HYV	(3) Boro Hybrid	(4) Boro Hybrid
Program	0.0634**	-0.00307	0.0756***	-0.00566
	(0.0303)	(0.0724)	(0.0123)	(0.0295)
Number of idiosyncratic shocks		0.0756***		0.00311
		(0.0153)		(0.00337)
Number of covariate shocks		-0.0374***		0.000769
		(0.0106)		(0.00319)
Program x Number of idiosyncratic shocks		-0.00170		0.0396***
		(0.0194)		(0.0101)
Program x Number of covariate shocks		0.0114		0.00586
		(0.0130)		(0.00591)
Constant	0.116***	0.237***	0.0250***	0.0172
	(0.0263)	(0.0658)	(0.00676)	(0.0173)
Observations	4,080	4,080	4,080	4,080
R-squared	0.275	0.306	0.049	0.061

Notes: Data from 2012 and 2014 surveys. Cluster-robust standard errors are in parentheses. The coefficients in the odd columns and even columns are intention-to-treat (ITT) estimates of the models (1) and (2) of the text respectively. The dependent variables in columns 1-4 show the likelihood of adopting different types of modern varieties in the Boro season. The baseline means reported at the bottom of each panel are calculated for the control areas that were randomly assigned not to receive BCUP credit. Asterisks denote statistical significance at the 10(*), 5(**) or 1(***) % level.

Table A.7: Heterogeneity in income from different sources by types of shocks

VARIABLES	(1) Rice farming	(2) Non-rice crop farming	(3) All crop farming	(4) Livestock and poultry	(5) Farm wage	(6) Total
Program	-6.4240**	-2.5803	-9.6011***	-0.4013	1.1153	10.5835
	(3.0761)	(2.0520)	(3.3925)	(0.7023)	(3.6653)	(19.2732)
Number of idiosyncratic shocks	0.9971**	0.3520	1.6452***	-0.0680	-1.0673	1.6118
	(0.3885)	(0.3860)	(0.5231)	(0.0915)	(0.7973)	(4.5178)
Number of covariate shocks	-1.4545***	0.4240	-1.3922***	-0.1449**	1.0974***	-2.6100
	(0.4441)	(0.2847)	(0.4983)	(0.0623)	(0.3835)	(1.5978)
Program x Number of idiosyncratic shocks	1.8453***	1.7557*	3.4170***	0.2194	0.5100	-6.5037
	(0.5829)	(1.0400)	(1.1626)	(0.1612)	(1.0535)	(5.9848)
Program x Number of covariate shocks	1.4186**	-0.0598	1.5489**	0.0593	-1.2521**	0.7410
	(0.5691)	(0.3803)	(0.6156)	(0.1369)	(0.6286)	(3.0323)
Constant	11.6088***	1.6410	16.1586***	2.3463***	6.5863***	92.6448***
	(2.4758)	(1.2243)	(2.8069)	(0.3210)	(1.9508)	(13.4439)
Observations	4,141	4,141	4,141	3,822	4,141	4,141
R-squared	0.2363	0.1166	0.1457	0.0040	0.1744	0.1549

Notes: Data from 2012 and 2014 surveys. Cluster-robust standard errors are in parentheses. The coefficients in the odd columns and even columns are intention-to-treat (ITT) estimates of the models (1) and (2) of the text respectively. The dependent variables in columns 1-12 show the likelihood of household income from major farming and non-farming sources and total income. The baseline means reported at the bottom of each panel are calculated for the control areas that were randomly assigned not to receive BCUP credit. All figures expressing monetary values are in BDT ('000) units The PPP exchange rate according to the latest World Bank figures is 25.97 BDT/1 USD (World Bank 2014). Asterisks denote statistical significance at the 10(*), 5(**) or 1(***) % level.

Table A.8: Heterogeneity in consumption independence by types of shocks

	Household members skipped days without meals in the most food-insecure month		Household sold farm equipment to purchase food in the most food-insecure month		Household used credit to purchase food in the most food-insecure month	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Program	-0.0165***	-0.00531	-0.00279	-0.00389	0.00721*	0.00923
	(0.00624)	(0.0144)	(0.00173)	(0.00555)	(0.00433)	(0.0136)
Number of idiosyncratic shocks		-0.00222		-0.000449		0.00431
		(0.00465)		(0.00110)		(0.00569)
Number of covariate shocks		0.00603**		-0.000929		0.000527
		(0.00247)		(0.000735)		(0.00138)
Program x Number of idiosyncratic shocks		0.00293		-0.000591		-0.00951
		(0.00572)		(0.00139)		(0.00636)
Program x Number of covariate shocks		-0.00276		0.000350		0.00258
		(0.00278)		(0.00104)		(0.00211)
Constant	0.0296***	0.00292	0.00696***	0.0119***	0.0130***	0.00451
	(0.00570)	(0.0121)	(0.00218)	(0.00416)	(0.00328)	(0.0103)
Observations	4,141	4,141	4,141	4,141	4,141	4,141
R-squared	0.005	0.008	0.003	0.003	0.001	0.004

Notes: Data from 2012 and 2014 surveys. Cluster-robust standard errors are in parentheses. The coefficients in the odd columns and even columns are intention-to-treat (ITT) estimates of the models (1) and (2) of the text respectively. The dependent variables in columns 1-6 show the likelihood of adopting different coping strategies in the most food-insecure months. The baseline means reported at the bottom of each panel are calculated for the control areas that were randomly assigned not to receive BCUP credit. A number of shocks refers to the total number of idiosyncratic and covariate shocks. Asterisks denote statistical significance at the 10(*), 5(**) or 1(***) % level.

Table A.9: Heterogeneity in subjective well-being by types of shocks

	(1)	(2)	(3)	(4)
	Whether economic condition changed in last one year? Whether economic condition changed in the last one year? (3= improved, 2=No change, 1=worsened): for sub-sample who took BCUP credit only in 2014 or who never took BCUP credit		Whether perception about income compared to others changed in the last one year? (3= improved, 2=No change, 1=worsened): for a full sample	
Program	-0.0024	-0.1269	0.0273**	0.0095
	(0.0424)	(0.1330)	(0.0108)	(0.0368)
Number of idiosyncratic shocks		-0.0550**		0.0003
		(0.0221)		(0.0078)
Number of covariate shocks		-0.0051		0.0004
		(0.0177)		(0.0034)
Program x Number of idiosyncratic shocks		0.0583*		-0.0009
		(0.0311)		(0.0118)
Program x Number of covariate shocks		0.0091		0.0043
		(0.0238)		(0.0060)
Constant	1.8999***	2.0085***	0.1517***	0.1491***
	(0.0515)	(0.1109)	(0.0174)	(0.0250)
Observations	3,796	3,796	4,094	4,094
R-squared	0.0221	0.0248	0.8000	0.8001

Notes: Data from 2012 and 2014 surveys. Cluster-robust standard errors are in parentheses. The coefficients in the odd columns and even columns are intention-to-treat (ITT) estimates of the models (1) and (2) of the text respectively. The dependent variables in columns 1-4 report different measures of elf-reported well-being of the households. The baseline means reported at the bottom of each panel are calculated for the control areas that were randomly assigned not to receive BCUP credit. A number of shocks refers to the total number of idiosyncratic and covariate shocks. Asterisks denote statistical significance at the 10(*), 5(**) or 1(***) % level.

Table B.1: Heterogeneity in BCUP participation by the number of covariate shocks

	(1)	(2)
VARIABLES	Participates in BCUP	Participates in BCUP
Program	0.198***	0.0652
	(0.0210)	(0.0422)
Number of covariate shocks		0.000348
		(0.000491)
Program x Number of covariate shocks		0.0298***
		(0.00969)
Constant	0.00242*	0.000696
	(0.00126)	(0.00213)
Observations	4,141	4,141
R-squared	0.108	0.123

Notes: Data from 2012 and 2014 surveys. Cluster-robust standard errors are in parentheses. The coefficients in columns (1) and (2) are intention-to-treat (ITT) estimates of the models (1) and (2) of the text respectively. The dependent variables in each column show the probability that a household participates into the BCUP program. The baseline means reported at the bottom of each panel are calculated for the control areas that were randomly assigned not to receive BCUP credit. Asterisks denote statistical significance at the 10(*), 5(**) or 1(***) % level.

Table B.2: Heterogeneity in the use of BCUP credit by the number of covariate shocks

VARIABLES	(1) Crop farming	(2) Non-crop farming	(3) Farming	(4) Others	(5) Total amount
Program	0.7744	0.263	1.037	0.366	1.403
	(0.5974)	(0.307)	(0.684)	(0.611)	(1.115)
Number of covariate shocks	0.0032	0	0.00315	-0.000578	0.00257
	(0.0058)	(0)	(0.00583)	(0.00397)	(0.00825)
Program x Number of covariate shocks	0.3835***	0.120	0.504***	0.477***	0.981***
	(0.1296)	(0.0848)	(0.161)	(0.154)	(0.275)
Constant	0.0076	-0	0.00759	0.0149	0.0225
	(0.0222)	(0)	(0.0222)	(0.0209)	(0.0415)
Observations	4,141	4,141	4,141	4,141	4,141
R-squared	0.0313	0.013	0.043	0.047	0.078

Notes: Data from 2012 and 2014 surveys. Cluster-robust standard errors are in parentheses. The coefficients in each column are intention-to-treat (ITT) estimates of the model (2) of the text. The dependent variables in columns 1-5 show the amount of BCUP credit use for different purposes (self-reported): crop farming (Column 1), non-crop framing (Column 2), non-farm business activities (Column 3), others including non-farm business use, consumption smoothing, household repairment, etc. (Column 4) and total amount of credit (Column 5). The baseline means reported at the bottom of each panel are calculated for the control areas that were randomly assigned not to receive BCUP credit. All figures expressing monetary values are in BDT ('000) unit. According to the latest World Bank figures, the PPP exchange rate is 25.97 Taka/1USD (World Bank 2014). Asterisks denote statistical significance at the 10(*), 5(**) or 1(***) % level.

Table B.3: Heterogeneity in land use by the number of covariate shocks

VARIABLES	(1) Own land	(2) Own land	(3) Share cropped-in	(4) Share cropped-in	(5) Leased-in	(6) Leased-in
Program	0.033	-11.345***	-2.365	-11.955**	6.675***	1.637
	(1.704)	(3.230)	(2.013)	(5.817)	(1.790)	(3.646)
Number of covariate shocks		-0.869*		-1.597*		0.485
		(0.484)		(0.936)		(0.294)
Program x Number of covariate shocks		2.461***		1.976*		1.191
		(0.778)		(1.098)		(0.785)
Constant	7.681***	12.099***	11.056***	18.978***	2.242***	-0.147
	(1.596)	(2.682)	(1.781)	(5.432)	(0.734)	(1.254)
Observations	4,080	4,080	4,080	4,080	4,080	4,080
R-squared	0.442	0.444	0.247	0.248	0.341	0.342

Notes: Data from 2012 and 2014 surveys. Cluster-robust standard errors are in parentheses. The coefficients in the odd columns and even columns are intention-to-treat (ITT) estimates of the models (1) and (2) of the text respectively. The dependent variables in columns 1-8 show the amount of amount of land cultivated under different tenancy arrangement. The baseline means reported at the bottom of each panel are calculated for the control areas that were randomly assigned not to receive BCUP credit. All land figures are in decimals. (1 acre=100 decimals). Number of shocks refers to the total number of idiosyncratic and covariate shocks. Asterisks denote statistical significance at the 10(*), 5(**) or 1(***) % level.

Table B.4: Heterogeneity in adoption of modern varieties by the number of covariate shocks

VARIABLES	(1) Boro HYV	(2) Boro HYV	(3) Boro Hybrid	(4) Boro Hybrid
Program	0.0634**	0.0317	0.0756***	0.0717***
	(0.0303)	(0.0637)	(0.0123)	(0.0255)
Number of covariate shocks		-0.0347***		0.000802
		(0.0102)		(0.00320)
Program x Number of covariate shocks		0.00327		0.000974
		(0.0125)		(0.00596)
Constant	0.116***	0.311***	0.0250***	0.0211
	(0.0263)	(0.0623)	(0.00676)	(0.0161)
Observations	4,080	4,080	4,080	4,080
R-squared	0.275	0.288	0.049	0.049

Notes: Data from 2012 and 2014 surveys. Cluster-robust standard errors are in parentheses. The coefficients in the odd columns and even columns are intention-to-treat (ITT) estimates of the models (1) and (2) of the text respectively. The dependent variables in columns 1-8 show the amount of amount of land cultivated under different tenancy arrangement. The baseline means reported at the bottom of each panel are calculated for the control areas that were randomly assigned not to receive BCUP credit. All land figures are in decimals. (1 acre=100 decimals). Number of shocks refers to the total number of idiosyncratic and covariate shocks. Asterisks denote statistical significance at the 10(*), 5(**) or 1(***) % level.

Table B.5: Heterogeneity in income from different sources by the number of covariate shocks

VARIABLES	(1) Rice farming	(2) Non-rice crop farming	(3) All crop farming	(4) Livestock and poultry	(5) Farm wage	(6) Total
Program	-2.2600	0.9809	-2.0683	-0.0189	1.4355	-0.8475
	(3.1056)	(2.1098)	(3.2549)	(0.7638)	(2.9085)	(14.7711)
Number of covariate shocks	-1.4182***	0.4314	-1.3549***	-0.1465**	1.0736***	-2.5735
	(0.4361)	(0.2847)	(0.4907)	(0.0612)	(0.3857)	(1.6098)
Program x Number of covariate shocks	1.0696*	-0.3047	0.9421	0.0432	-1.1655*	1.2568
	(0.5773)	(0.4014)	(0.6435)	(0.1421)	(0.6052)	(2.9387)
Constant	12.7379***	2.0968*	18.2246***	2.2574***	5.2056***	94.6457***
	(2.5448)	(1.1203)	(2.7569)	(0.3298)	(1.6238)	(11.2709)
Observations	4,141	4,141	4,141	3,822	4,141	4,141
R-squared	0.2228	0.1136	0.1326	0.0035	0.1736	0.1545

Notes: Data from 2012 and 2014 surveys. Cluster-robust standard errors are in parentheses. The coefficients in each column are intention-to-treat (ITT) estimates of model (2) of the text. The dependent variables in columns 1-12 show the likelihood of household income from major farming and non-farming sources and total income. The baseline means reported at the bottom of each panel are calculated for the control areas that were randomly assigned not to receive BCUP credit. All figures expressing monetary values are in BDT ('000) unit. According to the latest World Bank figures, the PPP exchange rate is 25.97 BDT/1 USD (World Bank 2014). Asterisks denote statistical significance at the 10(*), 5(**) or 1(***) % level. .