Credit Lines as Insurance: Evidence from Bangladesh

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Abstract

Lending institutions often withhold credit from borrowers who have suffered an income shock because they are concerned about default risk. This can be especially debilitating in low-income countries because households have few resources to manage these shocks. I show that a loan product that *guarantees* credit access to agricultural households following a negative shock increases their welfare through two channels: an ex-ante insurance effect, whereby households increase investments in risky but profitable production; and an ex-post effect, whereby households use the loan to smooth consumption. Repayment is high and the loan is profitable for the lender – demonstrating that guaranteed credit is a valuable risk-mitigation tool for households that need not jeopardize lenders profits.

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1 Introduction

Households in low-income countries are vulnerable to a host of shocks and stressors that can drive them into poverty. Without access to strong social safety nets, households have to adopt costly coping strategies – lowering their food consumption, selling productive assets, and pulling children out of school Hoddinott (2006); Janzen and Carter (2018). In an effort to minimize their exposure to these events, households often skew their investments towards lower-risk activities that also limit their long-run earning potential (Karlan et al., 2014). While insurance markets and financial tools such as index insurance are designed to overcome this problem by providing coverage in the event of a negative shock, they are typically absent or suffer from low demand in rural economies (Jensen and Barrett, 2017; Cole and Xiong, 2017).

A realistic alternative is to *guarantee* households an additional credit line when they are hit by a shock, and thus when the marginal utility of additional consumption is high. In this paper, I develop a model to show how this type of guaranteed credit can increase investment in productive activities, and smooth household consumption. This builds on existing theoretical work by (Deaton, 1991, 1992) that recognizes credit's ability to act as a buffer against income fluctuations. Testing these predictions empirically is challenging because most credit providers are hesitant to lend to households when disaster strikes. They are concerned that borrowers are likely to default, which will jeopardize their institutions' profits. This effectively creates a positive correlation between current income and households' access to credit, which limits credit's utility as a buffer against risk (Demont, 2014; Fulford, 2015; Labie, Laureti, and Szafarz, 2017; McCulloch et al., 2016).

I overcome this challenge by working closely with BRAC, a large micro-finance institution (MFI) in Bangladesh that was willing to guarantee credit to households affected by a shock – effectively breaking the link between current income and credit access.[1] The financial tool I developed with BRAC was called the Emergency Loan, and it guaranteed credit to households affected by a *flood*. We randomized the availability of the Emergency Loan across 200 BRAC branches located in flood-prone areas. We contacted over 300,000 clients in 100 treatment branches one month before planting, and informed them that they had been pre-approved to take the Emergency Loan should a flood occur in their area during the rest of the agricultural season. This notice was delivered well before any cropping decisions were

[1] BRAC recognized that supplying additional credit to households in the aftermath of a shock could increase their profits if borrowers' repayment rates improved. We explore this further in the model section, which demonstrates that MFI profits can increase if borrowers use the additional liquidity to maintain consumption and repay the MFI. If default rates are high because borrowers are unable to repay their loans despite the additional liquidity, MFI profits will fall.

made to give households enough time to consider investing in more profitable opportunities – a more appealing endeavor with the availability of the loan. This guarantee meant that households could benefit from the loan even if no additional credit was disbursed. Treatment households could choose to take the loan provided a validated flood occurred in their area. Control branches continued their normal microfinance operations.

The experiment documents three primary results. First, I find that households respond to the notification that they were pre-approved for the Emergency Loan by significantly increasing their risky investments. Treated households increase the amount of land dedicated to agricultural cultivation by 15%, an effect that is concentrated among the most risk-averse households. This suggests that households recognize guaranteed liquidity access can reduce their exposure to flood risk, which encourages them to make investments they may have otherwise avoided.

Second, I document that emergency credit, unlike many other microcredit products, improves household outcomes. Pre-approval for the Emergency Loan leads to a 17% increase in crop production and an 8% increase in per-capita consumption. There are two potential channels that can explain these results: households' ex-ante investments can translate into higher production, and households can activate their loans in the event of a flood and use the additional credit to support consumption. I find strong evidence for the former, and suggestive evidence of the later. In the absence of a flood, when no additional liquidity is disbursed, I find that crop production increases by 33% and per capita consumption is weakly higher among treated households. This confirms that farmers respond to BRAC's *guarantee* by finding new investment opportunities that yield substantial returns, even though no additional credit was made available. In the presence of a flood, when households have the option to activate their loans, we find increased levels of consumption relative to control areas that also experienced a flood. While some of this effect could be driven by ex-ante investments' continued payoffs, we find that households who suffered more from a flood are also more likely to activate the option for additional liquidity. This suggests that the Emergency Loan is used to boost consumption post-flood – though we interpret this result with some caution because the number of households that took the loan is relatively small.

Third, I find that this product is potentially valuable for MFIs (the suppliers of credit in low-income countries) and valued by borrowers. On the supply side, I find that the extension of guaranteed credit in the aftermath of shocks marginally improves overall MFI performance. Borrowers with access to the Emergency Loan improve their repayment rates after a flood shock, thereby improving their repayment rates overall. Branch profits increase, with the largest increases in profits coming from "marginal" clients. This result is encouraging for MFIs, which have traditionally withheld credit in the aftermath of aggregate shocks. In particular, it shows there need not be a tension between borrower welfare and lenders' incentives to minimize default risk. However, it is worth highlighting these results may not generalize to contexts where repayments rates are low to begin with.

On the demand side, I rely on a subset of my sample (15%) to show that households value this product as well. This sub-sample of borrowers had access to a more traditional BRAC loan called the Good Borrower Loan when they were informed about their eligibility for the Emergency Loan. The Good Borrower Loan offered the same amount of credit as the Emergency Loan, but it was only available for the next two months (the planting season), rather than being triggered by a flood (which typically occur between planting and harvest). Any client who chose to take the Good Borrower loan would then lose their access to the Emergency Loan. I find that a significant share of these borrowers are willing to forgo taking credit in the pre-period through the Good Loan in order to preserve access to Emergency Loan in the post-period, suggesting they value the precautionary benefits of credit access. Estimates suggest that these households value credit access after a shock approximately 1.8 more times than credit access in the pre-period.

This research speaks to a large literature on the implications of shocks and stressors for rural households. Of particular concern is the decision by many agricultural households to invest in less profitable technologies because they are less susceptible to shocks (Rosenzweig and Binswanger, 1993). Households ability to overcome this constraint and make higher-return investments will depend on the set of financial services that are made available (Conning and Udry, 2007). On the one hand, there are insurance products that are designed to reduce households' exposure to risk. On the other hand, there are credit products that encourage new investments. The Emergency Loan I develop combines aspects of microcredit and insurance, resolving some of the key limitations that both products have faced.

In the insurance literature, index insurance has been promoted as the most viable alternative to traditional indemnity insurance in low-income settings. By linking payouts to easily measurable and exogenous indices such as rainfall, index insurance removes moral hazard concerns and reduces the need to collect additional data on household-specific losses. Index insurance has been found to generate positive results but suffers from low demand (Cole and Xiong, 2017). Low demand appears to be linked to the requirement that insurance payments be collected ex-ante, which can be difficult for households that are potentially credit constrained, present-biased, face basis risk, and lack trust in their insurers' ability make pay-outs (Cole et al., 2013; Clarke, 2016). In some contexts, low demand can be overcome by allowing the upfront insurance premium to be paid after harvest. However, this solution is only feasible when there is the possibility of an interlinked transaction. This can take the form of a monopsony buyer that can credibly collect payments from farmers after the fact (Casaburi and Willis, 2018), or tying insurance payments to credit contracts (McIntosh, Sarris, and Papadopoulos, 2013).

The Emergency Loan I develop with BRAC provides similar risk reducing benefits to index-insurance while largely overcoming the problem of low demand. Similar to index insurance, it avoids high administrative costs and moral hazard by making the availability of the additional credit contingent on an exogenous indicator (floodwater height). However, unlike index insurance, households are not required to purchase the product during the planting season. Households can benefit from the security of the credit line even if they choose *not* to take a loan after a shock. My experiment confirms that many households who do not take the Emergency Loan increase their ex-ante investment in response to the offer, suggesting a reduction in perceived risk.

In the credit literature, micro-loans were initially touted as an effective tool for helping households invest in new business ventures. However, recent work has shown that micro-credit has modest impacts on households' well-being (Karlan and Zinman, 2011; Angelucci, Karlan, and Zinman, 2015; Banerjee et al., 2015; Banerjee, Karlan, and Zinman, 2015). This stems partly from the fact that microcredit only solves the problem of credit access, without remedying the underlying risks that prevent households from optimally investing (Karlan et al., 2014). Indeed, risky investments are difficult to undertake when loans have strict re-payment schedules and are tied to group lending – features that were introduced early on to overcome moral hazard and adverse selection. Recent work suggests that delaying the start of repayment installments, reducing payment frequency and allowing lump sum re-payments post harvest reduces borrower transaction costs, and encourages greater investments and profits (Field and Pande, 2010; Field et al., 2013; Beaman et al., 2014). The Emergency Loan builds on this movement towards more flexible credit, not by changing when payments are due, but by changing when credit is made available. Specifically, it offers credit after income shocks when this liquidity is likely to be most beneficial. This is similar to the insight explored by Fink, Jack, and Masiye (2020) where loans are offered during the agricultural lean season enabling households to reallocate labor to their farms.

Lastly, additional research has focused on understanding how new credit products affect MFI profits. Field et al. (2013) develop a structural model to show that longer grace periods are not sustainable for MFIs, while Barboni (2017) uses lab-in-the-field experiments to show that flexible repayment schedules could increase profits for lenders. An advantage of my setting is the partnership with BRAC, which allows for an *empirical* examination of the impact of this new product on overall MFI profitability. This has been difficult to pin-down because MFIs are typically risk-averse and hesitant to experiment (Karlan and Zinman, 2018). However, I find that BRAC derives positive profits from the product, a result that could induce more lending institutions to extend credit after an income shock when the marginal utility of consumption is high.

The rest of the paper is organized as follows: Section 2 describes the new credit product in detail. Section 3 lays out a theoretical framework which provides predictions. Section 4 describes the main research design and execution of the experiment. Finally, section 5 presents the results of the experiment and section 6 concludes.

2 The Emergency Loan

Approximately 70% of Bangladesh's population lives in rural areas and more than 80% of rural households depend on agriculture (World Bank, 2016). Extreme weather events are frequent, and are projected to worsen with the advent of climate change. Approximately 80% of the country is located on floodplains, and floods occur yearly with varying degrees of severity (Brammer, 1990). Therefore, the experiment focuses on flood risk and the randomized control trial was conducted in areas bordering the major rivers, where investments are frequently exposed to flooding.[2] While households' frequent exposure to floods may have induced them to adopt strategies that mitigate the negative impact of any one event, the ability of these adaptation strategies to shield households against income losses does not limit the value of the Emergency Loan. Indeed, guaranteed liquidity allows households to re-optimize investments in ways that are more profitable and were not previously considered.

I worked with Bangladesh's largest MFI (BRAC) to create the Emergency Loan – a product that guarantees credit access to households who suffer a flood shock. Clients were eligible for the Emergency Loan provided they had a credit score above a fixed threshold. We created this new credit score for each borrower based on their past repayment behavior (including past percentage of missed payments, average percent behind on loan payments, maximum percent behind on any loan, and the number of months as an active BRAC microfinance member).[3] We assessed each client's eligibility in April, before the Aman planting season and several months before the flooding season. Borrowers retained their

[2] The fertile land along the riverbanks ensures that agricultural investments – renting land for cultivation, using synthetic fertilizers, purchasing improved seeds – offer significant upside potential. However, the risk of floods also implies greater potential losses. Even non-agricultural business investments are exposed to flood risk, as physical businesses assets may be lost or damaged and demand may fall after a local shock.

[3] Each variable received a weight determined by a linear regression of these variables on a binary indicator for loan default. This weighted sum was then normalized to a 0-100 scale. These specific variables were chosen because 1) they were relevant for predicting future default; 2) they were easily available in BRAC's records; 3) they could be easily explained to borrowers for transparency. To determine relevance for predicting default, the complete set of possible variables was assessed in two historical training samples and then confirmed using more recent data. Linear regression was used rather than more complex techniques such as machine learning to make the credit scoring transparent and easily adjustable in the future.

eligibility for the duration of the Aman cropping season. Approximately 40% of borrowers within a BRAC branch were eligible to receive the loan. Targeting based on credit score did not result in richer households being selected over poorer ones. Eligible and ineligible borrowers are fairly similar along most dimensions (Table B3), although eligible borrowers are a few years older, and have slightly less annual income, livestock and savings.

We informed borrowers that they were pre-approved for this loan in April by distributing referral slips to eligible clients. Each slip contained the borrower's name, BRAC ID, and details of the Emergency Loan they were eligible to take – including the amount they were pre-approved to borrow and the conditions when the loan would be made available. BRAC loan officers read a script that explained how the institution was extending a guaranteed credit line to eligible borrowers should a flood occur. They emphasized borrowers' pre-approval status repeatedly because this concept was new. Random branch visits conducted in June confirmed that borrowers received the referral slips, and understood what *guaranteed* credit meant. Eligible households were approved to borrow up to 50% of the total principal amount of their last regularly approved loan. An eligible borrower who took a 10,000 taka loan ($125) for example was guaranteed to borrow up to 5,000 taka ($63) should a flood occur regardless of her existing loan balance at the time of disbursal. Clients were eligible for the Emergency Loan regardless of whether or not they currently had an active loan.[4]

Eligible clients could then request an Emergency loan if flooding occurred in their branch service area. Flooding was validated in two ways. First, a government maintained river gauge associated with the branch area had to report water levels above the pre-determined danger level for at least one day.[5] Second, a non-microfinance BRAC employee had to confirm that at least 20% of the branch service area had experienced flooding. Once these checks were completed, *all* eligible clients within a treatment branch were informed they could take the Emergency Loan. It is worth noting that the activation threshold for a flood was relatively low, and the branch service area was relatively large, which meant that many eligible households within a branch did not suffer damages from a flood. This implies that the Emergency Loan's take-up rate could be low when calculated as the fraction of households who were eligible.

Working with BRAC was beneficial for a number of reasons. First, BRAC has over 2000 branches throughout the country, where each branch serves 20 to 60 village organizations (VO's). This allowed us to focus on areas bordering the major rivers, where productive investments are frequently exposed to flooding. Second, BRAC's clients are familiar with

[4]For clients without an active loan, the amount was based on the size of their most recently repaid loan

[5]The danger level is not the water height at which the river overflows it banks, but the height at which there is estimated to be a high probability of significant property damage in the area. This level was set by water engineers in the Bangladesh Water Development Board.

credit and have high repayment rates. Loan officers visit each village organization weekly to collect scheduled loan repayments from active borrowers, and answer inquiries about new loans. This provided a robust platform for introducing a new loan product.

Finally, it is important to review how the Emergency Loan interacts with existing BRAC products. BRAC's most common loan is called the *Dabi* loan. Dabi loans are typically small in value (approximately 15,000 taka ($187)), charge 25% interest, and must be repaid within a year. During the repayment period borrowers are not allowed to apply to other BRAC loans, with one exception. Clients who make every loan payment on-time for the first six months of their loan cycle are eligible to take a top-up loan called the "Good Loan".[6] The Good Loan is capped at 50% of the principal amount of the currently held Dabi loan. The offer expires two months after they become eligible at the 6 month mark on their current Dabi loan cycle. In every other respect, Good Loans are identical to normal Dabi loans.

Eligibility for the Emergency Loan did not depend on whether clients had an open Dabi loan. However, the Emergency Loan and Good Loan were mutually exclusive. The Emergency Loan resembled the Good Loan in the amount disbursed, the interest rate, and the repayment period. However, it differed in two key ways. First, it was offered 6-8 months into the normal Dabi Loan cycle rather than after a flood. Second, Good Loans had to be requested from branch managers who could deny the request, while the Emergency Loan was guaranteed to borrowers based on their credit score. Historical data confirms that Good Loans were much less likely to be disbursed after aggregate income shocks. Clients could be *eligible* for the Good Loan and the Emergency Loan. However, if they took a Good Loan they would lose the ability to withdraw an Emergency Loan should a flood occur. Figure B2 summarizes borrower choices related to the Good Loan and Emergency Loan. Clients who were *eligible* for the Emergency Loan and the Good Loan in the planting season (15% of the total sample) then faced a tradeoff: they could take the Good Loan immediately and forgo the option of accessing additional liquidity in the event of a flood in the rest of agricultural season; or they could preserve their credit access as a buffer against future flood risk.

3 Theory

3.1 Framework For Effect of Guaranteed Credit

This section provides a simple theoretical framework building on Karlan and Udry (2015) in which MFI clients make decisions across three periods. In the first period (pre-planting season) must decide how many inputs to invest (e.g. land to cultivate, inputs to use, business

[6] 37% of my sample were eligible for a Good Loan during the planting season

investments), and how much to borrow. They are also informed about their eligibility for the Emergency Loan. In the second period (harvest season), clients may be exposed to flooding. If flooding does occur, each eligible borrower is informed that the Emergency Loan is available for them to access. Borrowers must decide whether or not to take the Emergency Loan (if it is available), and whether or not to repay any existing loans they took in the first period. Finally, in the third period (post-harvest) borrowers who took the Emergency Loan must choose whether to repay it.

3.2 Baseline Model

The model has three periods $t = (1, 2, 3)$ that correspond to planting, harvest, and post-harvest periods respectively. The model incorporates risky production and a credit market with constraints, and assumes that no insurance is available. For ease, I limit the harvest realization to two possible states, $s \in \{G, B\}$ that are realized in $t = 2$ and occur with probability $\pi_B = q$ and $\pi_G = (1 - q)$. Further, I assume that the MFI is the only provider of credit. Preferences are over consumption c, with discount factor β:

$$u(c^1) + \beta \sum_{s \in G,B} \pi_s u(c_s^2) + \beta^2 \sum_{s \in G,B} \pi_s u(c_s^3)$$

In period 1, a household starts with exogenous cash on hand Y and has access to a risk free asset b^1 which it can buy (up to a limit) or sell on the market at interest rate R (positive values of b represent net borrowing, while negative values of b represent net saving). The household also has access to a concave production function $m_s f(x)$, which takes input x and provides output in the second period. The production function has a state dependent marginal product m_s which changes with the realized state s. In period two, the state of the world is resolved and the household decides whether to repay its initial loan (ND) with interest (Rb^1) or default (D) by paying zero. I also allow for borrowing in the bad state of the world b_B^2, with the Emergency Loan.[7] In period three, the household pays (or receives) return R on any period two loans, provided they have not already defaulted, and also receive exogenous risk free income (I). Finally, households that default are penalized K, which is the household-specific loss in utility from losing access to future dealings with the MFI. The basic household problem can be stated as:

[7] I do not allow savings from period 2 to 3 – this simplifying assumption does not change the core results.

$$\max_{x,b^1,b^2_B,D,ND}\{u(c^1)+\sum_{s\in G,B}\max\{\beta\pi_s u(c^2_s|ND)+\beta^2\pi_s u(c^3_s|ND),\\ \beta\pi_s u(c^2_s|D)+\beta^2\pi_s u(c^3_s|D)-K\}\} \quad s.t.$$

$$\begin{aligned}
c^1 &= Y - x + b^1\\
c^2_G &= \mathbb{1}[ND]\left[m_G f(x) - Rb^1\right] + \mathbb{1}[D]\left[m_G f(x)\right]\\
c^2_B &= \mathbb{1}[ND]\left[m_B f(x) - Rb^1 + b^2_B\right] + \mathbb{1}[D]\left[m_B f(x) + b^2_B\right]\\
c^3_G &= I\\
c^3_B &= \mathbb{1}[ND]\left[-Rb^2_B + I\right] + \mathbb{1}[D]\left[\ I\ \right]\\
x &\geq 0\\
b^1 &\leq \bar{B}_1\ ,\ (\lambda_1)\\
b^2_B &\leq \bar{B}_2\ ,\ (\lambda_2)
\end{aligned}$$

A household can borrow up to $\bar{B}_j$ in each period where borrowing is possible. To begin, I will assume $\bar{B}_2 = 0$, meaning there is no credit available in the bad state. I also assume that it is never optimal for a household to default on its loan when the good state is realized ($s = G$), which rules out households that take first period loans in bad faith and always default. Finally, I normalize the marginal product of x as zero in the bad state, i.e. $m_B = 0$.[8]

The rest of this section is organized as follows. First, I describe the optimal borrowing and input choices assuming 1) households do not default; and 2) households default in the event of a shock. Second, I compare these two scenarios and find the condition that induces households to repay or default. Third, I allow for borrowing in the bad state, and observe how this changes household choices of inputs, borrowing, and the choice to default. Finally, I examine the implications of extending bad state borrowing on MFI performance.

[8]Note that this normalization also implies a shift in the utility function such that the utility of a negative value does not imply zero or negative utility.

3.2.1 No Default

I derive the optimal choice of first period input use and borrowing assuming that the borrower will not default in the event of a shock. The household's problem is:

$$\begin{aligned}\max_{x,b^1} \;\; & u(Y - x + b^1) + q\beta u\left(-Rb^1\right) + (1-q)\beta u\left(m_G f(x) - Rb^1\right) + \\ & q\beta^2 u(I) + (1-q)\beta^2 u(I) + \lambda_1[\bar{B}_1 - b^1]\end{aligned} \tag{1}$$

where λ_1 is the Lagrange multiplier associated with the first period borrowing constraint. The first order condition (FOC) with respect to x:

$$m_G \frac{\partial f}{\partial x} = R\left[\frac{q}{1-q}\frac{u'(c_B^2)}{u'(c_G^2)} + 1\right] + \frac{\lambda_1}{\beta(1-q)u'(c_G^2)} \tag{2}$$

This condition differs from an unconstrained scenario (without risky production or credit constraints), where the agent will invest in x until the marginal product equals the return on the risk-free asset R. The FOC above illustrates two potential sources of distortion from that standard result. The first term in brackets is greater than 1, and reflects the presence of a risky production technology that has no return in the event of a bad outcome. Second, the first period credit constraint could bind ($\lambda_1 > 0$), which drives a wedge between the marginal product of the input and R. Both these distortions lower the choice of x relative to the unconstrained optimum. Next, the FOC with respect to the amount borrowed b:

$$u'(c^1) = \beta R\left[qu'(c_B^2) + (1-q)u'(c_G^2)\right] + \lambda_1 \tag{3}$$

Again, we see two potential distortions. First, the gap between second period consumption in the bad and good state ($qu(c_B^2)$ and $(1-q)u(c_G^2)$) will increase the RHS (due to concavity), and imply reduced consumption in period one. Less consumption, combined with fewer inputs, implies an overall reduction in borrowing. Second, if the first period credit constraint binds ($\lambda_1 > 0$), this reduces borrowing relative to the unconstrained case.

3.2.2 Default

I now assume that the household will choose not to repay their period 1 loans if the bad state occurs in period 2. This changes the optimal use of inputs and borrowing in the first period. The optimal choice of inputs is now defined by:

$$m_G \frac{\partial f_G}{\partial x} = R + \frac{\lambda_1}{\beta(1-q)u'(c_G^2)} \tag{4}$$

Households that know they will default in the bad state will equalize the marginal return of inputs in the good state to the interest rate R, with the only possible distortion resulting from the first period credit constraint (λ_1). Next, the FOC with respect to the amount borrowed b is:

$$u'(c_1) = (1-q)\beta R u'(c_2^G) + \lambda_1 \tag{5}$$

Households equate the marginal utility in period 1 with discounted marginal utility in period 2, with the only possible distortion arising from the borrowing constraint.

3.2.3 Repayment Decision

A household will choose to repay their loan if their utility under repayment (ND) is higher than their utility if they default (D):

$$U^{ND} \geq U^D$$

which is given by:

$$\begin{aligned} & u(c^1_{ND}) + q\beta u\left(-Rb^1_{ND}\right) + (1-q)\beta u\left(m_G f(x_{ND}) - Rb^1_{ND}\right) + q\beta^2 u(I) + (1-q)\beta^2 u(I) \\ & \geq \\ & u(c^1_D) + q\beta u\left(0\right) + (1-q)\beta u\left(m_G f(x_D) - Rb^1_D\right) + q\beta^2 u(I) + (1-q)\beta^2 u(I) - qK \end{aligned} \tag{6}$$

To simplify the expressions, I define M as the difference in utility between those who default and those who repay – restricted to the differences that stem from first period investment and second period outcomes in the good state.[9] Rearranging, I can define K^*:

$$K^* = \frac{M}{q} + \beta\left[u(0) - u(-Rb_r^1)\right] \tag{7}$$

[9]

$$M = \underbrace{\left[u(c_d^1) - u(c_r^1)\right]}_{First\ Period} + \underbrace{\left[(1-q)\beta u\left(m_G f(x_d) - Rb_d^1\right) - (1-q)\beta u\left(m_G f(x_r) - Rb_r^1\right)\right]}_{Second\ Period\ Good\ State}$$

The difference in these terms is *only* due to the different optimal choices of x and b^1 in the first period, rather than the repayment (or non-repayment) of loans. Therefore, because I know that $x_d > x_r$ and $b_d^1 > b_r^1$, the utility received when a client defaults is higher than the repayment utility. Therefore $M > 0$.

where K^* is the cost of lost access to microfinance that would make household indifferent between repayment and default.[10] If a household's actual K is larger than K^*, they will repay; if it is lower, they will default. Therefore, assuming K is a random variable defined by the CDF F_K, the proportion of households that will default after a shock is given by $F_K(K^*)$.

3.3 Adding Liquidity in the Bad State (Emergency Loan)

I explore how the optimal choices of x and b^1 change when I introduce the possibility of borrowing in the bad state in period 2 (b_B^2).

3.3.1 No Default

With no default the household's problem is now:

$$\begin{aligned}\max_{x,b^1,b_B^2} \quad & u(Y-x+b^1)+q\beta u\left(-Rb^1+b_B^2\right)+(1-q)\beta u\left(m_G f(x)-Rb^1\right)+ \\ & q\beta^2 u(I-Rb_B^2)+(1-q)\beta^2 u(I)+\lambda_1[\bar{B}_1-b^1]+\lambda_2[\bar{B}_2-b_B^2]\end{aligned} \tag{8}$$

I focus on the case where first period credit constraints do not bind ($\lambda_1=0$), which allows for first period choices of x and b^1 to adjust in response to the additional credit. The optimal choice of x is defined by:

$$m_G\frac{\partial f_G}{\partial x}=R\left[\frac{q}{1-q}\frac{u'(c_B^2)}{u'(c_G^2)}+1\right] \tag{9}$$

Introducing credit after a second-period shock will increase consumption in this state (c_B^2). Thus, $u'(c_B^2)$ decreases as does the ratio $\frac{u'(c_B^2)}{u'(c_G^2)}$, and the entire RHS of equation (10). Thus, optimal first period input use will rise.[11] Turning to borrowing decisions, the optimal choice is defined by:

$$u'(c^1)=\beta R\left[qu'(c_B^2)+(1-q)u'(c_G^2)\right] \tag{10}$$

Again, the gap between $u'(c_B^2)$ and $u'(c_G^2)$ is reduced in equation 11 because of higher period 2 consumption, which causes the entire RHS of the equation to fall. This prospect of higher

[10] Note that K^* is monotonically increasing in b^1, implying the more indebted a household, the higher value of K necessary to ensure repayment.

[11] Appendix A shows a more formal derivation of the comparative statics of x and b^1 with respect to b_B^2.

consumption in period 2 leads to an increase in period one consumption and borrowing.

Last, I examine what factors determine the choice of b_B^2. The optimal choice of bad state borrowing is defined by the standard condition:

$$u'(c_B^2) = \beta R u'(c_B^3) + \lambda_2 \tag{11}$$

Households will be more likely to borrow in the bad state if they have a low value of c_B^2 or have a high value of c_B^3. Therefore, I would expect more demand for the Emergency Loan from households that are hit hardest by a flood shock and those that have high expected future income I.

Therefore, the model yields four predictions that result from extending a credit line in the bad state:

- Prediction 1: Consumption increases after a shock
- Prediction 2: First period investment increases
- Prediction 3: First period borrowing increases
- Prediction 4: Probability of taking the Emergency Loan increases among those who experience heavy damage from flooding or those with good post-harvest income opportunities

3.3.2 Default

If households can default after a shock, only prediction 1 will carry through. Consumption in the bad state will still rise, which leads to higher consumption in period 1. However, because households already planned to default if a shock occurred, neither ex-ante input choice or first period borrowing will be impacted by changes in the level of c_B^2 relative the baseline case (See equations 5 and 6). Further, households will choose to borrow the maximum amount possible in the bad state $b_B^2 = \bar{B}_2$ because there are no additional consequences of failing to repay this extra credit.

3.3.3 Repayment

We want to understand how the introduction of second period borrowing in the bad state changes borrowers' loan repayment decisions. With the introduction of the Emergency Loan, we can redefine K^*, which expands to include the option to borrow in the second period bad state, and to repay in the third period:

$$K^* = \frac{M}{q} + \beta\left[u(b_B^2) - u(-Rb_r^1 + b_B^2)\right] + \beta^2\left[u(I) - u(I - Rb_b^2)\right] \tag{12}$$

To see how the repayment rates change with the introduction of the Emergency Loan, we need to sign $\frac{\partial K^*}{\partial b_B^2}$ when evaluated at $b_B^2 = 0$.

$$\frac{\partial K^*}{\partial b_B^2} = \underbrace{\frac{1}{q}\frac{\partial M}{\partial b_B^2}}_{-} + \beta\underbrace{\left[u'(0) - u'(-Rb_r^1)\left(1 - R\frac{\partial b_r^1}{\partial b_B^2}\right)\right]}_{-} + \underbrace{\beta^2 R u'(I)}_{+} \tag{13}$$

The first and second term above are negative – they capture improved good state outcomes and the reduced cost of repayment respectively when the Emergency Loan is available. However, the last term is positive and captures the added benefit of defaulting when more credit is available. Therefore, the overall effect on repayment is ambiguous.

3.4 MFI Problem

I now move beyond the household and consider the implications of offering guaranteed credit after a shock from the MFI's perspective. We are interested in whether it is profitable for the MFI to do so or not. I assume that the lender is maximizing interest revenue minus the cost of defaults. For simplicity, I ignore the cost of capital and assume loans are either repaid in full (earning the MFI $b(R-1)$), or lost completely, costing the branch the full loan amount b. When a shock occurs, I define $F(K^*)$ to be the proportion of borrowers who will default on their loan. As before, I assume that there is no default under the good state. The MFI's expected profit from lending to a particular household (defined by parameters Y and I) is therefore given by:

$$\Pi = q\left[(1 - F(K^*))(R-1)b - F(K^*)b\right] + (1-q)(R-1)b \tag{14}$$

We can use equation (14) to explore what happens to expected profits with the Emergency Loan, when the amount borrowed (b) is allowed to move from b^1 to $(b^1 + b_B^2)$.[12] The MFI will want to offer the Emergency Loan if $\Pi_E \geq \Pi_{NE}$, where E and NE stand for Emergency

[12] I assume households will take the Emergency Loan in the bad state.

Loan and No Emergency Loan respectively. This is given by:

$$\begin{aligned}&q\left[(1-F(K_E^*))(R-1)(b_E^1+b_B^2)-F(K_E^*)(b_E^1+b_B^2)\right]+(1-q)(R-1)b_E^1\\ \geq &q\left[(1-F(K_{NE}^*))(R-1)(b_{NE}^1)-F(K_E^*)(b_E^1)\right]+(1-q)(R-1)b_{NE}^1\end{aligned} \tag{15}$$

Where K_E^*, K_{NE}^* and b_E^1, b_{NE}^1 represent the indifference points for repayment and optimal first period borrowing choice with and without the Emergency Loan respectively. By rearranging equation (15) and signing terms, we see that the impact of offering the Emergency Loan on MFI profits is ambiguous (see Appendix A for details). It will depend on i) the extent to which the Emergency Loan increases households' repayment rates and ii) how the number of loans the MFI extends (Dabi, Good, and Emergency) change.

4 Research Design and Data

4.1 Research Design

I measure the impact of the Emergency Loan using a randomized control trial with a sample of 200 BRAC branches that were randomly selected from a group that satisfied several criteria. First, I only included branches located in flood-prone areas. Second, I limited the sample to branches that were located within 15 kilometers of a river gauge run by the government's Flood Forecasting and Warning Center (FFWC) so that flooding could be monitored remotely. Last, I analyzed 15 years of historical data from the FFWC river gauges and selected areas of the country where flooding had exceeded the danger height levels at least twice (Figure B1). It is important to highlight that households in these flood-prone areas may have partially adapted to flood shocks already, and the impact of any one shock may be less severe as a result. This would not limit the value of the Emergency Loan, which is designed to encourage households to invest in new opportunities. I assigned 100 branches to the treatment group, and the remaining 100 branches to the control group, stratified by district. Appendix table B2 provides descriptive statistics from households sampled from the treatment and control branches and shows that the randomized branches are balanced on baseline observable characteristics.

The experiment began in April 2016 when I created the Emergency Loan eligibility lists across the 200 experimental branches. BRAC then notified eligible borrowers in *treatment* branches that they were pre-approved for a loan should a validated flood occur in their area. This additional credit was guaranteed for the rest of the agricultural season. We communicated pre-approval status to borrowers one month before the planting season to provide households enough time to change their investment decisions (see Section 2 above for further details about the Emergency Loan).

We also needed to inform eligible clients when a validated flood occurred so they could request a loan. I scraped the FFWC's website and generated alerts whenever measured water levels exceeded the pre-determined flood-danger threshold. A BRAC research employee visited the branches that were matched to gauges exhibiting these dangerous water levels, and met with local officials within these branches. If more than 20% of the branch's catchment area was flooded, the branch was "activated".[13] The branch manager received instructions from headquarters to notify all eligible borrowers that Emergency Loans were available through their normally scheduled village organization (VO) meetings or by calling clients directly. Eligible clients were reminded about the Emergency Loan's availability at every subsequent VO meeting until the expiration of the offer in November.

Over the course of the 2016 Aman season, 92 branches were activated: 40 control and 51 treatment.[14] However, 2016 was not a major flooding year and the water levels in the majority of activated branches did not cause widespread damage. As a result, BRAC decided to continue piloting the Emergency Loan for a second year in 2017. From 2016 to 2017, the experimental protocol remained the same. Only small improvements were made to the loan officers' description of the product. New creditscores were created for all branches and so some previously eligible households lost their eligibility.[15] In 2017, 136 branches were activated, 73 control and 63 treatment. Flooding in 2017 was more severe than in 2016, and several locations suffered significant damages to crop land and physical structures.

4.2 Data

I rely on data from two primary sources. First, I use BRAC's administrative loans records for all clients in the experimental branches. This dataset contains borrower's decisions to take loans, loan repayments activities. Detailed repayment data are available from April 2016 until January 2018, while loan disbursal data extends 1-4 years back depending on the branch. Within the loans data set, we observe approximately 300,000 unique individuals and 1.3 million unique loans.

Second, I use survey data collected from 4,000 BRAC clients, and 800 BRAC staff, across the 200 experimental branches. Branch staff surveys document the most important income generating activities in the area, perceptions of flood risk, and aggregate flood damage at the branch level. For the borrower survey, I sampled three village organizations at random from

[13]Importantly, the sector specialists did not know about the 20% threshold needed to activate each branch or whether the visited area served treatment or control branches.

[14]The difference is not statistically significant.

[15]Appendix Tables B9 to B15 account for possible differential selection into eligibility in 2017. Results are stable when excluding 2017 data or when instrumenting for eligibility using branch treatment status.

each branch. I then randomly selected fifteen eligible borrowers and five ineligible borrowers from these VOs.[16] Three rounds of data collection took place: a baseline survey in April 2016 before borrowers in treatment branches were informed about their eligibility status; a follow-up survey in December 2016 after the first rainy season; and a second follow-up in December 2017 after the second rainy season. Survey rates were high due to BRAC's network, 99% in the first follow-up and 98.9% in the second follow-up.

5 Results

To estimate the effects of guaranteed credit lines on household level outcomes, I compare *eligible* BRAC microfinance members across treatment and control branches. Eligible clients in control branches are those with credit scores that were high enough to qualify for the Emergency Loan had they been in a treatment branch. The baseline specification for household outcomes is therefore:

$$Y_{ibdt} = treatment_{ibd}\beta + \alpha_d + \phi_t + \mathbb{X}_{ibd}\gamma + \varepsilon_{ibdt}$$

Where Y_{ibdt} is an observed outcome for an eligible household i in branch b and district d during year t. I regress each outcome on an indicator for treatment, a district fixed effect (the stratification variable), a year fixed effect, and a vector of baseline controls to increase precision.[17] Data from both years of the experiment are pooled together (unless noted otherwise) and standard errors are always clustered at the branch level. For "ex-post" outcomes that occur after the flood season, I run the same regression with an additional indicator for flooding during the growing season and its interaction with treatment.

A similar approach is followed for MFI level outcomes (e.g. loan uptake decisions, repayments), with a few notable exceptions. Because I examine observations at the branch-month level, I add month m fixed effects in addition to year and district fixed effects to the estimating equation.[18]

$$Y_{bdmt} = treatment_{ibd}\beta + \alpha_d + \phi_t + \rho_m + \varepsilon_{bdmt}$$

[16] Appendix Tables B16 to B18 report on spillovers to ineligible borrowers. In general, I find no evidence of spillovers; therefore the main analysis discussed in this paper focuses only on eligible BRAC members.

[17] Controls include land owned by the household, household size, and head of household age and education unless specified otherwise

[18] Some regressions have only a single observation per year, in which case month fixed effects are dropped. Note that this dataset does not contain baseline controls and hence they are not included in the regression

5.1 Ex-Ante Household Investment

Theory predicts that the extension of a guaranteed credit line will encourage households to invest more in the planting period because they have access to the Emergency loan in the post-planting period should a flood occur (prediction 2). I focus on changes to agricultural investments because it is the most important income generating activity for the majority of rural households in Bangladesh. Moreover, these investments are more likely to be exposed to flood shocks, and are sensitive to interventions that reduce household flood risk.

Table 1 presents the amount of land devoted to agriculture during the rainy season. The first three columns separately identify the impact for three different types of land tenure (owned, rented, and sharecropped land), while column 4 aggregates these three measures. The last column is a binary indicator for planting any crops during the Aman season. Households that knew they were eligible for the loan increased the amount of land they *rented* by 30%, and the *total* land they cultivated by 15%. Neither owned nor sharecropped land showed any significant change. This result is not altogether surprising because finding additional land to rent is relatively straightforward. Conversely, expanding the cultivation of owned land requires farming previously fallow land or purchasing additional crop land, which is more costly and requires more planning. Similarly, expanding the amount of sharecropped land is less appealing now that farmers can reduce their exposure to risk with the Emergency loan. Finally, along the extensive margin, the number of households planting crops increases by approximately 4 percentage points. This represents a 10% increase in the probability that a household cultivates crops during the Aman season.

Next, we investigate whether households increase the intensity of input usage now that they are less exposed to risk. Columns 1 and 2 in Table 2 show that the amount of fertilizer and pesticides applied per acre of land increases, though neither point estimate is statistically significant. Similarly, columns 3 and 4 show that the amount of money spent on seeds and all other inputs per acre also increases but remains insignificant. At a minimum, these results confirm that treatment households are maintaining normal levels of input usage per acre despite the overall expansion of cultivated land. Finally, column 5 of Table 2 examines changes to non-agricultural business investments. We see a marginally significant increase of 30% ($12 USD) over the control group. However, this result should be interpreted with some caution because it is only statistically significant in the second year of the experiment, and is weakly significant overall.

These results are consistent with the theory that guaranteed credit lines can boost investment by effectively insuring farmers against floods. To support the interpretation that the product is affecting farmers' perceptions of risk I examine how the treatment effect varies by farmers' risk-aversion (as measured at baseline).[19] Appendix Table B5 confirms that more risk-averse households are more likely to increase the amount of land they rent, and the total land they cultivate in response to the guaranteed loan. While their investment in inputs are also higher, the results are not statistically significant (Appendix Table B6). The fact that the effects are strongest among risk averse households suggests this product is particularly valuable at correcting a negative distortion for this subgroup.

It is possible that these effects will dissipate over time if households that experience a flood decide that the Emergency Loan is no longer useful. In this case we would expect to see 2017 Aman season investments among flooded households decrease to pre-treatment levels because they no longer perceive any risk reduction benefits from accessing guaranteed credit. To test this, I examine how investment decisions change in the second year of the experiment based on whether households experienced a flood shock in the first season. If flood-afflicted treatment households decide that the Emergency Loan is not useful anymore, we should see smaller treatment effects among these households relative to treatment households that did not experience a flood shock. Appendix Table B7 illustrates how flooding in the first year affects different investment categories. The treatment effect on investments does not appear to differ for treated households that were flooded in the first year relative to treated households that were not. This suggests that households that experienced a flood in 2016 still perceive the Emergency Loan as offering viable protection against flood risk.

5.2 Ex-Post Household Outcomes

I examine the effect of treatment on four household outcomes: log weekly consumption per capita, log income during the previous month, crop production from the Aman season, and for those that operate small businesses the value of their current stock. Panel A of Table 3 shows that pre-approval lead to positive results. Per capita consumption increase by 8% on average in treatment households, while crop production increased 50 kilograms, a 17% increase. We find no effect of the treatment on household income, however we do find that the value of business stock rises by 23%.

The model suggests there are two potential channels driving these ex-post results. First, increases in investment in the planting season can translate into improved outputs. Second, treatment households that take the loan will have additional liquidity. I can explore these

[19] Risk aversion was measured by asking borrowers a series of choices between a certain payout and a larger but uncertain payout. Each successive choice increased the probability that the uncertain payout would be realized (see Sprenger 2015 for more details). The resulting risk aversion spread is continuous but normalized to a 0-1 scale so that the most risk averse households have a value of one and the most risk loving a value of zero. Households exhibiting the highest level of risk aversion households represent 27% of the sample and generally invest less at baseline.

mechanisms further by separately estimating the impact of the Emergency Loan for households that experienced a flood and those that do not. Specifically, I regress the household outcomes listed above on an indicator for treatment, an indicator for experiencing a flood shock, and an interaction between the two. The coefficient on treatment captures the impact of increases in ex-ante investments. Absent a flood, the only difference in outcomes between treatment and control households stems from changes in investments in the pre-period. In contrast, the sum of the coefficients on treatment and the interaction between treatment and flood will capture the payoffs of pre-period investments (i.e. those that were not destroyed by the shock) *and* improved liquidity access post-flooding.

We see strong evidence of the first channel. In branches that did *not* experience flooding, we see a 33% increase in crop production among treated households, which suggests that pre-period investments are paying off (Table 3 Panel B). We do not see significant differences in consumption between treatment and control households, although the point estimate is positive. This suggests that households reap the benefits of greater investments absent a flood even if they do not translate into significantly higher levels of consumption. This is not altogether surprising as households may choose to re-invest some of the production gains into their businesses or save it, rather than consuming more at a time when their marginal propensity to consume is low (they just harvested their crop and there were no floods). The point estimate on business stock for non-flooded households is positive, though we loose some statistical significance when we focus on this sub-sample.[20]

The second channel is more difficult to isolate on its own. The effect of treatment on ex-post outcomes in branches that *did* experience a flood will include any returns to investment that were not damaged by a flood, *and* the impact of any additional liquidity that treated households choose to take. Overall, we see that treated households loose 90% of the crop production gains they experience when a flood does not occur (Column 2). These losses are much larger than those observed in the control group, suggesting that treatment households expand cultivation on land that is particularly susceptible to floods. Nevertheless, treated households experience a rather large 10% increase in consumption compared to control households that also experienced a flood. This suggests that the availability of the Emergency Loan allows households to preserve some consumption, and maintain their asset levels after an income shock.[21]

[20]The non-negative effect of flooding can be rationalized by two factors. First, BRAC service areas are large, and many households within activated branches may not suffer from flooding. Second, floods are relatively common shocks and many households may have adopted mitigation strategies that limit the negative impact of any one shock.

[21]There is a concern that multiple shocks may reduce the usefulness of credit as a risk mitigation tool if households accumulate excessive debt or exhaust their credit line. Appendix Table B8 examines this hypothesis. I expand the regression specification from Table 3 to include an indicator for whether households

These higher consumption levels for treated households affected by a flood could stem from the fact that not all of their new investments were destroyed, or that households took the Emergency Loan. We can use data on Emergency Loan take-up rates to investigate this further. In 2016, only 2.9% of households chose to take the loan, which likely reflects the lack of severe flooding in most locations. In 2017, floods were much more damaging and uptake of the Emergency Loan increased to 5.4%. Low ex-post uptake of this product is not entirely unexpected because flood damage is highly idiosyncratic within these large branch service areas, such that certain households may be dramatically affected while others will not.[22] Table 4 further explores which types of households are most likely to take the Emergency Loan. We find higher take-up rates among households that were less well prepared for a flood, and among those that experienced higher levels of distress in the event of a flood (see Appendix Figure B5). These results confirm that the most vulnerable and worst affected households are the most likely to take advantage of the guaranteed credit offer. This is consistent with Prediction 4 in the model, and provides some rational for why consumption rates might have been so high in the treatment group: vulnerable households' marginal propensity to consume will be high post-flood, and they are likely to utilize the additional liquidity from the Emergency Loan to boost their consumption. Nevertheless, the low magnitude of these take-up rates also suggests that any pre-period investments that remained post flood were still a driving force behind the consumption results we observe.

5.3 Value of Guaranteed Credit

Value for Borrowers - Credit Line Preservation

We have seen that the Emergency Loan improves household outcomes by reducing their exposure to the downside risks associated with severe flooding, thereby encouraging profitable investment. This suggests that households should value the product. However it is unclear if borrowers recognize these benefits and are willing to take costly actions to preserve their access to guaranteed credit. To shed light on this question, I work with a subset of my sample (15%) that were eligible to take a Good borrower Loan when they were informed about their

experience flooding in both years, and an interaction of this indicator with treatment. To determine whether the usefulness of guaranteed credit is reduced after successive shocks, I examine the interaction of the double flood indicator and the treatment indicator. These coefficients are all statistically insignificant, but a joint test of all the treatment coefficients shows that treatment households are still better off after a double shock. Overall, this suggests that the gains in consumption and asset preservation due to treatment are not completely eliminated by successive shocks. However, it is worth interpreting these results with some caution because the 2016 shock was not particularly damaging, and may not reflect responses to larger shocks.

[22] Additionally, low take-up rates do not imply that households did not value or benefit from the Emergency loan's availability. As seen in the results above, households responded to the offer of a loan before flooding occurred by increasing investments which in turn generated greater output.

eligibility for the Emergency Loan. These loans were mutually exclusive, which meant these borrowers faced a tradeoff. They could take the Good Loan in the planting season and forgo the Emergency Loan should a flood occur, or decline the Good Loan in order to preserve the option to take the Emergency Loan should a flood occur in the post-planting season. According to the theoretical model (prediction 5), forward looking households will want to preserve credit access as a buffer against this risk. I test this prediction by comparing the probability of taking a Good Loan in the pre-period among Good Loan eligible clients in treatment branches, where the Emergency Loan *was* available, to Good Loan eligible clients in control branches, where the Emergency Loan *was not* available.

Table 9 shows the results from comparing Good Loan eligible borrowers across treatment and control branches (where the regressions are run at the branch level). Column 1 shows that the availability of the Emergency Loan reduces the probability of taking a Good Loan by two percentage points, or 15% in treatment branches. Column 2 and 3 examine the extent to which this effect varies based on branch clients' need for liquidity, and their perceived risk of local flooding.[23] While I do not see any significant differences by liquidity needs, I do find that branches are even less likely to take the Good Loan when the perceived risk of flooding is higher. This confirms our theoretical prediction that some households view guaranteed credit as offering effective insurance against shocks and want to preserve their access to it.

Households that forgo the Good Loan in order to preserve their access to the Emergency Loan are giving up certain credit today in order maintain credit access in the future (should a flood occur). I calculate what this implies about the value households' assign to the Emergency Loan relative to credit in the pre-period under conservative and more realistic assumptions. First, I estimate that households' marginal utility of accessing credit after a flood is at least 1.85 times more than the marginal utility of certain credit in the pre-period. This assumes that households can correctly predict the probability that a loan will be offered (54% over the two years of the study), that they will take the loan if it is made available, and that they do not discount the future. However, under more realistic assumptions, I calculate that the marginal utility of a loan after a flood is 20.5 times greater than in the pre-period. This assumes that households expect to use the Emergency Loan at the same rates observed in the experiment (5%), and they have an annual discount rate of 6%.[24]

To further understand which borrowers are most likely to preserve their credit access, I estimate a local average treatment effect across bins of the Emergency Loan credit score

[23] I proxy the need for liquidity with an indicator for whether the branch manager reports farming to be the primary occupation in the area. Farming requires significant investments in the pre-period to prepare seedbeds for cultivation.

[24] This assumes a waiting time of five months between the decision to forgo the Good Loan and the decision to take the Emergency Loan.

(pooling all treatment and control branches together, respectively). Figure 1a plots the treatment effect on Good Loan uptake by credit score bin for eligible clients. There is some evidence of heterogeneous treatment effects: the reduction in the probability of taking a Good Loan is highest among eligible clients with high credit scores. Column 1 of Table 8 fits a linear trend to this relationship and shows that this effect is (marginally) statistically significant. This suggests that clients with the best repayment histories are more likely to preserve credit access to hedge against future shocks. We might expect this result if clients with higher credit scores have lower discount rates, or if they are less present biased.

Value for MFI Operations

The provision of guaranteed credit has been limited by MFIs who are concerned about default risk. Our theory says the impact on BRAC branch performance is actually ambiguous. To establish whether there is indeed a tension between household gains and MFI outcomes we need to calculate branch profitability. There are two key outcomes that determine branch profitability: the number of loans disbursed and the repayment rates of those loans.

I begin by examining how the total number of loans BRAC disburses changes. We know that the number of Emergency Loans increases, but the number of Good Borrower Loans fall. I also test how the Emergency Loan affects the likelihood that borrowers take a regular Dabi loan in the pre-period. As detailed in Proposition 3, treated households should be more willing to make risky investments, and borrow to do so.[25] The results in Table 5 show that treatment causes the probability of taking a Dabi loan to increase by 11% (0.7 percentage points) in the pre-period – and does not differ by borrower credit score (Figure 1b; Table 8 Column 2).[26] The overall effect on the total loans disbursed is therefore ambiguous.

In addition to loan disbursals, impacts on repayment rates are critical to establish the sustainability of the Emergency Loan. Table 6 shows how the probability of missed payments differs between treatment and control branches both with and without a flood. In the absence of a shock, the coefficient on treatment shows that access to the Emergency Loan has no effect on repayment rates for all loans. In the presence of flood, the number of missed payments across all loans increases by approximately 3.9 percentage points (40% percent)

[25] All members were included in the analysis so that the denominator of eligible borrowers remained constant throughout the study time period and did not change in response to endogenous loan take-up decision.

[26] It is possible that the increase in loan disbursement during the pre-period comes at the expense of future loans (for example, if households simply move up their previously planned investment timeline). Appendix Figure B7 plots the monthly probability of Dabi loan up-take by treatment status from 2015 until the end of the study period. We can see that the probability of taking a new Dabi loan is higher in the treatment branches during the pre-period, but is otherwise fairly similar. This suggests that the extra Dabi loans disbursed in the pre-period represent additional loans that would not otherwise have been disbursed.

in control branches. In treatment branches this effect is overcome by a reduction in missed payments of 4 percentage points, thereby returning repayment rates to approximately normal rates. Furthermore, the repayment rate of the Emergency Loan itself is almost identical to other loans during the same period (10% missed payments for the Emergency Loan as compared with 9.6% on all loans). This result is even more meaningful when we remember that households that took the Emergency Loan experienced greater damages from the flood. Overall, these results demonstrate that the availability of the Emergency Loan improved repayment for the MFI in the aftermath of the flood (on a branch wide basis).

Next, I look for heterogeneity in repayments rates by borrowers' credit score. Figure 1c plots repayment rates by treatment status across credit scores.[27] This shows that the effect of treatment on repayment rates is largest among clients with scores that are close to the eligibility threshold. The treatment effect is much smaller at higher credit scores (column 3 of Table 8 shows that this heterogeneity is statistically significant). This likely stems from the fact that borrowers with high credit scores already repay at such high rates that further improvements are difficult to make.

Overall branch profitability is derived from the number of loans disbursed and the repayment rates on those loans. To capture the overall effect on the branch, we can directly compare the profitability of branches that offered the Emergency Loan to those that did not. Table 7 shows the estimated effects of treatment on three measures of MFI profitability: the net present value (NPV) of each loan disbursed, the monthly profitability of the branch in aggregate, and the per-member monthly profitability of each branch.[28] The first two results show positive point estimates, but neither is statistically significant. However, column 3 shows a 4% increase in the per-person profits in treatment branches. In sum, these results suggest a modest increase in branch profitability, and rule out MFI losses.

Finally, in column 4 of Table 7 I examine the effect of treatment on the expected NPV of the branch portfolio as a whole. I estimate the NPV of the branch following Karlan and Zinman (2018). I estimate the average profitability of clients grouped by treatment status and ex-ante credit score. I then assign these values to the stock of clients that existed in each branch at the beginning of the experiment. I then aggregate up to the branch credit-score level:

$$NPV_{bc} = \sum_{members} \sum_{t} \left(revenue_{bct} - cost_{bct}\right) / discount^{t}$$

[27] Appendix Figure B8 plots the levels of repayment rate.

[28] To calculate net present value for each loan, I assume an annual cost of capital of 6%. Branch profit is calculated as the sum of discounted repayments minus the cost of new disbursements, while per-member profitability takes this measure and divides it by the number of branch members.

Where b indicates the branch, c indicates the credit score, and t is month. Note this NPV measure only applies to the set of clients that existed when the experiment began, and ignores any additional clients that may have joined BRAC as a result of the Emergency Loan. The estimates in column 4, show that average branch NPV increases by 2,129,951 taka (approx. $25,000) as a result of treatment.

We can also examine the extent to which the effects on profitability vary by borrower credit score. Figure 1d plots the treatment effect on per-person profitability by credit score decile. Yet again, we see that the treatment effect is highest for clients with credit scores closer to the eligibility cutoff and decreases steadily until it is negative for those with higher credit scores (column 4 of Table 8 show that this heterogeneity is statistically significant). These results have interesting implications for the targeting of the Emergency Loan. The Emergency Loan was targeted to the top 40% of borrowers based on a credit score that reflected their past loan behavior. This system was designed to reduce the downside risk for the MFI in case repayment rates from the Emergency Loan were low. However, the results suggest that BRAC could do even better by lowering the eligibility threshold. Assuming the measured treatment effects are continuous across the threshold, this would extend access to clients who are most likely to improve MFI profitability.

6 Conclusion

Millions of households across the world are exposed to severe income risk and live in areas where insurance markets are non-existent. When shocks strike, they are forced to use costly coping mechanisms in order to survive. Under these circumstances, it becomes important to develop tools that can decrease households' exposure to risk and help them self-insure. One solution is to provide households with a guaranteed credit line in the event of a shock. While theory suggests this should improve household welfare, MFI's concerns about default risk could limit supply. To test this empirically, I run a large scale RCT offering guaranteed credit in rural regions of Bangladesh where annual flood risk is high. First, I show that households that were informed about their guaranteed credit access increase their investments in productive activities in the pre-period. This increase in investments yields higher production levels absent a flood, and higher consumption levels when a shock occurs.

I also show that the extension of a guaranteed credit line after a shock is valued by borrowers and confers benefits to lenders. On the borrowers side we see that many households choose to preserve their access to guaranteed credit at the expense of additional liquidity in the pre-period. This behavior is consistent with a model where households utilize their credit access as a buffer against the risk of future shocks. I also find that the introduction of the

Emergency Loan has largely positive effects for MFI profits. Members take additional loans in the pre-period in response to the added security, repayment rates after a shock improve, and the NPV of the branch portfolio increases. This suggests that guaranteed credit can be offered by MFIs without third party subsidies, provided that loan repayment rates remain similar in other settings. This is an important finding because MFIs are ubiquitous in low income countries and can easily offer this type of product using their existing infrastructure.

In light of these results it may seem puzzling that the Emergency Loan has not been widely adopted by the microfinance industry. I suggest two obstacles that may prevent adoption despite benefits to households and lenders. First, some MFIs do not keep adequate records, and lack the lending history necessary to create a credit score that targets responsible borrowers. It is important for MFIs be able to identify who these households are – as the results are unlikely to generalize to poorly performing clients. Second, a guaranteed credit product does not necessary align with branch managers' incentives. Branch level officials may be concerned that the Emergency Loan will exacerbate post-shock defaults, which could put their own jobs at risk, and perceive little upside. Our results provide the first empirical evidence that this tension need not exist, as borrowers improve repayments rates and take more loans in the pre-period as a result of the guaranteed credit, improving overall branch performance.

From a policy perspective, this research suggests that credit can be a useful tool to address uninsured risk in places where traditional insurance markets have failed. As the frequency and severity of weather shocks increases with climate change, providing households with an easily accessible tool that reduces exposure to risk is important. The tool I explore here is appealing because MFI loans are already understood in rural areas worldwide. Moreover, guaranteed credit does not require any up-front commitments from the beneficiary, bypassing one of the main drivers of low demand for insurance. Additionally, because the decision to utilize additional credit is made after shock damages are realized, households can opt-in after assessing ex-post costs and benefits. Therefore, guaranteed credit can crowd-in ex-ante investment even if households choose not to use the product in the aftermath of a shocks.

References

Angelucci, Manuela, Dean Karlan, and Jonathan Zinman. 2013. "Win Some Lose Some? Evidence from a Randomized Microcredit Program Placement Experiment by Compartamos Banco." Working Paper 19119, National Bureau of Economic Research.

———. 2015. "Microcredit Impacts: Evidence from a Randomized Microcredit Program Placement Experiment by Compartamos Banco." *American Economic Journal: Applied Economics* 7 (1):151–182.

Banerjee, Abhijit, Esther Duflo, Rachel Glennerster, and Cynthia Kinnan. 2015. "The Miracle of Microfinance? Evidence from a Randomized Evaluation." *American Economic Journal: Applied Economics* 7 (1):22–53.

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.

Barboni, Giorgia. 2017. "Repayment Flexibility in Microfinance Contracts: Theory and Experimental Evidence on Take up and Selection." *Journal of Economic Behavior & Organization* 142:425–450.

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

Brammer, H. 1990. "Floods in Bangladesh: Geographical Background to the 1987 and 1988 Floods." *The Geographical Journal* 156 (1):12–22.

Breza, Emily and Cynthia Kinnan. 2018. "Measuring the Equilibrium Impacts of Credit: Evidence from the Indian Microfinance Crisis." Working Paper 24329, National Bureau of Economic Research.

Bryan, Gharad, Shyamal Chowdhury, and Ahmed Mushfiq Mobarak. 2014. "Underinvestment in a Profitable Technology: The Case of Seasonal Migration in Bangladesh." *Econometrica* 82 (5):1671–1748.

Burgess, Robin and Rohini Pande. 2005. "Do Rural Banks Matter? Evidence from the Indian Social Banking Experiment." *The American Economic Review* 95 (3):780–795.

Carroll, Christopher D. 1997. "Buffer-Stock Saving and the Life Cycle/Permanent Income Hypothesis." *The Quarterly Journal of Economics* 112 (1):1–55.

Casaburi, Lorenzo and Jack Willis. 2018. "Time vs. State in Insurance: Experimental Evidence from Contract Farming in Kenya." *American Economic Review* .

Clarke, Daniel J. 2016. "A Theory of Rational Demand for Index Insurance." *American Economic Journal: Microeconomics* 8 (1):283–306.

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.

Cole, Shawn, Xavier Giné, and James Vickery. 2017. "How Does Risk Management Influence Production Decisions? Evidence from a Field Experiment." *The Review of Financial Studies* 30 (6):1935–1970.

Cole, Shawn A. and Wentao Xiong. 2017. "Agricultural Insurance and Economic Development." *Annual Review of Economics* 9 (1):235–262.

Conning, Jonathan and Christopher Udry. 2007. "Rural Financial Markets in Developing Countries." In *Handbook of Agricultural Economics*, vol. 3, edited by Prabhu Pingali Robert Evenson and T. Paul Schultz, chap. 15. Amsterdam: Elsevier.

Crépon, Bruno, Florencia Devoto, Esther Duflo, and William Parienté. 2015. "Estimating the Impact of Microcredit on Those Who Take It Up: Evidence from a Randomized Experiment in Morocco." *American Economic Journal: Applied Economics* 7 (1):123–150.

Daley-Harris, Sam. 2006. "State of the Microcredit Summit Campaign Report 2006 — Microcredit Summit Campaign." Tech. rep.

de Janvry, Alain, Craig McIntosh, and Elisabeth Sadoulet. 2010. "The Supply- and Demand-Side Impacts of Credit Market Information." *Journal of Development Economics* 93 (2):173–188.

Deaton, Angus. 1991. "Saving and Liquidity Constraints." *Econometrica* 59 (5):1221–1248.

———. 1992. "Household Saving in LDCs: Credit Markets, Insurance and Welfare." *Scandinavian Journal of Economics* 94 (2):253–73.

Demont, Timothée. 2014. "Microcredit as Insurance: Evidence from Indian Self-Help Groups." Tech. Rep. 1410, University of Namur, Department of Economics.

Dercon, Stefan. 2002. "Income Risk, Coping Strategies, and Safety Nets." *The World Bank Research Observer* 17 (2).

Donovan, Kevin. 2016. "Agricultural Risk, Intermediate Inputs, and Cross-Country Productivity Differences." *Unpublished Paper, University of Notre Dame* .

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.

Fafchamps, Marcel, Jan Willem Gunning, and Remco Oostendorp. 2001. "Inventories and Risk in African Manufacturing." *The Economic Journal* 110 (466):861–893.

Field, Erica and Rohini Pande. 2010. "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." *The American Economic Review* 110 (11):42.

Fischer, Greg. 2013. "Contract Structure, Risk-Sharing, and Investment Choice." *Econometrica* 81 (3):883–939.

Fulford, Scott L. 2015. "How important is variability in consumer credit limits?" *Journal of Monetary Economics* 72:42 – 63.

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 Evidencefrom Malawi." *Journal of Development Economics* 89 (1):1–11.

Gross, David B. and Nicholas S. Souleles. 2002. "Do Liquidity Constraints and Interest Rates Matter for Consumer Behavior? Evidence from Credit Card Data." *The Quarterly Journal of Economics* 117 (1):149–185.

Guiteras, Raymond, Amir Jina, and A. Mushfiq Mobarak. 2015. "Satellites, Self-Reports, and Submersion: Exposure to Floods in Bangladesh." *American Economic Review: Papers and Proceedings* 105 (5):232–236.

Hazell, Peter B. R. 1992. "The Appropriate Role of Agricultural Insurance in Developing Countries." *Journal of International Development* 4 (6):567–581.

Hoddinott, John. 2006. "Shocks and Their Consequences Across and Within Households in Rural Zimbabwe." *The Journal of Development Studies* 42:301–321.

Hsiang, Solomon and Daiju Narita. 2012. "Adaptation to Cyclone Risk: Evidence from the Global Cross-Section." *Climate Change Economics* 3.

Hsiang, Solomon M and Amir S Jina. 2020. "The Causal Effect of Environmental Catastrophe on Long-Run Economic Growth: Evidence From 6,700 Cyclones." Working Paper 20352, National Bureau of Economic Research. Series: Working Paper Series.

Janzen, Sarah A and Michael R Carter. 2018. "After the Drought: The Impact of Microinsurance on Consumption Smoothing and Asset Protection." *American Journal of Agricultural Economics* 101 (3):651–671.

Jensen, Nathaniel and Christopher Barrett. 2017. "Agricultural Index Insurance for Development." *Applied Economic Perspectives and Policy* 39 (2):199–219.

Kaboski, Joseph P. and Robert M. Townsend. 2011. "A Structural Evaluation of a Large-Scale Quasi-Experimental Microfinance Initiative." *Econometrica* 79 (5):1357–1406.

Karlan, Dean. 2014. "Innovation, Inclusion and Trust: The Role of Non-Profit Organizations in Microfinance." Tech. rep., Innovations for Poverty Action.

Karlan, Dean and Nathanael Goldberg. 2011. "Microfinance Evaluation Strategies: Notes on Methodology and Findings." World Scientific Book Chapters, World Scientific Publishing Co. Pte. Ltd.

Karlan, Dean, Jake Kendall, Rebecca Mann, Rohini Pande, Tavneet Suri, and Jonathan Zinman. 2016. "Research and Impacts of Digital Financial Services." Working Paper 22633, National Bureau of Economic Research.

Karlan, Dean, Robert Osei, Isaac Osei-Akoto, and Christopher Udry. 2014. "Agricultural Decisions after Relaxing Credit and Risk Constraints." *The Quarterly Journal of Economics* 129 (2):597–652.

Karlan, Dean and Jonathan Zinman. 2011. "Microcredit in Theory and Practice: Using Randomized Credit Scoring for Impact Evaluation." *Science* 332 (6035):1278–1284.

———. 2018. "Long-Run Price Elasticities of Demand for Credit: Evidence from a Countrywide Field Experiment in Mexico." *The Review of Economic Studies* 86 (4):1704–1746.

Labie, Marc, Carolina Laureti, and Ariane Szafarz. 2017. "Discipline and flexibility: a behavioural perspective on microfinance product design." *Oxford Development Studies* 45 (3):321–337.

Maccini, Sharon and Dean Yang. 2009. "Under the Weather: Health, Schooling, and Economic Consequences of Early-Life Rainfall." *American Economic Review* 99 (3):1006–1026.

Maes, J. and L. Reed. 2011. "State of the Microcredit Summit Campaign Report 2012." Paper, Microcredit Summit Campaign.

McCulloch, Stewart, Charles Winter, Charlotte Benson, Michael Kellogg, and Jerry Skees. 2016. "Disaster-Resilient Microfinance: Learning From Communities Affected by Typhoon Haiyan." Tech. rep., Asian Development Bank.

McIntosh, Craig, Alexander Sarris, and Fotis Papadopoulos. 2013. "Productivity, Credit, Risk, and the Demand for Weather Index Insurance in Smallholder Agriculture in Ethiopia." *Agricultural Economics* 44 (4-5):399–417.

Mobarak, Ahmed Mushfiq and Mark Rosenzweig. 2012. "Selling Formal Insurance to the Informally Insured." Tech. Rep. 1007, Economic Growth Center, Yale University.

———. 2014. "Risk, Insurance and Wages in General Equilibrium." Working Paper 19811, National Bureau of Economic Research.

Morduch, Jonathan. 1999. "The Microfinance Promise." *Journal of Economic Literature* 37 (4):1569–1614.

Quisumbing, Agnes R. 2007. "Poverty Transitions, Shocks, and Consumption in Rural Bangladesh: Preliminary Results from a Longitudinal Household Survey." Tech. Rep. 105, Chronic Poverty Research Centre Working Paper.

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.

Santos, Indhira, Iffath Sharif, Hossain Zillur Rahman, and Hassan Zaman. 2011. *How Do the Poor Cope with Shocks in Bangladesh? Evidence from Survey Data*. Policy Research Working Papers. The World Bank.

Serfilippi, Elena, Michael Carter, and Catherine Guirkinger. 2018. "Insurance Contracts When Individuals "Greatly Value" Certainty: Results from a Field Experiment in Burkina Faso." Working Paper 25026, National Bureau of Economic Research.

Udry, Christopher. 1994. "Risk and Insurance in a Rural Credit Market: An Empirical Investigation in Northern Nigeria." *The Review of Economic Studies* 61 (3):495–526.

———. 1995. "Risk and Saving in Northern Nigeria." *The American Economic Review* 85 (5):1287–1300.

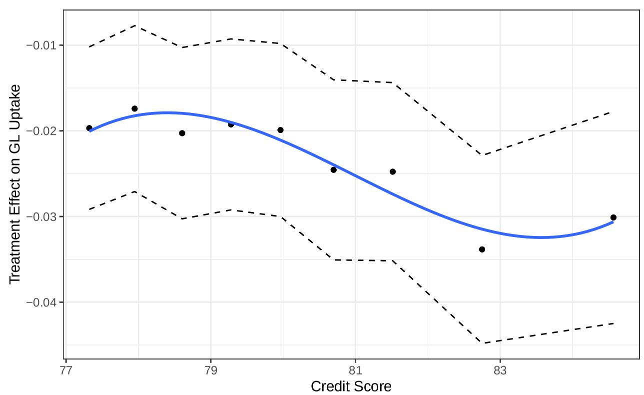
UNDP. 2015. "MDG Bangladesh Progress Report." Tech. rep., UNDP.

World Bank. 2016. "Bangladesh: Growing the Economy through Advances in Agriculture." http://www.worldbank.org/en/results/2016/10/07/bangladesh-growing-economy-through-advances-in-agriculture.

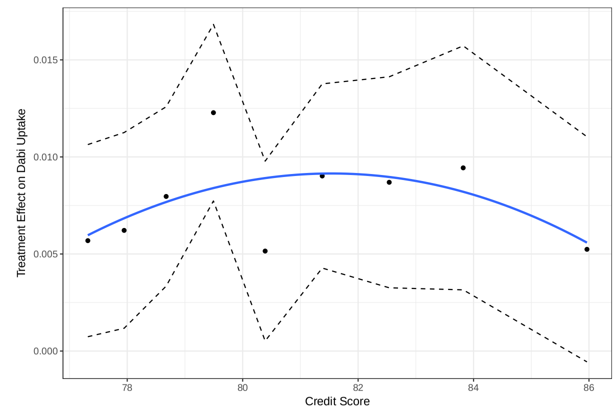
Figures

Figure 1: Heterogeneity by Credit Score

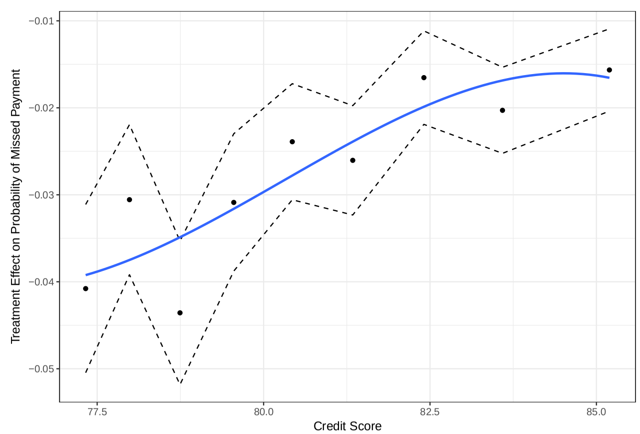
(a) Good Loan Uptake



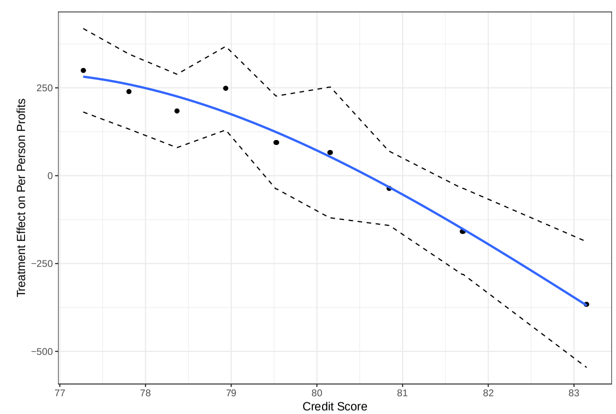
(b) Dabi Loan Uptake



(c) Missed Payment



(d) Per-Person Profits



Notes: Plots the treatment effect on the outcome in treatment branches by decile of borrower credit score. The regression run on each decile includes year and district fixed effects. Sample is comprised of Emergency Loan eligible borrowers. For Good Loan uptake, sample is limited to those who were also eligible for a Good Loan in the pre-flood period. Standard errors are clustered at the branch level. Table 8 tests whether the treatment effect heterogeneity is significant.

Tables

Table 1: Land Farmed

	(1) Own land	(2) Rented land	(3) Sharecrop land	(4) Total land	(5) Any Cult.
Treatment	0.000	0.063***	-0.004	0.058**	0.044*
	(0.013)	(0.016)	(0.004)	(0.026)	(0.024)
Controls	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
Mean Dep. Var	0.13	0.20	0.02	0.35	0.46
Observations	4744	4740	4743	4739	4745

Notes: Sample includes only eligible BRAC members from both treatment and control groups. Data is pooled from both the 2016 and 2017 Aman season. Controls are included for precision, and are comprised of baseline measures of total land owned, household size, and the age and education of the head of household. Standard errors clustered at the branch level. Land measured in acres. Total land is the sum of own land, rented land, and sharecropped land. Any Cult. is an indicator for whether or not a household planted any crops during the season.

Table 2: Ex-Ante Investments

	(1) Fert. Applied	(2) Pest. Applied	(3) Input Cost per Acre	(4) Non-Ag Invest
Treatment	6.51	0.26	2.06	12.13*
	(5.30)	(0.17)	(2.17)	(6.64)
Controls	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Mean Dep. Var	140.47	1.58	65.85	38.69
Observations	2183	2140	2017	4745

Notes: Sample includes only eligible BRAC members from both treatment and control groups. Data is pooled from both the 2016 and 2017 Aman season. Controls are included for precision, and are comprised of baseline measures of total land owned, household size, and the age and education of the head of household. Standard errors clustered at the branch level. Fertilizer and pesticide measured in kg/L per acre. Input cost per acre is the sum of the cost of fertilizer, pesticide, and seeds (measured in dollars). Non-Ag Invest are business investments – measured by the total value of newly purchased (or repaired) business assets.

Table 3: Ex-Post Outcomes

	Panel A: Ex-Post Outcomes by Treatment			
	(1) Log Cons PerCap	(2) Crop Prod. (Kg)	(3) Log Income	(4) Bus. Stock Value
Treatment	0.080**	47.896*	-0.019	205.693*
	(0.031)	(28.093)	(0.029)	(111.556)
Mean Dep. Var	5.93	275.22	10.77	864.89
Observations	4743	4745	4531	799
Controls	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Week Interviewed FE	Yes	No	No	No

	Panel B: Ex-Post Outcomes by Treatment and Flood Realization			
	(1) Log Cons PerCap	(2) Crop Prod. (Kg)	(3) Log Income	(4) Bus. Stock Value
Treatment	0.047	97.088**	-0.016	182.041
	(0.045)	(41.030)	(0.044)	(174.600)
Flood X Treatment	0.061	-88.492*	-0.005	44.445
	(0.062)	(51.942)	(0.064)	(231.634)
Flood	-0.051	5.509	0.049	-68.940
	(0.058)	(37.383)	(0.059)	(193.055)
Mean Dep. Var	5.93	275.22	10.77	864.89
Observations	4743	4745	4531	799
Treat + Flood X Treat	0.01	0.81	0.61	0.13
Controls	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Week Interviewed FE	Yes	No	No	No

Notes: Sample includes only eligible BRAC members from both treatment and control groups. Data is pooled from both the 2016 and 2017 Aman season. Controls are included for precision, and are comprised of baseline measures of total land owned, household size, and the age and education of the head of household. Week interviewed fixed effects are included for the log consumption regression due to the presence of holidays over the course of the survey period that changed standard consumption patterns. Standard errors clustered at branch level. Income is measured in dollars. Flood is an indicator that equals one if flooding occurred and the Emergency Loan was activated. The row Treat + Flood X Treat reports p-values for the null hypothesis that the sum of the two treatment coefficients is equal to zero.

Table 4: Emergency Loan Uptake

	(1) Took Emergency Loan	(2) Took Emergency Loan
Baseline HH Income	-0.393	
	(0.267)	
Risk Aversion	0.007	
	(0.013)	
Baseline Time Preference	-0.003	
	(0.002)	
Number of Past Floods	-0.007	
	(0.005)	
Have Ex-post Investment Opportunity		0.020
		(0.015)
Flood preparation (1=low, 5=high)		-0.026*
		(0.013)
Distress from flood (1=low, 5=high)		0.054***
		(0.014)
Controls	Yes	Yes
District FE	Yes	Yes
Mean Dep. Var	0.03	0.05
Observations	1193	525

Notes: Sample includes only treatment BRAC members who were eligible to take an Emergency Loan in an activated branch. The outcome variable is an indicator for the borrower taking the offered Emergency Loan. Standard errors clustered at branch level. Column 1 shows results predicting Emergency Loan take-up using data collected at baseline. Yearly household income is measured in thousands of dollars. Risk aversion ranges 0 to 1, where 0=most risk loving and 1=most risk averse. Time preference ranges from 1 to 9, where 1 = most impatient and 9 = most patient. Number of past floods is the number of flood shocks experienced by the household over the previous five years (2011-2016). Column 2 predicts Emergency Loan take-up using data gathered at endline and only has observations from 2017. Flood preparation was measured at baseline. Ex-post investment opportunity is an indicator for whether the household reported having a good investment opportunity after the flood. Preparation for flood and distress from flood were self-reported by households.

Table 5: Dabi Loan Uptake by Emergency Loan Availability

	Loan Uptake
Treatment	0.007***
	(0.002)
Year & Month F.E.	Yes
District F.E.	Yes
Mean of Dep. Var.	0.062
Unique Borrowers	108,446
Observations	462,172

Notes: Sample is comprised of all Emergency Loan eligible clients in the pre-flood period. Observations at the month-person level. Data is pooled from both the 2016 and 2017. Standard errors clustered at branch level. The outcome variable is an indicator for whether or not the client took a new dabi loan in the period before the flood season.

Table 6: Repayment by Emergency Loan Availability

	Missed Payment
Treatment	0.011
	(0.024)
Treat x Flood	−0.040*
	(0.020)
Flood	0.039*
	(0.023)
Year & Month F.E.	Yes
District F.E.	Yes
Mean of Dep. Var.	0.096
Unique Borrowers	109,647
Observations	378,216

Notes: Sample includes only Emergency Loan eligible clients. Standard errors clustered at branch level. Observations at the loan-month level. The outcome variable is an indicator for whether or not the client missed a loan payment in a given month. The variable flood is an indicator for anytime after a flood until the following March.

Table 7: Branch Profit by Emergency Loan Availability

	Profit (Taka)			NPV
	Per Loan	Monthly Branch	Monthly Per Person	
	(1)	(2)	(3)	(4)
Treatment	161	76,312	96**	2,129,951**
	(233)	(95,405)	(46)	(974,008)
District F.E.	Yes	Yes	Yes	Yes
Month F.E.	No	Yes	Yes	No
Mean of Dep. Var.	2,823	1,745,794	2202	26,061,643
Observations	106,695	3,706	3,706	3,797

Notes: Sample includes only Emergency Loan eligible clients. Standard errors clustered at branch level. The outcome in column 1 is the probability of taking an offered Good Loan among Good Loan eligilbe clients in the pre-flood period. The outcome in column 2 is the probability of taking a Dabi Loan in the pre-flood period. The outcome in column 3 is the probability of missing a loan payment in a given month. The outcome in column 4 is the measured profit in Bangladeshi taka per branch member assuming an annual cost of capital of 6% for the MFI. The outcome in column 5 is is branch NPV as measured at the start of the experiment.

Table 8: Effect MFI Outcomes by Credit Score

	Good Loan Uptake	Dabi Uptake	Missed Payment	Per Person Profit	NPV
	(1)	(2)	(3)	(4)	(5)
Treatment	-0.020^{*}	0.008^{***}	-0.027^{**}	169^{**}	$33{,}500{,}846^{**}$
	(0.011)	(0.002)	0.013)	(14,520,366)	
Credit Score x Treatment	-0.003^{*}	0.000	0.004^{*}	-25^{*}	$-390{,}553^{***}$
	(0.002)	(0.0002)	(0.002)	(14.7)	(176,826)
Credit Score	0.004^{***}	-0.0001	-0.010^{***}	13^{**}	$3{,}072{,}508^{***}$
	(0.0001)	0.0002)	(0.002)	(5.740)	(131,194)
District F.E.	Yes	Yes	Yes	Yes	Yes
Month F.E.	No	Yes	Yes	No	No
Year F.E.	Yes	Yes	Yes	No	No
Mean of Dep. Var.	0.13	0.062	0.096	2202	26,061,643
Observations	37,392	3,706	190,862	40,514	3,797

Notes: Sample includes only Emergency Loan eligible clients. Standard errors clustered at branch level. The outcome in column 1 is the probability of taking an offered Good Loan among Good Loan eligilbe clients in the pre-flood period. The outcome in column 2 is the probability of taking a Dabi Loan in the pre-flood period. The outcome in column 3 is the probability of missing a loan payment in a given month. The outcome in column 4 is the measured profit in Bangladeshi taka per branch member assuming an annual cost of capital of 6% for the MFI. The outcome in column 5 is is branch NPV in taka as measured at the start of the experiment.

Table 9: Uptake of Good Loan by Emergency Loan Availability

	Took Good Loan		
Treatment	-0.020^{**}	-0.022^{**}	-0.020^{**}
	(0.008)	(0.009)	(0.008)
Farming x Treatment		0.006	
		(0.016)	
Farming Main Activity		-0.007	
		(0.010)	
Flood Risk x Treatment			-0.015^{***}
			(0.006)
Flood Risk			0.011^{***}
			(0.004)
Year F.E.	Yes	Yes	Yes
District F.E.	Yes	Yes	Yes
Mean of Dependent Var	0.130	0.130	0.129
Unique Borrowers	66,232	66,232	63,744
Observations	75,818	75,818	73,282

Notes: Sample is comprised of Good Loan eligible clients who were offered a Good Loan in the pre-flood period. Observations at the month-person level. Data is pooled from both 2016 and 2017. Standard errors clustered at branch level. The outcome variable is an indicator for whether or not the borrower took the offered Good Loan. Farming is a branch level indicator for farming being the major source of income for BRAC members in that branch. Flood risk is measured at the branch level on 1-5 scale where 1 = least risk and 5 = high risk.

Appendix A: Model Details (FOR ONLINE PUBLICATION)

Comparative Statics

Building on Section 3.3, we will more formally derive the comparative statics for input choice x and first period borrowing b^1 with respect to the increase in second period borrowing b_B^2. Starting with the maximization problem defined in equation 8:

$$\max_{x,b^1,b_B^2} \quad \mathcal{L} = u(Y - x + b^1) + q\beta u\left(-Rb^1 + b_B^2\right) + (1-q)\beta u\left(m_G f(x) - Rb^1\right) + \\ q\beta^2 u(I - Rb_B^2) + (1-q)\beta^2 u(I) + \lambda_1[\bar{B}_1 - b^1] + \lambda_2[\bar{B}_2 - b_B^2]$$

Where the FOCs are given by:

$$\begin{aligned}
\frac{\partial \mathcal{L}}{\partial x} =& - u'(c_1) + (1-q)\beta u'(c_G^2) m_G f' \\
\frac{\partial \mathcal{L}}{\partial b^1} =& u'(c_1) - q\beta R u'(c_B^2) - (1-q)\beta R u'(c_g^2) - \lambda_1 \\
\frac{\partial \mathcal{L}}{\partial b_B^2} =& q\beta u'(c_B^2) - qR\beta^2 u'(c_B^3) - \lambda_2
\end{aligned}$$

Note, we assume the constraints do not bind ($\lambda_t = 0$) so that the choice of x and b^1 can adjust. We also know from the implicit function theory that we can calculate $\frac{\partial x}{\partial b_B^2}$ and $\frac{\partial b^1}{\partial b_B^2}$ by:

$$\begin{bmatrix} \frac{\partial x}{\partial b_B^2} \\ \frac{\partial b^1}{\partial b_B^2} \end{bmatrix} = - \begin{bmatrix} \frac{\partial \mathcal{L}}{\partial x \partial x} & \frac{\partial \mathcal{L}}{\partial x \partial b^1} \\ \frac{\partial \mathcal{L}}{\partial b^1 \partial x} & \frac{\partial \mathcal{L}}{\partial b^1 \partial b^1} \end{bmatrix}^{-1} \begin{bmatrix} \frac{\partial \mathcal{L}}{\partial x \partial b_B^2} \\ \frac{\partial \mathcal{L}}{\partial b^1 \partial b_B^2} \end{bmatrix}$$

Calculating each term separately:

$$\frac{\partial \mathcal{L}}{\partial x \partial x} = u''(c_1) + (1-q)\beta m_G \left[(f')^2 u''(c_G^2) + f'' u'(c_G^2)\right] < 0$$
$$\frac{\partial \mathcal{L}}{\partial x \partial b^1} = -u''(c_1) - q\beta R m_G f' u''(c_G^2) > 0$$
$$\frac{\partial \mathcal{L}}{\partial b^1 \partial x} = -u''(c_1) - q\beta R m_G f' u''(c_G^2) > 0$$
$$\frac{\partial \mathcal{L}}{\partial b^1 \partial b^1} = u''(c_1) + \beta R^2 \left[q u''(c_B^2) + (1-q) u''(c_G^2)\right] < 0$$
$$\frac{\partial \mathcal{L}}{\partial x \partial b_B^2} = 0$$
$$\frac{\partial \mathcal{L}}{\partial b^1 \partial b_B^2} = -q\beta R u''(c_B^2) > 0$$

Inverting the matrix

$$\begin{bmatrix} \frac{\partial x}{\partial b_B^2} \\ \frac{\partial b^1}{\partial b_B^2} \end{bmatrix} = -\frac{1}{\frac{\partial \mathcal{L}}{\partial x \partial x}\frac{\partial \mathcal{L}}{\partial b^1 \partial b^1} - \frac{\partial \mathcal{L}}{\partial x \partial b^1}\frac{\partial \mathcal{L}}{\partial b^1 \partial x}} \begin{bmatrix} \frac{\partial \mathcal{L}}{\partial b^1 \partial b^1} & -\frac{\partial \mathcal{L}}{\partial x \partial b^1} \\ -\frac{\partial \mathcal{L}}{\partial b^1 \partial x} & \frac{\partial \mathcal{L}}{\partial x \partial x} \end{bmatrix} \begin{bmatrix} \frac{\partial \mathcal{L}}{\partial x \partial b_B^2} \\ \frac{\partial \mathcal{L}}{\partial b^1 \partial b_B^2} \end{bmatrix}$$

The denominator of the fraction is the determinate of a 2x2 hessian from a maximization problem, and is therefore positive. Then, the matrices are pre-multiplied by a negative value, which we will replace with $-\frac{1}{Det}$. Multiplying out the matrices we find

$$\frac{\partial x}{\partial b_B^2} = \underbrace{-\frac{1}{Det}}_{-} \underbrace{\left[\frac{\partial \mathcal{L}}{\partial b^1 \partial b^1} \cdot 0 - \frac{\partial \mathcal{L}}{\partial x \partial b^1}\frac{\partial \mathcal{L}}{\partial b^1 \partial b_B^2}\right]}_{-} > 0$$
$$\frac{\partial b^1}{\partial b_B^2} = \underbrace{-\frac{1}{Det}}_{-} \underbrace{\left[-\frac{\partial \mathcal{L}}{\partial b^1 \partial x} \cdot 0 + \frac{\partial \mathcal{L}}{\partial x \partial x}\frac{\partial \mathcal{L}}{\partial b^1 \partial b_B^2}\right]}_{-} > 0$$

Therefore, we conclude that the choice of inputs x and first period borrowing b^1 will both increase with the offer of the Emergency Loan.

Interaction with Good Loan

This section expands on interaction of the Good Loan with the Emergency Loan, outlined in Section **??**. The constrained maximization problem changes to:

$$\max_{x, b^1, b_B^2} \; u(Y - x + b^1) + q\beta u(-Rb^1 + b_B^2) + (1-q)\beta u(m_G f(x) - Rb^1) +$$
$$q\beta^2 u(I - Rb_B^2) + (1-q)\beta^2 u(I) + \lambda_1[1.5\bar{B} - b^1] +$$
$$\lambda_2[0.5\bar{B} - b_b^2] + \lambda_3[1.5\bar{B} - b^1 - b_B^2]$$

For simplicity, I assume $\lambda_2 = 0$, which means the borrower will not be credit constrained in the bad state once the emergency loan is made available. The ex-ante input choice optimality is now determined by:

$$\frac{\partial f_G}{\partial x} = R\left[\frac{q}{1-q}\frac{u'(c_B^2)}{u'(c_G^2)} + 1\right] + \frac{\lambda_1}{\beta(1-q)u'(c_G^2)} + \frac{q}{1-q}\left[\frac{u'(c_B^2) - \beta u'(c_B^3)}{u'(c_G^2)}\right] \tag{16}$$

The first two terms are the same as we have seen in equation 2. However, the last term is new and reflects the fact any additional credit taken via the Good Loan comes at the expense of credit in the bad state via the Emergency Loan. If this cross-period constraint binds ($\lambda_3 > 0$), then $u'(c_B^2)$ and $\beta u'(c_B^3)$ will not be equalized and the numerator in the last term will be positive, which increases the RHS of the equation 14. This implies that the increase in ex-ante inputs will be lower than for a Good Loan eligible client who did not have access to the Emergency Loan.

Turning to the first period borrowing choice, the condition (assuming $\lambda_2 = 0$) is now:

$$u'(c^1) = \beta R\left[qu'(c_B^2) + (1-q)u'(c_G^2)\right] + \lambda_1 + q\beta\left[u'(c_B^2) - \beta u'(c_B^3)\right] \tag{17}$$

Again, there is an additional term reflecting the potential gap between period two and three consumption in the bad state. As before, if the combined borrowing constraint binds, ($\lambda_3 > 0$) , then the third term will be positive. This implies that the increase in first period borrowing will be lower relative to a Good Loan eligible client who does not have access to the Emergency Loan.

MFI Profits

This section expands on the decomposition of the effect of the Emergency Loan on MFI profits overviewed in Section 3.4. Rearranging equation 15, we can write:

$$\begin{aligned}
&\underbrace{q(R-1)\left[(1-F(K_E^*)(b_E^1+b_B^2) - (1-F(K_{NE}^*)(b_{NE}^1)\right]}_{A} + \\
&\underbrace{q\left[F(K_{NE}^*)b_{NE}^1 - F(K_E^*)(b_E^1+b_B^2)\right]}_{B} + \\
&\underbrace{(1-q)(R-1)(b_E^1 - b_{NE}^1)}_{C} \geq 0
\end{aligned} \tag{18}$$

Term A captures the change in profits from repayments. We know that b_E^1 is at least as large as b_{NE}^1, such that $b_E^1 + b_B^2 \geq b_{NE}^1$.[29] However, as we saw in equation 15, the effect of the

[29] This is clear for households without access to the Good Loan; however for households *with* access to the Good Loan, the situation is less clear. Because the Good Loan and Emergency Loan are the same size by design, households with a preexisting Dabi loan will either be able to take a Good Loan or the Emergency Loan, leading to the same total borrowed amount. However, treated households may optimally increase

Emergency Loan on K^* is ambiguous. Thus, it is unclear whether $(1 - F(K_E^*))$ is greater or less than $(1 - F(K_{NE}^*))$. If the offer of the Emergency Loan improves repayment rates ($\frac{\partial K^*}{\partial b_B^2} < 0$) then A is positive. However, if the offer worsens repayment rates, then the sign of A is ambiguous.

Similarly, term B captures the lost capital from defaults. We know that $b_E^1 + b_B^2 \geq b_{NE}^1$, but it is unclear whether $F(K_{NE}^*)$ is greater or less than $F(K_E^*)$. As before, the sign of B depends on what the effect of the Emergency Loan is on repayment rates (i.e. the sign and magnitude of $\frac{\partial K^*}{\partial b_B^2}$). If $\frac{\partial K^*}{\partial b_B^2}$ is positive, then this term is clearly negative and there will be larger losses from default. However, if $\frac{\partial K^*}{\partial b_B^2}$ is negative, then the overall sign of B is ambiguous.

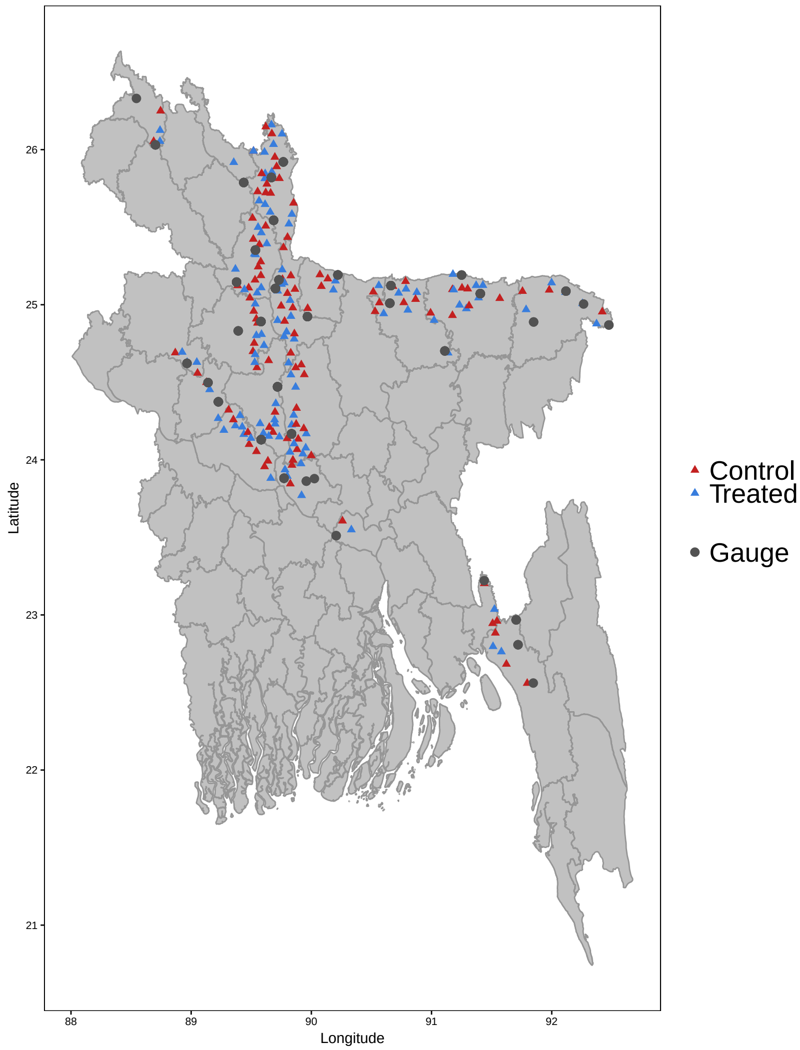
Finally, C captures profits when there is no shock. Again, this term is ambiguous. For households without access to the Good Loan in the pre-period, $b_E^1 \geq b_{NE}^1$. However, for households *with* access to the Good Loan, then b_E^1 could be less then b_{NE}^1 for clients who choose to preserve their access to the Emergency Loan. The size of these effects and the number of households that are in each situation will determine the overall sign of C. Therefore, taking all three terms into consideration, the overall change in MFI profits is ambiguous.

their Dabi loan size (this is unlikely in the first year of the program due to the timing of the pre-approval notification), in which case the borrowing amount will again be larger.

Appendix B: Tables and Figures (FOR ONLINE PUBLICATION)

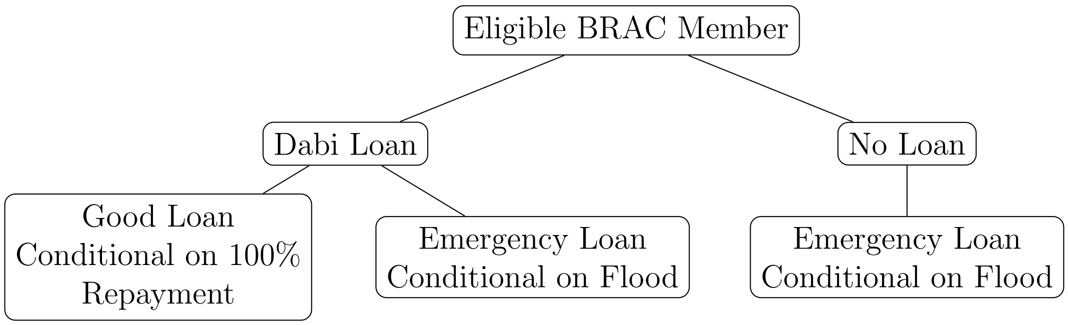
Figures

Figure B1: Map of Sample Branches



Notes: Map shows the locations of BRAC branches that participated in the experiment (triangles), their treatment status, as well as the water level gauges used to monitor flood water levels (circles). Branches were selected based on their history of flooding and proximity to a water level gauge maintained by the Bangladeshi government. The selected branches are concentrated in four main regions, including the Jamuna (Brahmaputra) basin, the Atrai river and Padma (Ganges) river basin, the Meghna river basin, and the Feni river basin.

Figure B2: Loan Choices for Eligible Members



Notes: The Figure above shows a schematic representation of the loan choices facing a BRAC microfinance member. There are three types of loans: the normal Dabi loan, the Good Loan, and the Emergency Loan. The Good Loan is only available to borrowers who have taken a Dabi Loan and have made all on-time payments through the first six months of the original loan. The offer of a Good Loan expires after two months. The Emergency Loan is only available after a flood has occurred, but it is offered whether or not the member currently has an active Dabi Loan. Members who take a Good Loan cannot also take an Emergency Loan when a flood occurs.

Figure B3: Referral Slip

brac

Referral Slip – Emergency Loan

Member Copy: Please keep

Branch Name:... Code: ☐☐☐☐ Branch contact #: ☐☐☐☐☐☐☐☐
Member Name:.. Member No: ☐☐☐☐ VO Code: ☐☐☐☐
PO Name: Sign: Branch Manager Sign:

If you have a completed form with a signature then you are guarenteed eligiblity for Emergency Loan

Loan Conditions:
- River overflow and local area flooding confirmed by BRAC

Loan Amount
- Can take up to 50% of current or last loan
- Maximum of 50,000 taka

Things to bring when getting Emergency Loan
- Referral slip
- Identification card

Ineligibility condition
- If you take a Good Loan
- Your branch area is not affected by flooding

- - - - - - - - - - - - - - - - Tear here - - - - - - - - - - - - - - - -

brac

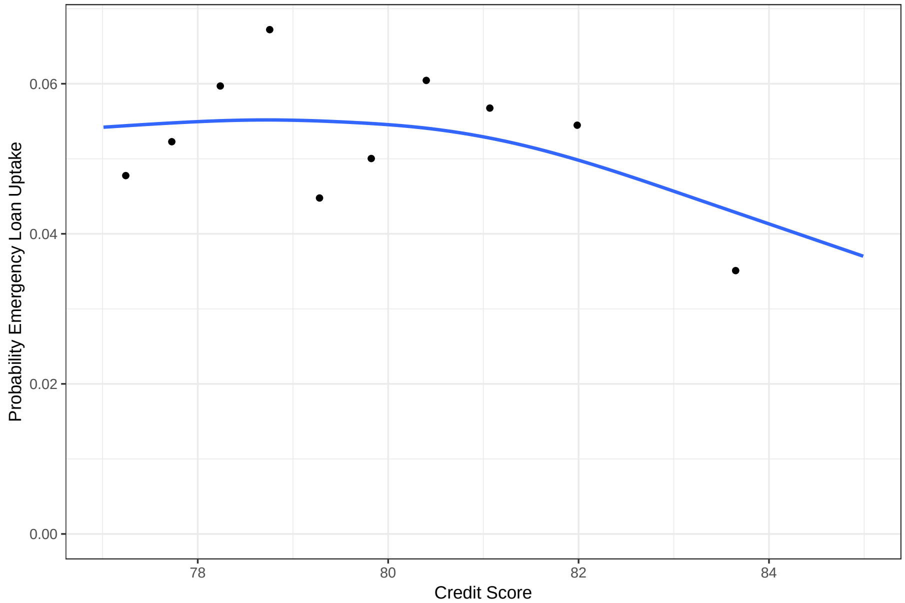
Referral Slip – Emergency Loan

Office Copy: Please keep

Branch Name:... Code: ☐☐☐☐ Member contact #: ☐☐☐☐☐☐☐☐
Member Name:.. Member No: ☐☐☐☐ VO Code: ☐☐☐☐
PO Sign: Branch Manager Sign: Accountant Sign:

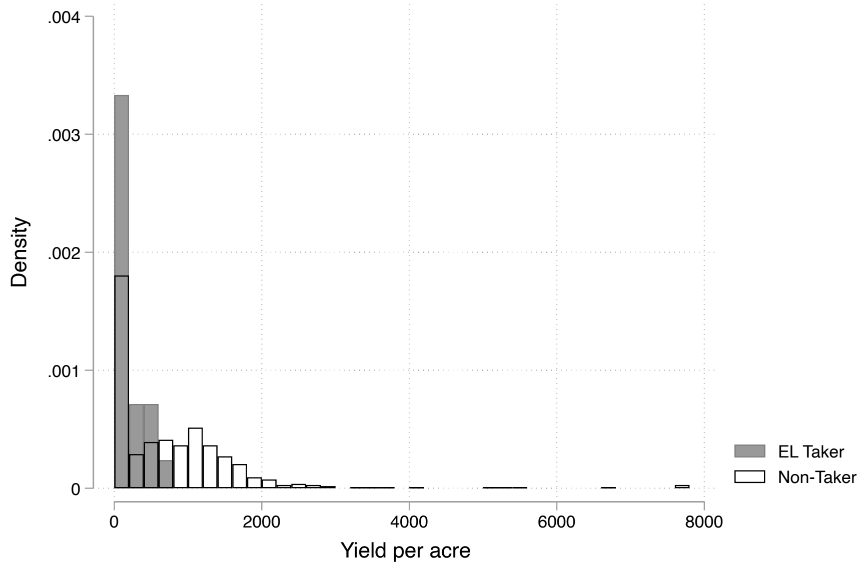
Notes: The Figure shows the referral slip (translated from Bangla) given to BRAC microfinance members eligible for the Emergency Loan. The slip records a client's name and BRAC identifiers, the maximum pre-approved loan size, as well as a brief description of the loan product. The bottom of the slip also contained the borrower's information and was kept by the branch manager to facilitate easy follow-up should a flood occur in the area.

Figure B4: Emergency Loan Uptake by Credit Score



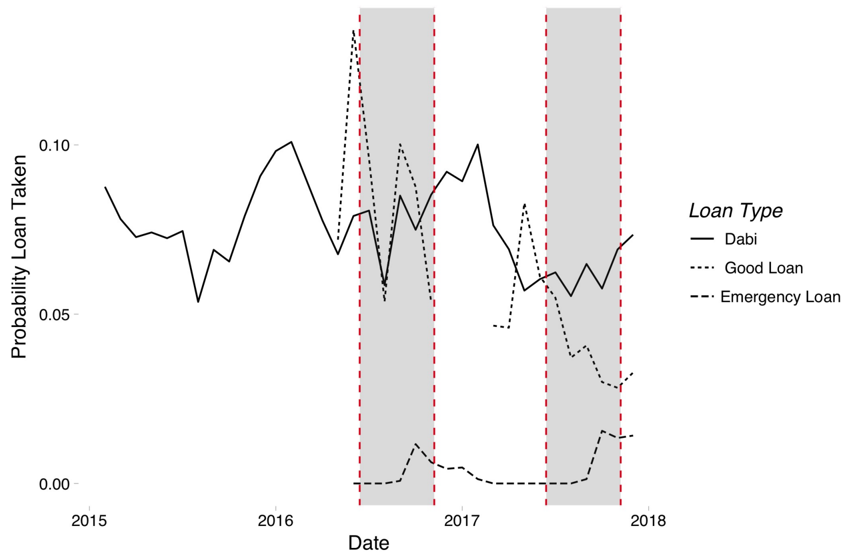
Notes: Plots the probability of Emergency Loan uptake by borrower credit score deciles. The cutoff for Emergency Loan eligibility is a score of 77. Sample pools data from both 2016 and 2017 and is limited to respondents who were Emergency Loan eligible and located in flooded branches.

Figure B5: Yield Per Acre by Emergency Loan Uptake



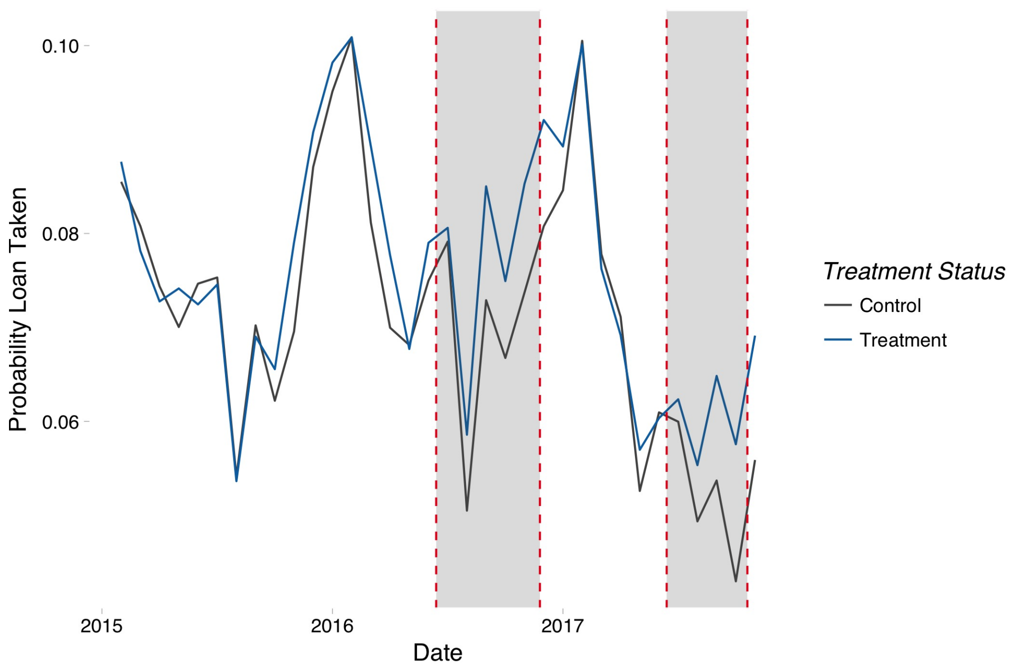
Notes: Histogram of the yield per acre for Emergency Loan takers and non-takers separately. Sample pools data from both 2016 and 2017 and is limited to respondents who were Emergency Loan eligible and located in flooded branches.

Figure B6: BRAC Loans



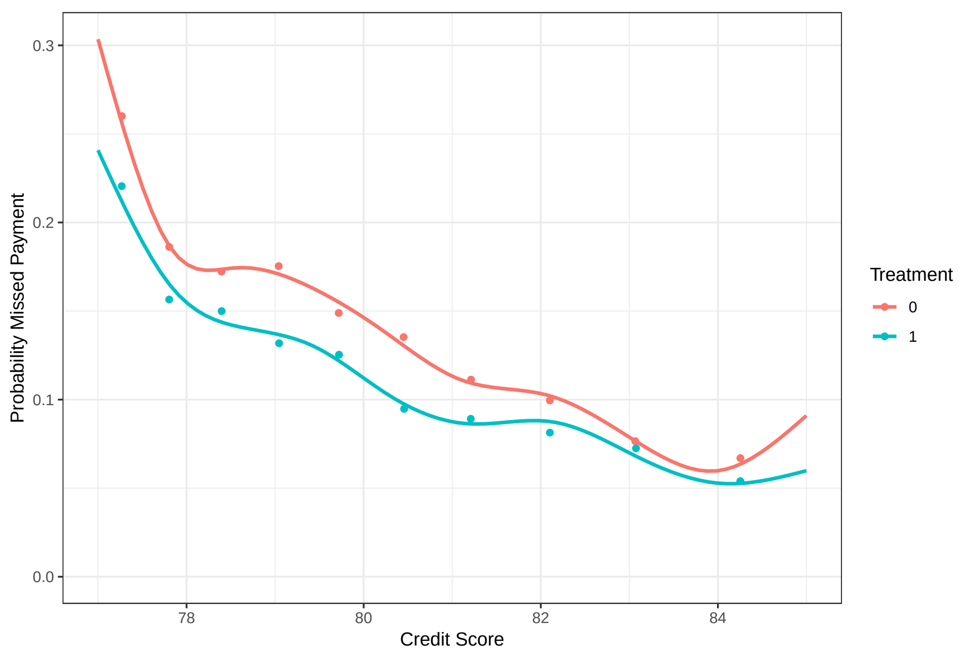
Notes: Figure shows the uptake of the three different BRAC loan products examined in the experiment. The solid line shows Dabi loan uptake as a proportion of overall branch membership. The Short-dashed line shows Good Loan uptake as a proportion of Good Loan eligible clients. The long-dashed line shows Emergency Loan uptake as a proportion of eligible clients. The shaded regions show the Aman cropping season. The Good Loan eligibility data set is not usually recorded by BRAC, therefore there is a gap in this data between the 2016 and 2017 Aman seasons when this data was not recorded because of uncertainty about the continuation of the experiment.

Figure B7: Dabi Loan Uptake Over Time



Notes: Plots the probability that an Emergency Loan eligible BRAC member takes a dabi loan in a given month in treatment and control branches separately. Probability of loan uptake is calculated using the complete number of BRAC members in each branch, regardless of whether or not they have a current dabi loan. This is to ensure that the denominator does not endogenously change based on pervious loan uptake decisions. The shaded regions are the "pre-period" before the beginning of the flood season in 2016 and 2017.

Figure B8: Missed Payment Heterogeneity



Notes: Plots the probability of a missed payment by decile of borrower credit score separately for treatment and control branches. The sample is comprised of only Emergency Loan eligible borrowers.

Tables

Table B1: Research Timeline

Oct 2015 - Jan 2016	Development of product.
Feb 2016	200 experimental branches selected.
Apr 2016	Baseline survey of 4,000 households; Year one credit scores created; Clients informed about eligibility.
Jun - Oct 2016	Flood monitoring and Emergency Loans made available as necessary.
Dec 2016	Follow-up survey of 4,000 households.
Apr 2017	Year two credit scores created; Clients informed about eligibility.
Jun - Oct 2017	Flood monitoring and Emergency Loans made available as necessary.
Dec 2017	Endline survey of 4,000 households.

Table B2: Balance Table

	(1) Control	(2) Treatment	(3) p-value of equality test
Household Size	4.867	4.874	0.910
	(0.047)	(0.046)	
Age Head of Household	40.883	40.374	0.339
	(0.371)	(0.381)	
Educ. Head of Household	2.542	2.464	0.564
	(0.095)	(0.095)	
Acres of Land Owned	0.394	0.436	0.202
	(0.021)	(0.025)	
Household Income	1594.585	1537.005	0.244
	(34.486)	(35.453)	
Weekly Expenditure	21.989	22.191	0.779
	(0.485)	(0.531)	
Flooded in Past Five Years	0.527	0.548	0.250
	(0.013)	(0.013)	
Electricity Access	0.707	0.724	0.326
	(0.012)	(0.012)	
Asset Count	1.724	1.658	0.076
	(0.026)	(0.027)	
Cows Owned	0.887	0.922	0.497
	(0.035)	(0.039)	
Risk Aversion	0.509	0.511	0.905
	(0.010)	(0.010)	

Notes: Table compares households in treatment and control branches at baseline conducted in April 2016 before treatment status was revealed. Asset count is the number of items a household reported owning of a gas or electric stove, radio, television, refrigerator, bicycle, and motorcycle. Risk aversion was measured by asking households to choose between a certain payoff and a lottery with increasing odds. The variable is a continuous measure but has been rescaled so that it ranges from 0 to 1, where 0=most risk loving and 1=most risk averse.

Table B3: Eligible Compared to Ineligible

	(1) Ineligible	(2) Eligible	(3) p-value of equality
Household Size	4.788	4.893	0.010
	(0.030)	(0.027)	
Age Head of Household	39.831	40.763	0.004
	(0.246)	(0.208)	
Educ. Head of Household	2.772	2.497	0.001
	(0.069)	(0.053)	
Acres of Land Owned	0.461	0.454	0.868
	(0.021)	(0.032)	
Household Income	1627.133	1560.817	0.042
	(26.429)	(20.100)	
Weekly Expenditure	22.256	22.330	0.873
	(0.344)	(0.305)	
Flooded in Past	0.537	0.543	0.598
	(0.009)	(0.007)	
Electricity Access	0.706	0.717	0.265
	(0.008)	(0.007)	
Asset Count	1.659	1.678	0.418
	(0.018)	(0.015)	
Cows Owned	0.741	0.916	0.000
	(0.023)	(0.021)	
Risk Aversion	0.499	0.513	0.147
	(0.007)	(0.006)	

Notes: Table compares households that were eligible for the Emergency Loan to those who were ineligible in both treatment and control branches at baseline in April 2016. Asset count is the number of items a household reported owning of a gas or electric stove, radio, television, refrigerator, bicycle, and motorcycle. Risk aversion was measured by asking households to choose between a certain payoff and a lottery with increasing odds. Risk aversion is a continuous measure but has been rescaled so that it ranges from 0 to 1, where 0=most risk loving and 1=most risk averse.

Table B4: Flood Summary

	Flooded 2016	
Treatment	No	Yes
No	60	40
Yes	49	51

	Flooded 2017	
Treatment	No	Yes
No	27	73
Yes	37	63

Table B5: Ex-Ante Land by Risk Aversion

	(1) Own land	(2) Rented land	(3) Sharecrop land	(4) Total land	(5) Any Cult.
Treatment	-0.014	0.035	-0.007	0.007	0.037
	(0.021)	(0.025)	(0.006)	(0.036)	(0.031)
Risk Aversion X	0.020	0.061*	0.006	0.097**	0.013
Treatment	(0.031)	(0.036)	(0.009)	(0.049)	(0.041)
Risk Aversion	0.182**	-0.003	-0.008	0.163*	0.075
	(0.071)	(0.053)	(0.011)	(0.089)	(0.078)
Controls	Yes	Yes	Yes	Yes	Yes
Controls X Risk Aversion	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
Mean Dep. Var	0.13	0.20	0.02	0.36	0.47
Observations	4479	4475	4478	4474	4480
p-value Treat + Risk X Treat	0.756	0.000	0.830	0.004	0.131

Notes: Sample includes only eligible BRAC members from both treatment and control groups. Data is pooled from both the 2016 and 2017 Aman season. Controls are included for precision, and are comprised of baseline measures of total land owned, household size, and the age and education of the head of household. Standard errors clustered at branch level. Land is measured in acres. Total land is the sum of own land, rented land, and sharecropped land. Any Cult. is an indicator for whether or not a household planted any crops during the season. Risk aversion is a continuous measure but has been rescaled so that it ranges from 0 to 1, where 0=most risk loving and 1=most risk averse.

Table B6: Ex-Ante Inputs by Risk Aversion

	(1) Fert. Applied	(2) Pest. Applied	(3) Cost Seeds per acre	(4) Input Cost per Acre	(5) Non-Ag Invest
Treatment	6.44	0.05	1.12	1.68	3.44
	(7.80)	(0.30)	(1.24)	(3.77)	(11.77)
Risk Aversion X	1.64	0.41	-1.34	0.65	16.06
Treatment	(13.18)	(0.43)	(1.78)	(5.41)	(16.62)
Risk Aversion	2.31	-0.96	-4.95	-17.61*	17.31
	(23.93)	(0.79)	(3.65)	(10.18)	(32.25)
Controls	Yes	Yes	Yes	Yes	Yes
Controls X Risk Aversion	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
Mean Dep. Var	138.71	1.53	16.08	65.50	33.08
Observations	2089	2048	1971	1932	4480
p-value Treat + Risk X Treat	0.358	0.060	0.833	0.463	0.028

Notes: Sample includes only eligible BRAC members from both treatment and control groups. Data is pooled from both the 2016 and 2017 Aman season. Controls are included for precision, and are comprised of baseline measures of total land owned, household size, and the age and education of the head of household. Standard errors clustered at branch level. Fertilizer and pesticide are measured in kg / L per acre. Input cost per acre is the sum of the cost of fertilizer, pesticide, and seeds. Cost and investment measured in dollars. Risk aversion is a continuous measure but has been rescaled so that it ranges from 0 to 1, where 0=most risk loving and 1=most risk averse.

Table B7: Investment After Shock

	(1) Fert. Applied	(2) Pest. Applied	(3) Total land	(4) Any Cult.	(5) Non-Ag Invest
Treatment	6.689	0.323*	0.055**	0.035	12.559*
	(5.795)	(0.192)	(0.028)	(0.025)	(6.397)
Flood Last Year X Treat	0.053	-0.339	0.021	0.063	0.358
	(23.333)	(0.556)	(0.044)	(0.046)	(24.457)
Flood Last Year	-4.615	-0.383	-0.033	-0.099**	-21.348
	(20.213)	(0.488)	(0.042)	(0.045)	(23.778)
Controls	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
Mean Dep. Var	140.47	1.58	0.35	0.46	38.69
Observations	2183	2140	4739	4745	4745
p-value Treat + Interaction	0.757	0.974	0.069	0.029	0.591

Notes: Sample includes only eligible BRAC members from both treatment and control groups. Data is pooled from both the 2016 and 2017 Aman season. Controls are included for precision, and are comprised of baseline measures of total land owned, household size, and the age and education of the head of household. Standard errors clustered at the branch level. Fertilizer and pesticide measured in kg/L per acre. Total land is the sum of own land, rented land, and sharecropped land. Any Cult. is an indicator for whether or not a household planted any crops during the season. Investment is measured in dollars.

Table B8: Ex-post After Successive Shocks

	(1) Log Cons PerCap	(2) Log Income	(3) Crop Prod. (Kg)	(4) Bus. Stock Value
Treatment	0.034	-0.016	98.494**	194.882
	(0.045)	(0.044)	(41.034)	(174.649)
Flood X Treatment	0.110	-0.011	-104.602*	82.651
	(0.067)	(0.073)	(54.886)	(241.435)
Flood Current Year	-0.053	0.050	11.414	-100.821
	(0.058)	(0.062)	(37.625)	(194.246)
Flood Both X Treat	-0.102	0.018	53.950	-341.715
	(0.095)	(0.096)	(45.056)	(218.639)
Flood Both Years	-0.204***	0.004	-0.007	443.019**
	(0.069)	(0.071)	(41.674)	(198.269)
Controls	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Week Interviewed FE	Yes	No	No	No
Mean Dep. Var	5.93	10.77	275.22	864.89
Observations	4743	4531	4745	799
p-value Sum Treatment Coef.	0.003	0.903	0.235	0.742

Notes: Sample includes only eligible BRAC members from both treatment and control groups. Data is pooled from both the 2016 and 2017 Aman season. Controls are included for precision, and are comprised of baseline measures of total land owned, household size, and the age and education of the head of household. Week interviewed fixed effects are included for the log consumption regression due to the presence of holidays over the course of the survey period that changed standard consumption patterns. Standard errors clustered at branch level. Income is measured in dollars. Flood Current Year is an indicator that equals one if flooding occurred in the current year. Flood Both Years is an indicator that captures the additional effect of successive shocks for branches that experienced flooding in 2017 and that also experienced flooding in 2016.

Eligibility Selection

In this section we examine whether selection into eligibility in 2017 matters for the results. First, we simply examine whether there was differential Emergency Loan eligibility in 2017 across treatment and control branches. We see in Table B9 shows that there is no statistically significant difference in the probability that households are Emergency Loan eligible between treatment and control branches. Ignoring statistical significance, the point estimate suggests that treatment branches were three percentage points *less* likely to be Emergency Loan eligible in 2017. This is the opposite effect as what might be expected ex-ante, that households in treatment branches improve repayment rates and are therefore more likely to become eligible. Finally, I also report ex-post outcomes without controlling for flooding.

Table B9: 2017 Eligiblity

	(1) EL Eligible
Treatment Branch	-0.030
	(0.029)
Flood Last Year	Yes
District FE	Yes
Observations	3939

Notes: Sample includes all surveyed households in 2017. The outcome variable is a binary indicator for the household being Emergency Loan eligible in 2017. Flood last year is an indicator for being flooded in 2016.

As a robustness check, I reproduce the results on household investment and ex-post outcomes with two different specifications. First, I limit the analysis to only 2016 when there are no selection concerns. Second, I instrument for eligibility using branch treatment status. With the exception of non-agriculture investment, the results are consistent with those found with the other specifications.

Table B10: Land Farmed 2016

	(1) Own land	(2) Rented land	(3) Sharecrop land	(4) Total land	(5) Any Cult.
Treatment	0.001	0.067***	-0.006	0.059*	0.034
	(0.014)	(0.020)	(0.004)	(0.030)	(0.027)
Controls	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
Mean Dep. Var	0.15	0.22	0.02	0.39	0.50
Observations	2986	2986	2986	2986	2986

Notes: Sample includes only eligible BRAC members from both treatment and control groups. Data is from only the 2016 Aman season. Controls are included for precision, and are comprised of baseline measures of total land owned, household size, and the age and education of the head of household. Standard errors clustered at the branch level. Land measured in acres. Total land is the sum of own land, rented land, and sharecropped land. Any Cult. is an indicator for whether or not a household planted any crops during the season.

Table B11: Ex-Ante Investments 2016

	(1) Fert. Applied	(2) Pest. Applied	(3) Cost Seeds per acre	(4) Input Cost per Acre	(5) Non-Ag Invest
Treatment	6.15	0.36*	1.05	1.20	1.09
	(5.62)	(0.18)	(0.89)	(2.49)	(3.35)
Controls	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
Mean Dep. Var	129.93	1.34	14.45	60.53	7.84
Observations	1479	1479	1375	1375	2986

Notes: Sample includes only eligible BRAC members from both treatment and control groups. Data is only from the 2016 Aman season. Controls are included for precision, and are comprised of baseline measures of total land owned, household size, and the age and education of the head of household. Standard errors clustered at the branch level. Fertilizer and pesticide measured in kg/L per acre. Input cost per acre is the sum of the cost of fertilizer, pesticide, and seeds. Cost and investment measured in dollars.

Table B12: IV Land Farmed

	(1) Own land	(2) Rented land	(3) Sharecrop land	(4) Total land	(5) Any Cult.
Treatment	-0.004	0.071***	-0.007*	0.057*	0.034
	(0.015)	(0.019)	(0.004)	(0.029)	(0.028)
Controls	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
Mean Dep. Var	0.13	0.18	0.02	0.33	0.44
Observations	5981	5977	5980	5976	5982

Notes: Sample includes all observations from both treatment and control groups. Treatment is instrumented using first year eligibility interacted by year. Data is pooled from both the 2016 and 2017 Aman season. Controls are included for precision, and are comprised of baseline measures of total land owned, household size, and the age and education of the head of household. Standard errors clustered at the branch level. Land measured in acres. Total land is the sum of own land, rented land, and sharecropped land. Any Cult. is an indicator for whether or not a household planted any crops during the season.

Table B13: IV Inputs

	(1) Fert. Applied	(2) Pest. Applied	(3) Input Cost per Acre	(4) Non-Ag Invest
Treatment	5.71	0.28	1.79	1.15
	(5.41)	(0.18)	(2.38)	(7.51)
Controls	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Mean Dep. Var	141.48	1.60	66.87	56.02
Observations	2638	2559	2431	5982

Notes: Sample includes all observations from both treatment and control groups. Treatment is instrumented using first year eligibility interacted by year. Data is pooled from both the 2016 and 2017 Aman season. Controls are included for precision, and are comprised of baseline measures of total land owned, household size, and the age and education of the head of household. Standard errors clustered at the branch level. Land measured in acres. Total land is the sum of own land, rented land, and sharecropped land. Any Cult. is an indicator for whether or not a household planted any crops during the season.

Table B14: Ex-Post Outcomes 2016

	(1) Log Cons PerCap	(2) Log Income	(3) Crop Prod. (Kg)	(4) Bus. Stock Value
Treatment	0.018	0.006	109.303**	76.035
	(0.048)	(0.049)	(45.874)	(203.380)
Flood X Treatment	0.139*	-0.096	-148.317**	267.265
	(0.074)	(0.077)	(66.101)	(306.489)
Flood	-0.082	0.075	-5.037	-134.170
	(0.075)	(0.076)	(52.015)	(259.976)
Controls	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Week Interviewed FE	Yes	No	No	No
Mean Dep. Var	5.86	10.73	308.88	902.89
Observations	2984	2841	2986	565
p-value Treat + Flood X Treat	0.004	0.130	0.397	0.077

Notes: Sample includes only eligible BRAC members from both treatment and control groups. Data is from only the 2016 Aman season. Controls are included for precision, and are comprised of baseline measures of total land owned, household size, and the age and education of the head of household. Week interviewed fixed effects are included for the log consumption regression due to the presence of holidays over the course of the survey period that changed standard consumption patterns. Standard errors clustered at branch level. Income is measured in dollars. Flood is an indicator that equals one if flooding occurred and the Emergency Loan was activated.

Table B15: IV Ex-Post Outcomes

	(1) Log Cons PerCap	(2) Log Income	(3) Crop Prod. (Kg)	(4) Bus. Stock Value
Treatment	0.040	-0.027	110.893**	82.903
	(0.053)	(0.053)	(46.853)	(201.650)
Flood X Treatment	0.066	0.014	-100.623*	85.788
	(0.062)	(0.065)	(51.432)	(234.244)
Flood Current Year	-0.019	0.029	-3.086	-7.445
	(0.047)	(0.049)	(31.068)	(164.267)
Controls	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Week Interviewed FE	Yes	No	No	No
Mean Dep. Var	5.94	10.78	258.54	906.66
Observations	5980	5726	5982	982
p-value Treat + Flood X Treat	0.004	0.738	0.747	0.204

Notes: Sample includes only eligible BRAC members from both treatment and control groups. Treatment is instrumented using first year eligibility interacted by year. Data is pooled from both the 2016 and 2017 Aman season. Controls are included for precision, and are comprised of baseline measures of total land owned, household size, and the age and education of the head of household. Week interviewed fixed effects are included for the log consumption regression due to the presence of holidays over the course of the survey period that changed standard consumption patterns. Standard errors clustered at branch level. Income is measured in dollars. Flood is an indicator that equals one if flooding occurred and the Emergency Loan was activated.

Spillovers

In this section I report the spillovers on the ineligible households for the main ex-ante and ex-post outcomes. In general, I find no evidence of significant spillovers onto the ineligible population.

Table B16: Spillovers: Ineligible Land Farmed

	(1) Own land	(2) Rented land	(3) Sharecrop land	(4) Total land	(5) Any Cult.
Treatment branch	0.000	-0.011	-0.005	-0.014	-0.036
	(0.015)	(0.014)	(0.003)	(0.022)	(0.022)
Controls	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
Mean Dep. Var	0.12	0.14	0.01	0.28	0.40
Observations	3193	3193	3193	3193	3193

Notes: Sample includes only ineligible BRAC members both treatment and control groups. Data is pooled from both the 2016 and 2017 Aman season. Controls are included for precision, and are comprised of baseline measures of total land owned, household size, and the age and education of the head of household. Standard errors clustered at the branch level. Land measured in acres. Total land is the sum of own land, rented land, and sharecropped land. Any Cult. is an indicator for whether or not a household planted any crops during the season.

Table B17: Spillovers: Ineligible Inputs

	(1) Fert. Applied	(2) Pest. Applied	(3) Cost Seeds per acre	(4) Input Cost per Acre	(5) Non-Ag Invest
Treatment branch	-0.69	-0.02	-0.87	1.30	-4.24
	(6.26)	(0.16)	(1.11)	(2.65)	(12.76)
Controls	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
Mean Dep. Var	140.23	1.45	18.44	68.65	71.63
Observations	1272	1209	1205	1147	3193

Notes: Sample includes only ineligible BRAC members from both treatment and control groups. Data is pooled from both the 2016 and 2017 Aman season. Controls are included for precision, and are comprised of baseline measures of total land owned, household size, and the age and education of the head of household. Standard errors clustered at the branch level. Land measured in acres. Total land is the sum of own land, rented land, and sharecropped land. Any Cult. is an indicator for whether or not a household planted any crops during the season.

Table B18: Spillovers: Ineligible Ex-Post Outcomes

	(1) Log Cons PerCap	(2) Log Income	(3) Crop Prod. (Kg)	(4) Bus. Stock Value
Treatment branch	0.078	-0.022	-3.673	-139.159
	(0.048)	(0.044)	(31.429)	(329.930)
Flood X Treatment	-0.019	-0.022	-8.746	182.137
	(0.061)	(0.063)	(39.474)	(389.154)
Flood Current Year	0.075	-0.016	-22.588	-22.386
	(0.053)	(0.057)	(33.129)	(271.576)
Controls	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Week Interviewed FE	Yes	No	No	No
Mean Dep. Var	6.01	10.82	210.12	838.80
Observations	3192	3072	3193	456
p-value Treat + Flood X Treat	0.122	0.285	0.641	0.784

Notes: Sample includes only ineligible BRAC members from both treatment and control groups. Data is pooled from both the 2016 and 2017 Aman season. Controls are included for precision, and are comprised of baseline measures of total land owned, household size, and the age and education of the head of household. Week interviewed fixed effects are included for the log consumption regression due to the presence of holidays over the course of the survey period that changed standard consumption patterns. Standard errors clustered at branch level. Income is measured in dollars. Flood is an indicator that equals one if flooding occurred and the Emergency Loan was activated.