Credit Lines as Insurance: Evidence from Bangladesh

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Abstract

Theory suggests that households without insurance can use credit to protect against adverse income shocks. However, concerns about default risk often prevent institutions from lending to people affected by negative shocks. I show that a loan product guaranteeing credit to agricultural households who experience a flood increases their welfare through two channels: an ex-ante insurance effect, whereby households increase investments in risky production; and an ex-post effect, whereby households use the loan to invest in productive assets. Repayment is high and the loan is profitable for the lender — showing that high default does not limit the product's commercial viability.

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1 Introduction

Households facing high levels of income variability stand to benefit from financial tools that help smooth their income over time. Insurance is one such product. Yet, traditional insurance markets in many parts of the world are often absent or incomplete, and alternative insurance models such as index insurance have been hampered by low demand (Jensen and Barrett, 2017; Cole and Xiong, 2017). Theory suggests that a realistic alternative to insurance is to provide households with a credit line that they can access when hit by a shock and thus when the marginal utility of additional consumption is high. While credit and savings models have long highlighted the precautionary value of credit access (Deaton, 1991, 1992), there is little empirical evidence that shows whether households can use credit in this way. This is primarily because many credit providers make it difficult for households who have suffered an income shock to take a loan. Providers typically conduct a financial evaluation of households when they apply for a loan, precisely when post-shock households will appear to have the highest default risk. This effectively creates a positive correlation between current income and households' access to credit, which limits credit's utility as a buffer against risk, as well microcredit's value overall (Demont, 2014; Fulford, 2015; Labie, Laureti, and Szafarz, 2017; McCulloch et al., 2016). This problem is not easily overcome because a lender's desire to minimize default risk may conflict with the provision of financial tools that maximize borrower welfare.[1]

This paper uses a large-scale randomized control trial to investigate the impact of a new financial product that guarantees credit to households affected by a shock – effectively breaking the link between current income and credit access. I partner with Bangladesh's largest microfinance institution (MFI), BRAC, to develop the product and make it available to over 300,000 microfinance clients across Bangladesh. BRAC clients are pre-approved for this Emergency Loan in the pre-planting season, and can take the loan should a verifiable flood occur in their area. This product is particularly appealing in a low-income country such as Bangladesh because most households rely on agriculture and small business profits, which are highly susceptible to harvest failures. Moreover, the consequences of this income risk are particularly severe. Poor households have access to a limited set of risk coping and risk mitigation strategies, many of which can leave them worse off in the long run (Dercon, 2002).[2]

BRAC has a longstanding presence across Bangladesh, and I work with the institution to randomize the availability of the Emergency Loan across 200 rural microfinance branches located in flood-prone areas. We contacted clients in 100 treatment branches one month before planting (the pre-period), to inform them that they had been pre-approved to take the Emergency Loan

[1] In developing countries, microfinance institutions do lend to relatively poor households. However due to the need to remain sustainable, MFIs still take into account current income when making lending decisions.

[2] Poor households have a limited set of risk coping and mitigation strategies, many of which leave them worse off in the long run. Many households adopt low-risk production technologies and under-invest in inputs, which negatively affects their future returns (Donovan, 2016). Some households are also forced to implement negative coping strategies such as lowering food consumption, selling productive assets, and reducing health and educational investments (Hoddinott, 2006; Janzen and Carter, 2018).

should a flood occur in their area (the post period). Control branches continued their normal microfinance operations. Loans were then extended to eligible treatment households who requested them, provided a validated flood occurred.

The experiment documents four primary results. First, I find that households value access to guaranteed credit and respond as theory would predict. I document this result using a BRAC rule that required households to choose between a more established loan in the pre-period, or the Emergency Loan in the post-period. I find that some households are willing to forgo credit in the pre-period in order to preserve access to the state-contingent Emergency Loan, suggesting that at least a subset of clients value the precautionary benefits of credit access. Estimates suggest that households value credit access after a shock approximately 1.8 more times than credit access in the pre-period.

Second, I find that households respond to the notification that they were pre-approved for credit in the event of a flood by significantly increasing their risky investments. Treated households increase the amount of land dedicated to agricultural cultivation by 15%, and there is suggestive evidence that non-agricultural business investments increase as well. Both of these effects are concentrated among the most risk-averse households. This suggests that households recognize that guaranteed liquidity access reduces their exposure to flood risk, and respond by increasing their investment in riskier, and potentially more profitable, investments.

Third, I document that emergency credit, unlike many other microcredit products, improves household welfare. In the absence of a flood, households' larger ex-ante investments translate into higher revenues. When flooding does occur, households are better able to maintain consumption and asset levels. Furthermore, we find that households who suffered the greatest losses from the flood, are the most likely to activate this option for additional liquidity. This suggests that the largest gains associated with guaranteed credit are concentrated among those who need it the most.

Finally, I find that extending guaranteed credit to clients in the aftermath of shocks does not harm (and marginally improves) overall MFI performance. Borrowers with access to the Emergency Loan improve their repayment rates after a flood shock, thereby improving their overall repayment rates. The evidence suggests that branch profits increase, with the largest increases in profits coming from "marginal" clients. This result is encouraging for MFIs that have traditionally withheld credit in the aftermath of aggregate shocks. It suggests that there need not be a tension between borrower welfare and lender incentives. Nevertheless, it is worth highlighting that these results may not generalize to contexts where repayments rates are already low.

The provision of guaranteed credit lines combines aspects of traditional microcredit and insurance products, both of which have been extensively studied in developing countries. The provision of traditional (loss-indemnity) insurance is almost completely absent among low-income households due to high administrative costs, adverse selection, and moral hazard (Jensen and Barrett, 2017). In recent years, index insurance has been promoted as a viable alternative. 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 by inducing more investment in agricultural production and reducing the sale of assets after shocks (Karlan et al., 2014; Janzen and Carter, 2018). Despite these benefits, demand for index insurance remains very low across many developing countries when offered without heavy subsidies (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 to pay out when the time comes (Cole et al., 2013; Clarke, 2016). In recent work, Serfilippi, Carter, and Guirkinger (2018) show that preferences for certainty also drive down demand for insurance contracts because premiums are always paid but payouts are uncertain. 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; specifically, this can take the form of a monopsony buyer that can credibly (and cheaply) collect payments from farmers after the fact, as in Casaburi and Willis (2018), or by tying insurance payments to credit contracts, as in McIntosh, Sarris, and Papadopoulos (2013).

This research demonstrates that emergency credit can function as a viable alternative to insurance products while offering several key advantages. Specifically, the Emergency Loan overcomes the challenges associated with the timing of insurance payments while maintaining many of the positive features associated with index insurance. 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 (or make any binding decisions) during the planting season. Providing coverage under a guaranteed credit scheme simply requires notifying households that they are eligible for the product. As long as a household understands the offer, and trusts that it will be executed if needed, the household is "treated." This feature ensures that credit-constrained or present-biased households that stand to benefit from the product will not be deterred from adopting it. As a result, guaranteed credit lines have the ability to provide coverage to a large number of households that might not otherwise choose to purchase insurance. Critically, households can benefit from the security of the credit line even if they choose *not* to take a loan after a shock. This arises because the decision to take credit is postponed until after uncertainty from the planting season has resolved. This means households can opt in or out depending on realized damages from the shock, and any alternative coping strategies that may be available. My experiment shows that many households increase their ex-ante investment, suggesting a reduction in perceived risk, even though many choose to not opt for the Emergency Loan ex-post.

It is important to note that there are some limitations associated with using guaranteed credit as a risk management tool, and it may not be suitable in some settings. First, the usefulness of credit for income smoothing can depend on the sequence of shocks. If a household experiences multiple successive shocks under a guaranteed credit scheme, they may accumulate excess debt or exhaust their available credit line. As a result this product may not be useful in locations where shocks are serially correlated. Second, extending credit to households after a shock is inherently risky for MFIs, and providing guaranteed credit may not be sustainable if repayment rates are poor. It follows that before adopting a product like the Emergency Loan, an MFI should be sufficiently established and focus on regions where repayment rates are not excessively low.

This research also contributes to the large literature on microcredit. Developed in Bangladesh in the 1970s, microcredit institutions have rapidly expanded, reaching over 137 million households worldwide (Maes and Reed, 2011). Despite this extensive growth and enthusiasm, the literature suggests microcredit has modest impacts at best on households' well-being (Karlan and Zinman, 2011; Angelucci, Karlan, and Zinman, 2015; Banerjee et al., 2015; Banerjee, Karlan, and Zinman, 2015). This may be partly attributable to 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 repayment schedules and are tied to group lending – features that were introduced early on to overcome moral hazard and adverse selection (Karlan, 2014). One line of research has focused on easing these constraints by matching repayment schedules to borrowers' cash flows. Field and Pande (2010) and Field et al. (2013) show that reducing payment frequency and delaying the start of repayment installments reduces borrower transaction costs and encourages greater investments and profits. Similarly, Beaman et al. (2014) study agricultural loans that allow repayments to come in a lump sum after harvest and find higher investments in the planting season. Finally Barboni (2017) shows that more productive borrowers opt into flexible repayment contracts even when they are more expensive. This paper illustrates another important limitation with micro-finance models, which is the inherent positive correlation between credit and income. The Emergency loan breaks this correlation and encourages households to invest in risky endeavors, which can lead to important improvements in outcomes.

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 due to adverse selection and moral hazard concerns. In contrast, Barboni (2017) uses theory and lab-in-the-field experiments to show that offering flexible repayment schedules could increase profits for lenders. An advantage of our relatively large experiment is that it allows for an *empirical* examination of the effects of this new product on overall MFI profitability, which is difficult in settings where risk-averse MFIs are hesitant to experiment (Karlan and Zinman, 2018). A priori, MFIs may be hesitant to offer welfare improving guaranteed credit lines to households if they are concerned about default risk. However, I find that MFI's derive positive profits, with the largest returns coming for borrowers with credit scores right above the loan eligibility threshold. This shows that lenders and borrowers can both benefit from guaranteed credit, 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 context of the experiment and 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 and section 5 describes the data used in the analysis. Finally, section 6 presents the results of the experiment and section 7 concludes.

2 Context and Product Description

Bangladesh and Income risk

This project takes place in Bangladesh, a country with over 165 million people that is covered by the Bengal delta (a confluence of the Ganges, the Brahmaputra and the Megna rivers). Approximately 70 percent of Bangladesh's population lives in rural areas and more than 80 percent of rural households rely on agriculture for some part of their income (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). Recent projections estimate that flood areas could increase by as much as 29% in Bangladesh (World Bank, 2016). Therefore, the experiment focuses on flood risk over other shocks, and the randomized control trial was conducted in areas bordering the major rivers, where productive investments are frequently exposed to flooding.[3]

BRAC Microcredit

BRAC operates over 2000 branches throughout the country, where each branch serves 20 to 60 village organizations (VO's). These organizations are designed to facilitate coordinated activities between borrowers at the village level. Loan officerts visit these organizations weekly to collect scheduled loan repayments from active borrowers, and answers inquiries about new loans.

BRAC's most common loan is called the *Dabi* loan. It targets poor households and is only issued to women.[4] 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 for most other BRAC loans, and are discouraged from taking any additional loans from other microfinance institutions or local money lenders. There is, however, 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". 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.

[3]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 flooding risk in these areas, as physical businesses assets may be lost or damaged and demand may fall after a local shock.

[4]Nevertheless, it is common for these loans to be used for broader household investments such as agriculture or a business that is run by the official borrower's husband.

Product Description

I worked with BRAC to create the Emergency Loan, a product designed to help borrowers exposed to floods while limiting BRAC's exposure to risky loans. Clients were eligible to access the Emergency Loan provided they had a credit score above a fixed threshold. We created a credit score specifically for this product, which was based on each borrower's past repayment behavior.[5] The threshold was set so that approximately 40% of borrowers were eligible at any given branch (77 out of a maximum score of 100). Targeting based on credit score does not select richer households over poorer ones. Table B3 examines differences in observable characteristics between eligible and ineligible borrowers. The two groups look fairly similar, but differ along a few dimensions. Eligible borrowers have slightly less annual income, they are a few years older, have fewer years of education, and own more livestock and savings.

We assessed each client's eligibility in April, just before the Aman planting season and several months before the flooding season.[6] Borrowers could retain their eligibility for the duration of the Aman cropping season regardless of their repayment behavior during that time. Eligible clients were guaranteed to be able to borrow up to 50% of the total principal amount of their last regularly approved loan. For example, an eligible borrower who took a 10,000 taka loan ($125) in May from BRAC 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. Emergency Loans were then made available to eligible clients who requested them if flooding occurred. 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.[7] Second, a non-microfinance BRAC employee had to confirm that at least 20% of the branch service area had experienced flooding.

While the Emergency Loan is identical to the Good Loan in the amount disbursed, the interest rate, and the repayment period, it differs in two ways. First, it is offered 6-8 months into the normal Dabi Loan cycle rather than after a flood. Second, Good Loans must be requested from branch managers who can deny the request, while the Emergency Loan is guaranteed to borrowers

[5]The score was created from four metrics: 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. 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 due to the desire to make the credit score transparent, and easily adjustable in the future.

[6]The eligibility list were given to branch managers who could veto up to 10% of the names on the list based on their private knowledge of a borrower's credit worthiness. Branch managers in the control group performed this same veto process for a future identical product rather than the emergency loan itself. The final lists were then shared with headquarters for verification. These steps were put in place to minimize the risk that BRAC extended loans to borrowers that might fail to repay the loan. For the purposes of the experimental results, I do not consider Branch Manager vetos and include all clients who were determined to be eligible based on the credit score alone.

[7]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.

based on their credit score. Historical data confirms that Good Loans were much less likely to be disbursed in the aftermath of aggregate income shocks.

Clients in the sample could be *eligible* for the Good Loan or the Emergency Loan, both, or neither. However, we informed borrowers that they could not hold a Good Loan *and* an Emergency Loan – 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.[8] Clients who were *eligible* for the Emergency Loan and the Good Loan then faced a tradeoff: they could take the Good Loan before the flood season occurred and forgo the option of accessing additional liquidity in the event of a flood; or they could preserve their credit access as a buffer against future flood risk. Clients who had access to the Good Loan but not the Emergency Loan did not face this tradeoff.

3 Theory

3.1 Framework For Effect of Guaranteed Credit

This section provides a simple theoretical framework in which MFI clients make decisions across three periods. In the first period (pre-planting season), clients are informed about their eligibility for the Emergency Loan, and must decide how many inputs to invest (e.g. land to cultivate, inputs to use, business investments), and how much to borrow. 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 existing loans. Finally, in the third period (post-harvest) borrowers must choose whether to repay any loans they took during the floods. Decisions across the 3 periods are summarized below:

First Period Decisions

1. *Productive Investments:* Households decide how much to invest in production, whether in agricultural land and inputs, or in other business investment.
2. *Dabi Loan Uptake:* Each member will decide whether and how much they wish to borrow before the start of the season.
3. *Good Loan Uptake:* For members who are eligible to take a Good Loan, they will decide whether or not to take this additional credit to invest for the pre-planting season.

Second Period Decisions

1. *Emergency Loan Uptake:* In the event of a flood, borrowers will decide whether to take an Emergency Loan.

[8] Of the 350,000 individuals in the data, approximately 165,000 (47%) were eligible for a Good Loan at some point during the experiment. Of these, 66,000 (40%) were also eligible for the Emergency Loan.

2. *First Period Loan Repayment:* Once borrowers choose whether or not to take the Emergency Loan, they will need to decide how (or whether) to repay the loans they have.

Third Period Decisions

1. *Second Period Repayment:* Borrowers choose whether to repay the Emergency Loan if they took one in the second period.

Below, I present a simple framework for understanding how the extension of guaranteed credit could impact each of these decisions in turn.

3.2 Baseline Model

The model has three periods $t = (1, 2, 3)$ that correspond to planting, harvest, and post-harvest periods respectively.[9] 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.[10] 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:

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

[9] Based on a model from Karlan and Udry (2015)

[10] For simplicity, I do not allow savings from period two to three – this assumption does not change the core results.

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

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. $m_B = 0$.[11]

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 for the performance of the lending MFI.

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 con-

[11] 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.

straints), 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:

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

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.[12] Rearranging, I can define K^*:

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

where K^* is the cost of lost access to microfinance that would make a household indifferent between repayment and default.[13] 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^2_B).

3.3.1 No Default

With no default the household's problem is now:

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

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

[12]

$$M = \underbrace{\left[u(c^1_d) - u(c^1_r)\right]}_{First\ Period} + \underbrace{\left[(1-q)\beta u\left(m_G f(x_d) - Rb^1_d\right) - (1-q)\beta u\left(m_G f(x_r) - Rb^1_r\right)\right]}_{Second\ Period\ Good\ State}$$

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 $b^1_d > b^1_r$, the utility received when a client defaults is higher than the repayment utility. Therefore $M > 0$.

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

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.[14] Turning to borrowing decisions, the optimal choice is defined by:

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

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 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.

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

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 Interaction with the Good Loan

I now consider the situation faced by clients who have access to the Good Borrower loan. Without access to the Emergency Loan, these households solve the same baseline model as in 3.2, but their first period borrowing constraint is $1.5\bar{B}_1$. However, with the introduction of the Emergency Loan, which is mutually exclusive with the Good Loan, the problem facing these households changes. The borrowing constraints facing a household in this situation are:

$$\begin{aligned} b^1 &\leq 1.5\bar{B}\ , \\ b_B^2 &\leq 0.5\bar{B} \\ b^1 + b_B^2 &\leq 1.5\bar{B}\ , \end{aligned}$$

Any borrowing above $\bar{B}$ in the first period (i.e. using the Good Loan) comes at the expense of available liquidity after a shock. This set of clients must now decide whether they should preserve their credit line for a time of need, which means forgoing current period investment. This extra cost to pre-period credit implies the availability of the Emergency Loan will *reduce* the optimal amount of credit and inputs used in the first period among Good Loan eligible clients. This will encourage households who expect to be credit constrained in the bad state to forgo the Good Loan.[15]

[15] More details on the interaction with the Good Loan are detailed in Appendix A.

- Prediction 5: The offer of the Emergency Loan will *reduce* first period investment and borrowing for Good Loan eligible clients.
- Prediction 6: The offer of the Emergency Loan will *reduce* the probability that eligible clients take the Good Loan if they expect to be credit constrained in the bad state.

3.5 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 $(b^1 + b^2_B)$.[16] The MFI will want to offer the Emergency Loan if $\Pi_E \geq \Pi_{NE}$, where E and NE stand for Emergency Loan and No Emergency Loan respectively. This is given by:

$$\begin{aligned} &q\left[(1-F(K^*_E))(R-1)(b^1_E + b^2_B) - F(K^*_E)(b^1_E + b^2_B)\right] + (1-q)(R-1)b^1_E \\ \geq &q\left[(1-F(K^*_{NE}))(R-1)(b^1_{NE}) - F(K^*_E)(b^1_E)\right] + (1-q)(R-1)b^1_{NE} \end{aligned} \tag{15}$$

Where K^*_E, K^*_{NE} and b^1_E, b^1_{NE} 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

I measure the impact of the Emergency Loan using a randomized control trial with a sample of 200 BRAC branches. These 200 branches were randomly selected from a group of branches 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

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

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. Appendix Figure B1 shows a map of the selected branches, their treatment status, and the matched water level gauges. 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. 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 observables.

The experiment began in April 2016 when the Emergency Loan eligibility lists were created across the 200 experimental branches. BRAC created referral slips (see Figure B3) for each eligible borrower in the treatment branches and distributed them at VO meetings in April. Each slip contained the borrower's name, BRAC identification numbers, and details of the Emergency Loan they were eligible to take – including the amount they had been pre-approved to borrow, the conditions when the loan would be made available, and the fact that they would lose their eligibility status should they take a Good Loan. Borrowers kept the top half of the slip to serve as "proof" of their eligibility status, and to remember the details of the loan.[17]

During the Aman season, 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."[18] The branch manager received instructions from headquarters to notify all eligible borrowers that Emergency Loans were available. Borrowers were notified through their normally scheduled VO meetings or by calling clients directly.[19]

Over the course of the 2016 Aman season, 92 branches were activated: 40 control and 51 treatment.[20] 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 officer's description of the product. 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

[17]BRAC distributed the referral slips throughout the month of April during the normal VO meetings for each branch. The loan officer read a script that explained the purpose and the key features of the product. Pre-approval was emphasized repeatedly because this concept was new to borrowers. Loan officers asked borrowers questions about the Emergency Loan to validate their understanding, and time was allocated to answering any questions that eligible clients had about the product. Random branch visits were conducted in June, and confirmed relatively good execution of the pre-approval notifications.During random spot checks almost all borrowers had received the referral slips and understood that the Emergency Loan was available in the event of a flood.

[18]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.

[19]Eligible clients were reminded about the Emergency Loan's availability at every subsequent VO meeting until the expiration of the offer in November.

[20]The difference is not statistically significant.

and physical structures.

5 Data

I rely on data from two primary sources. First, I use BRAC's administrative loans and savings records for all clients in the experimental branches. This dataset contains borrower's decisions to take loans, loan repayments and savings activities. Detailed repayment and savings data are available from April 2016 until January 2018, while loan disbursal data extends back for 1-4 years depending on the branch. Within the loans data set, we observe approximately 300,000 unique individuals and 1.3 million unique loans. Eligibility for the Good Loan, which was not included in this data set, was compiled separately by BRAC for the purposes of this research.

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 (VOs) at random from each branch. I then randomly selected fifteen eligible borrowers and five ineligible borrowers from these VOs.[21] 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 good, 99% in the first follow-up and 98.9% in the second follow-up.[22]

6 Results

Emergency Loan Take Up

I first examine households' decision to take the Emergency Loan after a flood shock. Uptake of the Emergency Loan among eligible households was relatively low in both years. 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%. It is important to note that low take-up rates do not imply that households did not value or benefit from the Emergency loan's availability. While I address this point in more detail below, it is important to highlight that households can respond to the offer of a loan before flooding has even occurred. We will see that the Emergency Loan stimulates higher investments and greater output, suggesting it offers important protection in the pre-period against shocks. Furthermore, low ex-post uptake of this product is not entirely unexpected because flood damage is highly idiosyncratic within a branch service area, such that certain villages may be dramatically affected while other villages within the same branch will not be hit at all.

[21] Tables B20 to B22 in the appendix reports 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.

[22] Survey rates were helped tremendously by BRAC's network, which enabled easy tracking of households that relocated within and between communities.

Table 1 reports which household characteristics correlate with higher take-up rates among the set of households that were offered the Emergency Loan (i.e. those that were in a treatment branch after a flood). Column 1 focuses on baseline characteristics and shows that households that took the Emergency Loan are quite similar to households that did not along most dimensions (risk aversion, time preferences, flooding history and income). Column 2 focuses on households' experience with flooding, and finds 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. Furthermore, Figure 1 highlights lower yields among households that took the Emergency Loan.[23] Overall, these results suggest that the most vulnerable and worst affected households are the most likely to take advantage of the guaranteed credit offer. This result is consistent with Prediction 4 from the model.

Estimation Strategy

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.[24] Data from both years of the experiment are pooled together (unless noted otherwise) and standard errors are always clustered at the branch level.[25] 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.[26]

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

[23] Figure 2 also shows that there is no significant difference in the probability of Emergency Loan uptake by borrower credit score

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

[25] Tables B8 to B18 in the appendix accounts for possible differential selection into eligibility in 2017. Results are stable when excluding 2017 data or when instrumenting for eligibility using branch treatment status.

[26] 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

Credit Line Preservation

As mentioned above, low take-up rates do not necessarily reflect the value that households attribute to the Emergency Loan. Households can experience benefits from the loan even if they decide not to take it. Access to the loan improves welfare by reducing households' exposure to the downside risks associated with severe flooding. To test whether households recognize this crucial feature of the Emergency loan, I investigate two phenomena. First, I document whether households choose to preserve their credit access to insure themselves against bad times. Next, I investigate whether households invest more in the pre-period because they know they will have access to an additional loan in the event of a flood.

To investigate credit preserving behavior, I take advantage of the tension between the Emergency Loan and the Good Borrower Loan: households that take the Good Loan in the pre-period lose access to the Emergency Loan. Eligible households have to choose whether to take a Good Loan 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 after a shock. 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 2 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.[27] While I do not see any significant differences by liquidity needs, I do find that branches where the perceived risk of flooding are higher are even less likely to take the Good Loan. This confirms our theoretical prediction that some households view guaranteed credit access as offering effective insurance against shocks and want to preserve their access to it, especially in areas where the perceived risks of flooding are high.

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

[27] 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.

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%.[28]

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 (pooling all treatment and control branches together, respectively). Figure 3 plots the treatment effect on Good Loan uptake by credit score bin for eligible clients. There appears to be 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 11 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.

Ex-Ante Household Investment

Theory also predicts that the extension of a guaranteed credit line will encourage households to invest more in the pre-period because they have access to the Emergency loan in the post-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. Nevertheless, I also investigate the impacts on non-agricultural business investments because the sample is comprised of microfinance clients that are more likely to be business owners and less likely to cultivate land than the general rural population.

I begin with Table 3, which showcases 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 also less appealing now that farmers can reduce their exposure to risk with the Emergency loan instead of using a sharecropping contract. 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.

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

With an expansion in cultivated land, total input use is likely to increase mechanically. However, households might also increase the intensity of input usage now that they are less exposed to risk. The first four columns of Table 4 present the effects of the intervention on inputs applied to cultivated farm land. Columns 1 and 2 show the amount of fertilizer and pesticides applied per acre of land. While both variables have positive point estimates, neither are statistically significant. Similarly, columns 3 and 4 show that the amount of money spent on seeds and all other inputs per acre, also increase but remains insignificant. At a minimum, these results indicate that treatment households are maintaining normal levels of input usage per acre despite the overall expansion of cultivated land. Finally, column 5 of Table 4 examines changes to non-agricultural business investments. We see a marginally significant increase of 30% ($12 USD) over the control group.[29] 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 initial results are consistent with the theory that guaranteed credit lines can increase investments by providing effective insurance against floods. However, to confirm that the product is operating on farmers' perceptions of risk, I investigate whether the treatment effects are higher among the most risk averse households (as measured at baseline).[30] These households represent a meaningful share of the sample (27% of households exhibit the highest level of risk aversion), and generally invest less at baseline. Tables 5 and 6 report these results, where the measure for risk aversion is normalized to a 0-1 scale (one representing the most risk averse households and zero the most risk loving). From Table 5 we see that all the point estimates on the interaction terms between risk aversion and treatment are positive. They are significant for rented and total land cultivated. Similarly, in Table 6 the interaction term is positive for fertilizer, pesticide, and non-agricultural investments, but as before none are statistically significant. 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 could be entirely driven by year one, and dissipate if households that experience a flood learn that the product is not useful. If households were to learn this, we would expect to see their 2017 Aman season investments decrease to pre-treatment levels because they no longer perceive any risk reduction benefits from accessing guaranteed credit. To test this theory, 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 learn that the Emergency Loan does not insure them against negative outcomes, we should see smaller treatment effects among these households relative to treatment households that did not experience a flood shock. Appendix Table B5 explores how flooding in the first year affects different investment categories. The treatment effect on investments does not appear to be different

[29]Business investment was measured by the total value of newly purchased (or repaired) business assets.

[30]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 was normalized to a zero to one scale so that the most risk averse households have a value of one and the most risk loving a value of zero.

for treated households that were flooded in the first year relative to treated households that were not. The interaction term is generally small in magnitude and not statistically significant for any outcome. Overall, this suggests that households that experienced flooding in 2016 still perceive the Emergency Loan as offering viable protection against flood risk.

Ex-Post Household Outcomes

Next, I examine how the Emergency Loan affects households after the Aman season, both in areas that experience flooding and those that do not. Recall from the model that offering the Emergency Loan will affect households differently depending on the state of the world. In the event of a flood, the emergency loan becomes available and treatment households will have access to more liquidity than control households. If a flood does not occur, increases in investment before the Aman season will translate into improved outputs.

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 the number of livestock animals owned by the household.[31] Table 7 shows the results of regressing these outcomes on an indicator for treatment, an indicator for experiencing a flood shock, and an interaction between the two.[32] 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 interaction between treatment and flood will capture the impact of pre-period investments *and* improved liquidity access post-flooding. After a flood, treatment households will have access to any output the flood did not destroy, and to the Emergency Loan should they choose to use it for recovery.

In branches that did *not* experience flooding, we see a 33% increase in crop production among treated households, which aligns with the pre-period investment results. We do not see significant differences in consumption, income, or livestock ownership between treatment and control households. This suggests that households reap the benefits of greater investments absent a flood even though this does not translate into higher levels of measured consumption or asset holdings. In branches that *did* experience a flood, treated households lost almost 90% of the gains they experienced when a flood did not occur (Column 3). 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. Moreover, they maintain a larger number of livestock among treatment households (Column 4).[33] This suggests that the availability of the Emergency Loan allows households to preserve some consumption, and maintain their asset levels after an income shock.[34]

[31]The estimation for log consumption adds week interviewed fixed effects because of holidays that occurred over the survey period which changed consumption patterns for some households.

[32]See Appendix B for ex-post results pooling both flooded and non-flooded branches.

[33]Livestock are a common form of household savings and are often sold when households need liquidity.

[34]There is a concern that multiple shocks may reduce the usefulness of credit as a risk mitigation tool if households

Impact on MFI Operations

I conclude the analysis by investigating how BRAC branches perform when the Emergency Loan is made available. As discussed in the theory section, it is unclear a-priori whether extending guaranteed credit after a shock will help or harm overall branch performance. Establishing an empirical result is therefore important, as the possibility of losses for the MFI despite expected gains to households creates a tension that has limited the provision of guaranteed credit. There are two key outcomes that determine branch profitability: the number of loans disbursed and the repayment rates of those loans. Therefore, to understand the effect of the Emergency Loan product, I will examine each of these outcomes in turn (recall we have already seen that the Emergency Loan reduces the number of Good Loans disbursed).

I begin by examining whether offering the Emergency Loan affects the likelihood that borrowers take a 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.[35] The results in Table 8 show that treatment causes the probability of taking a Dabi loan to increase by 11% (0.7 percentage points) in the pre-period.[36] Finally, as with the Good Loan analysis, I examine whether the increase in Dabi Loan uptake differs across credit scores. Figure 4 and column 2 in Table 11 shows that the increase in Dabi Loans (unlike the reduction in Good Loan uptake) does not differ by credit score.

In addition to loan disbursals, impacts on repayment rates are critical to establish the sustainability of the Emergency Loan. Table 9 shows how the probability of missed payments differs between treatment and control branches both with and without a flood. The coefficient on treatment shows that access to the Emergency Loan has no effect on repayment rates for all loans in the absence of a shock. The coefficient on flooding shows that the number of missed payments across all loans increases by approximately 3.9 percentage points (40% percent) in control branches in the event of a flood. However, 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

accumulate excessive debt or exhaust their credit line. Appendix Table B6 examines this hypothesis. I expand the regression specification from Table 7 to include an indicator for whether households 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.

[35]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.

[36]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 B5 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.

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 5 plots repayment rates differ by treatment status across credit scores.[37] This shows that the effect of treatment on repayment rates is largest among clients with scores that are close to the eligibility threshold of 77.[38] The effect falls quickly at higher credit scores (column 3 of Table 11 shows that this heterogeneity is statistically significant). This decrease 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. So far, we have seen that the effect on total loans disbursed is ambiguous – a decrease in the number of Good Loans taken, but an increase in the number of regular Dabi Loans and new Emergency Loans – while the effect on repayment rates appears to be positive. 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 10 shows the estimated effects of treatment on 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.[39] 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 10 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:

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

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

[37] Appendix Figure B6 plots the levels of repayment rate.

[38] The estimated treatment effect is from regressions pooling both flooded and non-flooded branches.

[39] 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.

score. Figure 6 plots the treatment effect on per-person profitability by credit score decile. 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 11 show that this heterogeneity is statistically significant). This result is consistent with previous findings, which showed higher repayments rates and more Good Loans issued to clients with credit scores closest to the cutoff.

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. In contrast, restricting access to the Emergency Loan to clients with the highest credit scores could lead to an overall reduction in branch profitability because they are less likely to take the Good Loan, and their repayment rates do not have room to improve.[40]

7 Conclusion

Millions of households across the world are exposed to severe income risk and live in areas where insurance markets are non-existent. Therefore, 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 value this product: when given the choice, 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. Households that were informed about their guaranteed credit access also increase their investments in productive activities in the pre-period. These effects are concentrated among risk-averse households. This increase in investments yields higher production levels absent a flood, and higher consumption and asset levels when a shock occurs.

[40] As a final check on MFI performance, Appendix Table B7 examines saving rates. BRAC benefits directly from the amount of savings stored by clients at the branch. The table shows how the savings rates differ between treatment and control branches and their differential response to flooding. Column 1 shows that in the pre-period – where we might have expected clients to draw down on their liquid assets – savings rates do not differ between treatment and control branches. However, column 2 shows that in the aftermath of a flood, eligible households are able to maintain higher savings rates by 45 taka on average (which represents a 62% increase on the average transaction amount, but less than a 1% increase on *total* savings). Column 3 shows that this effect does not vary by the level of localized damage inflicted by the flood.

I also show that the extension of a guaranteed credit line after a shock has modest but 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 lower 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. Finally, I show that this product can be beneficial for MFIs, a result that could induce other MFIs who have been concerned about default risk to offer a similar product.

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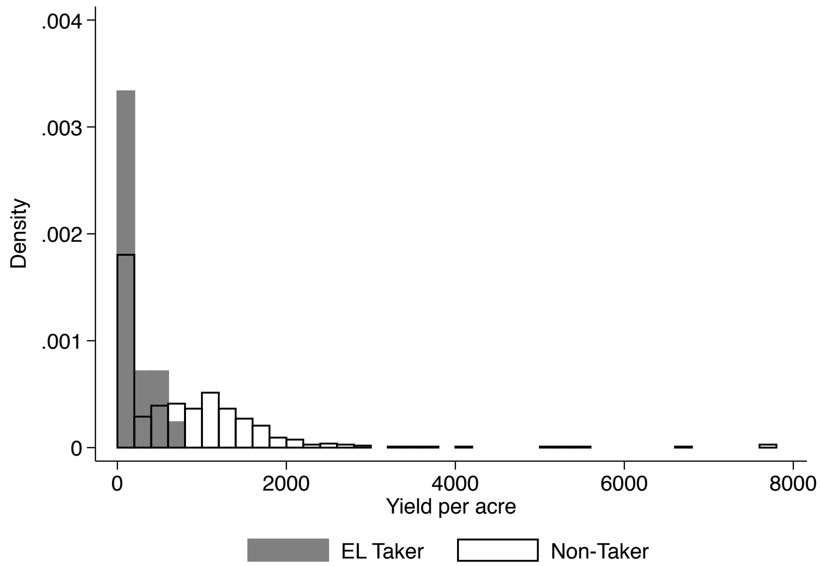
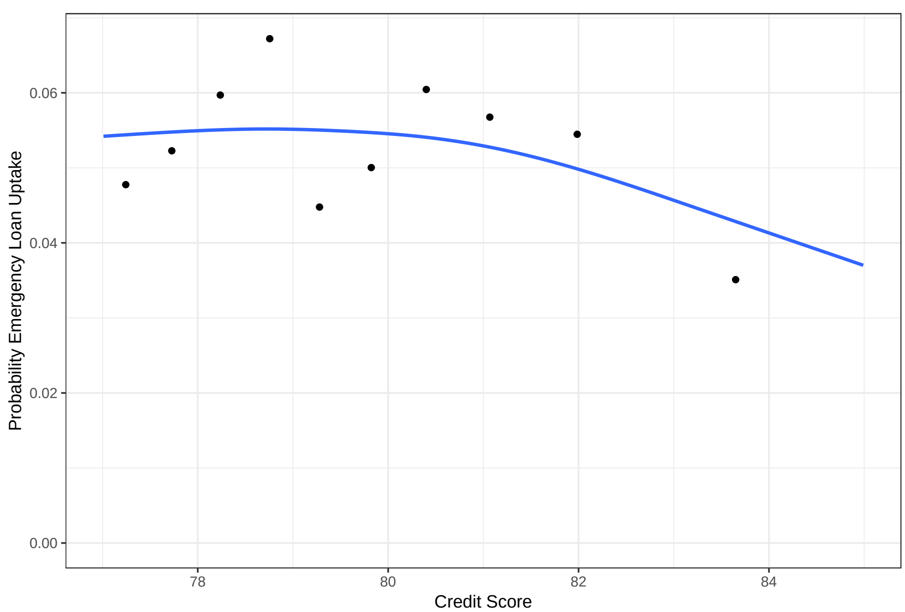
Figures

Figure 1: Yield Per Acre by Emergency Loan Uptake



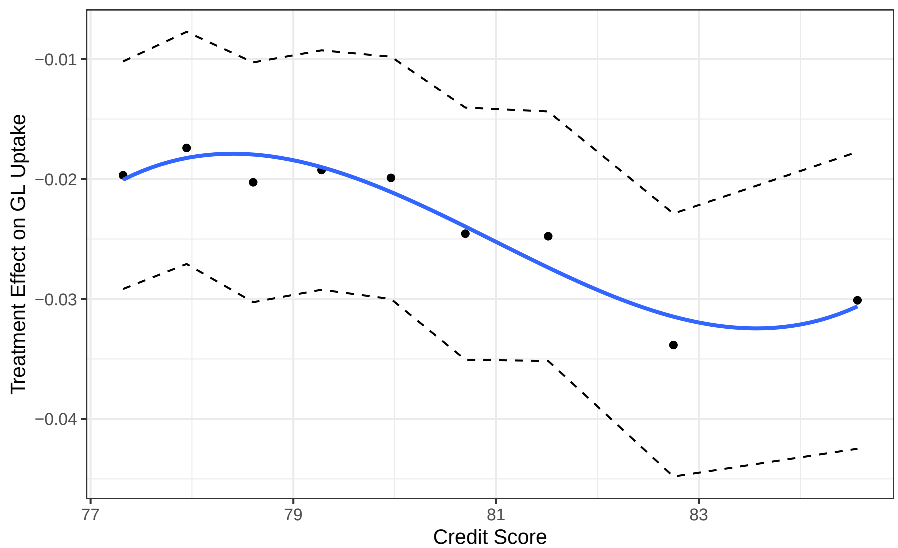
Notes: Histogram of the yield per acre for Emergency Loan takers and non-takers separately. Sample pools data from both 2016 and 2017 and is limited to respondents who were Emergency Loan eligible and located in flooded branches.

Figure 2: Emergency Loan Uptake by Credit Score



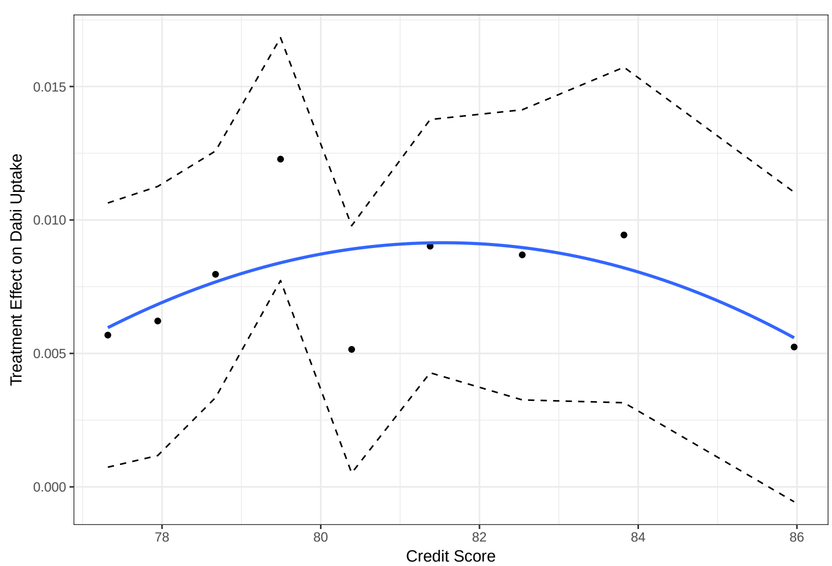
Notes: Plots the probability of Emergency Loan uptake by borrower credit score deciles. The cutoff for Emergency Loan eligibility is a score of 77. Sample pools data from both 2016 and 2017 and is limited to respondents who were Emergency Loan eligible and located in flooded branches.

Figure 3: Good Loan Uptake Heterogeneity



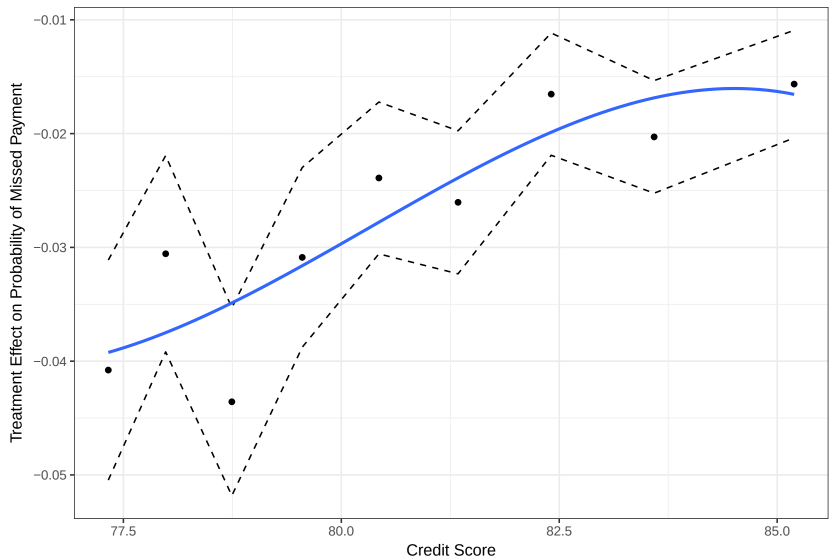
Notes: Plots the treatment effect on the uptake of the Good Loan in treatment branches by decile of borrower credit score. The regression run on each decile includes year and district fixed effects. Sample is comprised of Emergency Loan eligible borrowers who were also eligible for a Good Loan in the pre-flood period. Standard errors are clustered at the branch level. Table 11 tests whether the treatment effect heterogeneity is significant.

Figure 4: Dabi Loan Uptake Heterogeneity



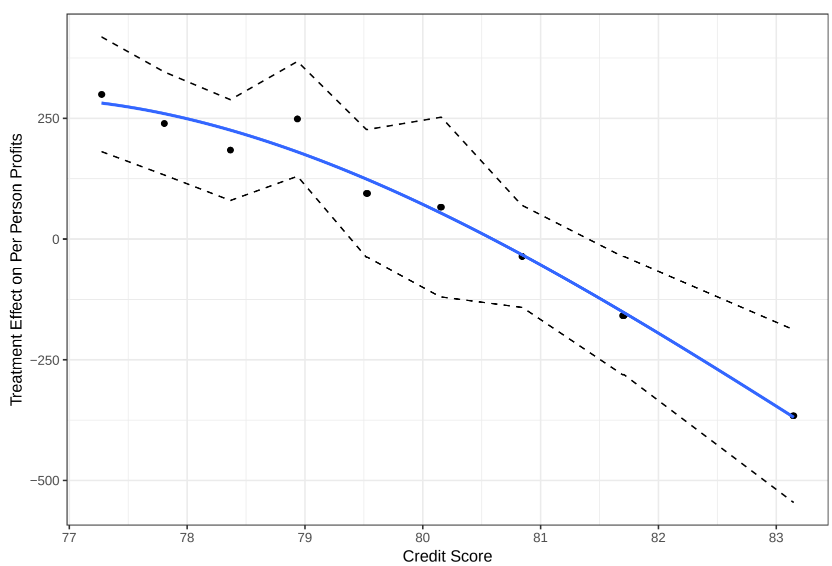
Notes: Plots the treatment effect on the uptake of the Dabi Loan by decile of borrower credit score. The regression run on each decile includes year, month, and district fixed effects. The sample includes only Emergency Loan eligible borrowers. Standard errors are clustered at the branch level. Table 11 tests whether the treatment effect heterogeneity is significant.

Figure 5: Missed Payment Treatment Effect Heterogeneity



Notes: Plots the treatment effect on the probability of a missed payment by decile of borrower credit score. The estimated treatment effect is the average change in repayment rate across both flooded and non-flooded branches. The regression run on each decile includes year, month, and district fixed effects. The sample includes only Emergency Loan eligible borrowers. Standard errors are clustered at the branch level. Table 11 tests whether the treatment effect heterogeneity is significant.

Figure 6: Per-Person Profits Heterogeneity



Notes: Plots the treatment effect on per-person MFI branch profits by decile of borrower credit score. Profits are measured in Bangladeshi taka ($1 = 84tk). The regression run on each decile includes year, month, and district fixed effects. The sample includes only Emergency Loan eligible borrowers. Standard errors are clustered at the branch level. Table 11 tests whether the treatment effect heterogeneity is significant.

Table 1: Emergency Loan Uptake

	(1) Took Emergency Loan	(2) Took Emergency Loan
Baseline HH Income	-0.005	
	(0.003)	
Risk Aversion	0.007	
	(0.013)	
Baseline Time Preference	-0.003	
	(0.002)	
Number of Past Floods	-0.008	
	(0.005)	
Ex-post Investment Opportunity		0.021
		(0.016)
Preparation for flood (1=low, 5=high)		-0.026*
		(0.014)
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 2: 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.

Table 3: 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 4: Ex-Ante Investments

	(1) Fert. Applied	(2) Pest. Applied	(3) Cost Seeds per acre	(4) Input Cost per Acre	(5) Non-Ag Invest
Treatment	6.51	0.26	0.32	2.06	12.13*
	(5.30)	(0.17)	(0.76)	(2.17)	(6.64)
Controls	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
Mean Dep. Var	140.47	1.58	16.18	65.85	38.69
Observations	2183	2140	2058	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. Cost and investment are measured in dollars.

Table 5: 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 Treatment	0.020	0.061^{*}	0.006	0.097^{**}	0.013
	(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 was measured at baseline and ranges 0 to 1, where 0=most risk loving and 1=most risk averse.

Table 6: 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 ranges 0 to 1, where 0=most risk loving and 1=most risk averse.

Table 7: Ex-Post Outcomes

	(1) Log Cons PerCap	(2) Log Income	(3) Crop Prod. (Kg)	(4) Livestock
Treatment	0.050	-0.024	92.10^{**}	-0.075
	(0.046)	(0.044)	(41.25)	(0.106)
Flood X Treatment	0.058	0.002	-83.15	0.353^{**}
	(0.062)	(0.063)	(51.96)	(0.144)
Flood	-0.046	0.030	-0.83	0.058
	(0.059)	(0.057)	(38.07)	(0.109)
Controls	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Week Interviewed FE	Yes	No	No	No
Mean Dep. Var	5.92	10.77	277.07	1.51
Observations	4699	4489	4701	4701
p-value Treat + Flood X Treat	0.011	0.609	0.800	0.007

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.

Table 8: 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 9: 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 10: 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 11: 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.

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:

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

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:

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

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 3.4. The constrained maximization problem changes to:

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

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 3.5. 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 $b_E^1 + b_B^2 \geq b_{NE}^1$.[41] However, as we saw in equation 15, the effect of the 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.

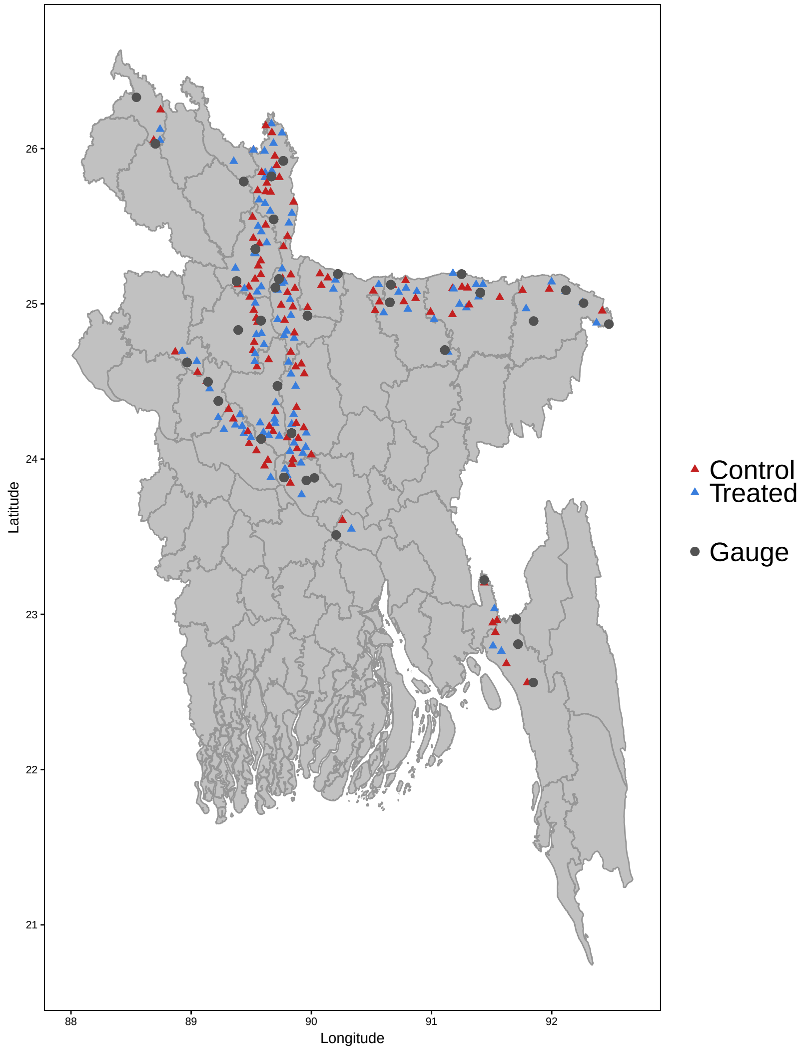
Finally, C captures profits when there is no shock. Again, this term is ambiguous. For households without access to the Good Loan in the pre-period, $b_E^1 \geq b_{NE}^1$. However, for households *with* access to the Good Loan, then b_E^1 could be less then b_{NE}^1 for clients who choose to preserve 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.

[41] 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 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)

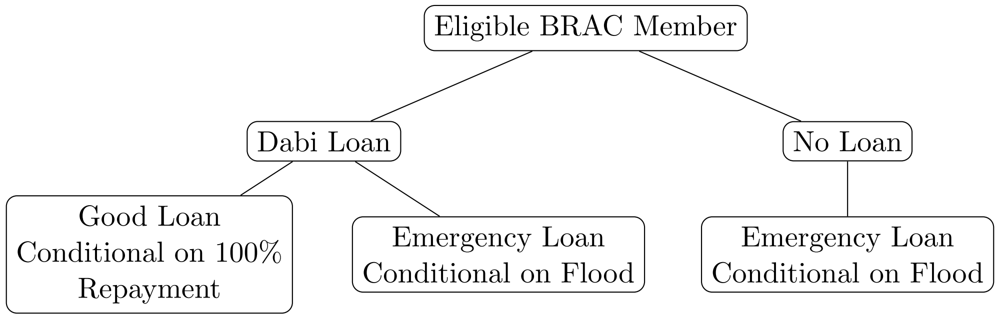
Figures

Figure B1: Map of Sample Branches



Notes: Map shows the locations of BRAC branches that participated in the experiment (triangles) 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.

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

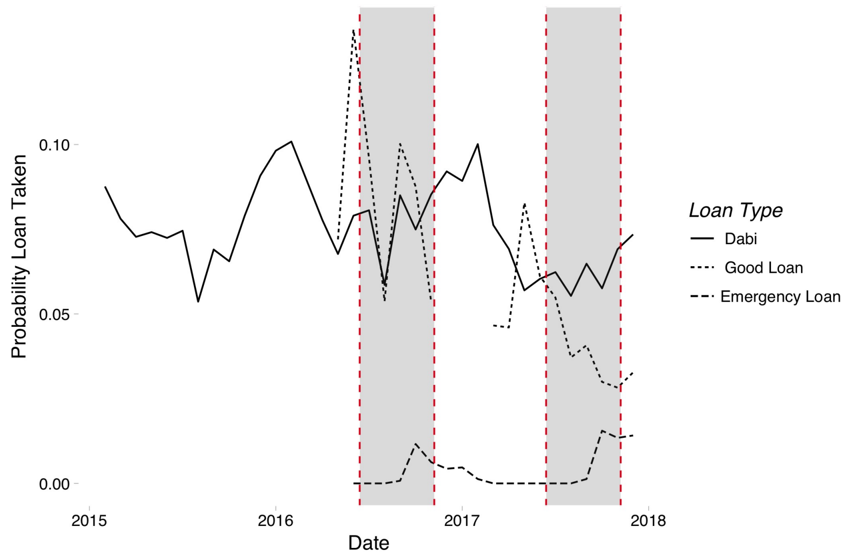
Referral Slip – Emergency Loan

Office Copy: Please keep

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

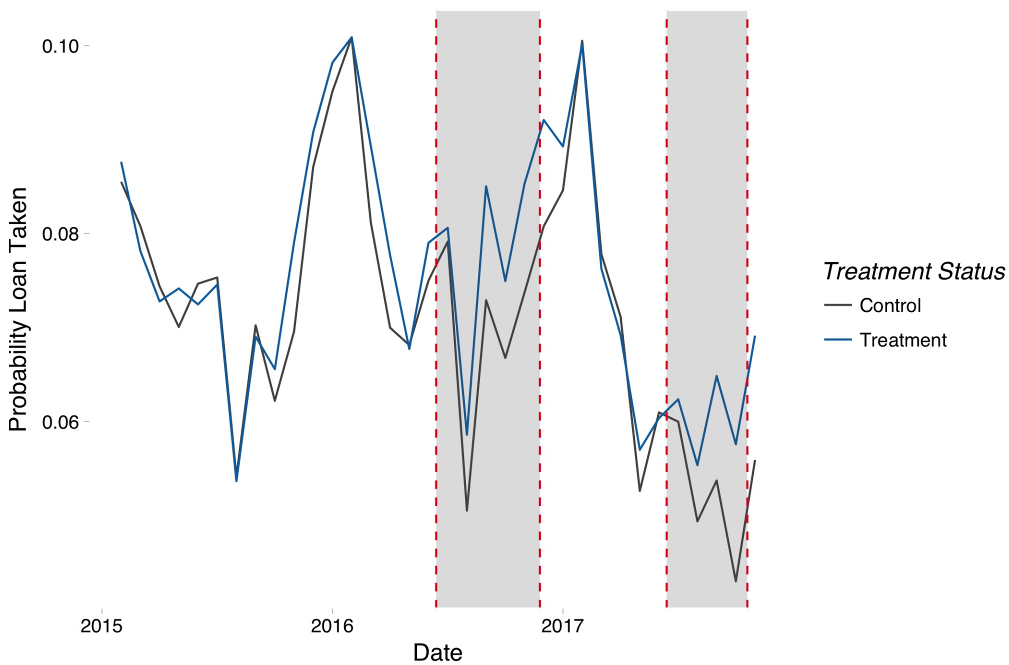
Notes: The Figure shows the referral slip (translated from Bangla) given to BRAC microfinance members eligible for the Emergency Loan. The slip records a client's name and BRAC identifiers, the maximum pre-approved loan size, as well as a brief description of the loan product. The bottom of the slip 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: BRAC Loans



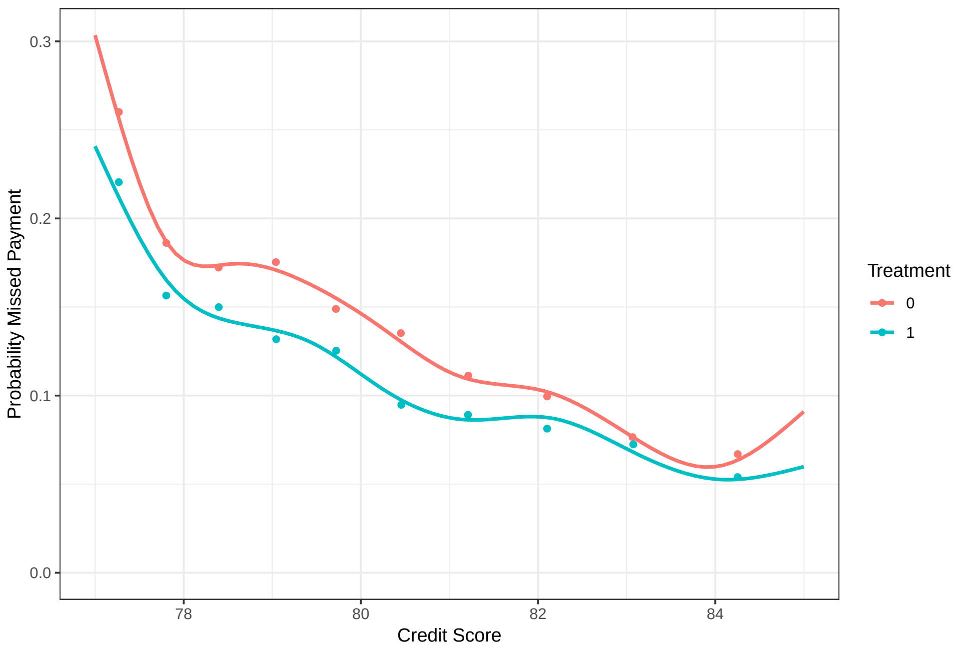
Notes: Figure shows the uptake of the three different BRAC loan products examined in the experiment. The solid line shows Dabi loan uptake as a proportion of overall branch membership. The Short-dashed line shows Good Loan uptake as a proportion of Good Loan eligible clients. The long-dashed line shows 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 B5: 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 B6: 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 measure ranges from zero to one, 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. The measure ranges from zero to one, 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: 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	0.053	-0.339	0.021	0.063	0.358
Treat	(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 B6: Ex-post After Successive Shocks

	(1) Log Cons PerCap	(2) Log Income	(3) Crop Prod. (Kg)	(4) Livestock
Treatment	0.036	-0.023	93.639**	-0.083
	(0.046)	(0.044)	(41.287)	(0.107)
Flood X Treatment	0.107	-0.003	-99.495*	0.379**
	(0.067)	(0.072)	(54.868)	(0.146)
Flood Current Year	-0.051	0.032	5.382	0.056
	(0.059)	(0.060)	(38.331)	(0.108)
Flood Both X Treat	-0.100	0.017	54.321	-0.055
	(0.095)	(0.096)	(44.995)	(0.171)
Flood Both Years	-0.199***	-0.000	-0.260	-0.100
	(0.069)	(0.072)	(41.944)	(0.131)
Controls	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Week Interviewed FE	Yes	No	No	No
Mean Dep. Var	5.92	10.77	277.07	1.51
Observations	4699	4489	4701	4701
p-value Sum Treatment Coef.	0.004	0.904	0.229	0.161

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.

Table B7: Savings Transactions by Emergency Loan Availability

	Savings Transctions		
	Pre-Period	All	All (2017)
	(1)	(2)	(3)
Treatment	8.85	−14.58	−55.73
	(9.34)	(18.57)	(43.11)
Treat x Flood		45.37**	34.75*
		(20.67)	(20.75)
Flood		−53.75**	−50.19**
		(24.60)	(22.19)
Flood Damage x Treatment			11.58
			(10.05)
Flood Damage			−17.15***
			(6.42)
Year & Month F.E.	Yes	Yes	Yes
District F.E.	Yes	Yes	Yes
Mean of Dep. Var.	82.6	71.8	64.5
Unique Accounts	108,446	109,647	75,477
Observations	622,551	1,150,895	711,184

Notes: Sample includes only Emergency Loan eligible clients. Standard errors clustered at branch level. Observations at the person-month level. The variable flood is an indicator for anytime after a flood until the following March. Column 1 uses observations only from the pre-flood period in both 2016 and 2017. Column 2 uses all observations. Flood damage data at the branch level is only available for 2017, therefore column 3 shows results only for this year. Flood damage is measured at the branch level and ranges from [1-5] with 1=least damage and 5=most damage.

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 B8 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 B8: 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 B9: 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 B10: 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 B11: 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 B12: IV Inputs

	(1) Fert. Applied	(2) Pest. Applied	(3) Cost Seeds per acre	(4) Input Cost per Acre	(5) Non-Ag Invest
Treatment	5.71	0.28	0.39	1.79	1.15
	(5.41)	(0.18)	(0.83)	(2.38)	(7.51)
Controls	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
Mean Dep. Var	141.48	1.60	16.88	66.87	56.02
Observations	2638	2559	2504	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 B13: Ex-Ante Land by Risk Aversion: 2016

	(1) Own land	(2) Rented land	(3) Sharecrop land	(4) Total land	(5) Any Cult.
Treatment	-0.02	0.04	-0.01*	-0.00	0.03
	(0.02)	(0.03)	(0.01)	(0.04)	(0.03)
Risk Aversion X Treatment	0.03	0.05	0.01	0.11*	0.00
	(0.03)	(0.05)	(0.01)	(0.06)	(0.05)
Risk Aversion	0.14*	0.09	-0.02	0.19*	0.12
	(0.08)	(0.06)	(0.01)	(0.10)	(0.09)
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	0.15	0.22	0.02	0.39	0.50
Observations	2986	2986	2986	2986	2986
p-value Treat + Risk X Treat	0.654	0.001	0.900	0.008	0.352

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 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 was measured at baseline and ranges 0 to 1, where 0=most risk loving and 1=most risk averse.

Table B14: Ex-Ante Inputs by Risk Aversion: 2016

	(1) Fert. Applied	(2) Pest. Applied	(3) Cost Seeds per acre	(4) Input Cost per Acre	(5) Non-Ag Invest
Treatment	7.40	0.25	1.85	2.02	-0.77
	(9.98)	(0.30)	(1.44)	(4.43)	(5.33)
Risk Aversion X Treatment	-3.29	0.20	-1.57	-1.89	3.58
	(16.87)	(0.44)	(1.88)	(6.52)	(8.29)
Risk Aversion	9.33	0.31	-4.80	-5.65	-8.93
	(28.41)	(0.81)	(3.56)	(12.56)	(13.77)
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	129.93	1.34	14.45	60.53	7.84
Observations	1479	1479	1375	1375	2986
p-value Treat + Risk X Treat	0.689	0.101	0.808	0.971	0.600

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 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 ranges 0 to 1, where 0=most risk loving and 1=most risk averse.

Table B15: IV Ex-Ante Land by Risk Aversion

	(1) Own land	(2) Rented land	(3) Sharecrop land	(4) Total land	(5) Any Cult.
Treatment	-0.032	0.044	-0.014*	-0.010	-0.007
	(0.026)	(0.036)	(0.007)	(0.051)	(0.053)
Risk Aversion X Treatment	0.033	0.055	0.015	0.115**	0.066
	(0.031)	(0.044)	(0.010)	(0.057)	(0.055)
Risk Aversion	0.094	0.040	-0.001	0.126	0.081
	(0.065)	(0.051)	(0.010)	(0.082)	(0.073)
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	0.18	0.02	0.33	0.44
Observations	5736	5732	5735	5731	5737
p-value Treat + Risk X Treat	0.949	0.000	0.964	0.001	0.031

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 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 was measured at baseline and ranges 0 to 1, where 0=most risk loving and 1=most risk averse.

Table B16: IV 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	-2.62	-0.05	0.62	-0.55	-13.80
	(9.41)	(0.40)	(1.75)	(4.98)	(25.64)
Risk Aversion X Treatment	17.52	0.55	-1.01	4.76	29.34
	(13.18)	(0.56)	(2.30)	(6.55)	(33.27)
Risk Aversion	-12.62	-0.95	-4.22	-20.20**	11.39
	(22.71)	(0.70)	(3.74)	(10.04)	(36.66)
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	140.08	1.56	16.83	66.61	52.67
Observations	2550	2473	2423	2352	5737
p-value Treat + Risk X Treat	0.051	0.054	0.722	0.157	0.172

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 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 ranges 0 to 1, where 0=most risk loving and 1=most risk averse.

Table B17: Ex-Post Outcomes 2016

	(1) Log Cons PerCap	(2) Log Income	(3) Crop Prod. (Kg)	(4) Livestock
Treatment	0.013	-0.004	128.861**	-0.118
	(0.048)	(0.050)	(55.976)	(0.114)
Flood X Treatment	0.144*	-0.090	-142.596*	0.310*
	(0.074)	(0.077)	(80.684)	(0.170)
Flood	-0.094	0.058	-20.675	0.037
	(0.076)	(0.077)	(60.773)	(0.142)
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	327.80	1.53
Observations	2969	2826	2971	2971
p-value Treat + Flood X Treat	0.005	0.120	0.797	0.130

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 B18: IV Ex-Post Outcomes

	(1) Log Cons PerCap	(2) Log Income	(3) Crop Prod. (Kg)	(4) Livestock
Treatment	0.040	-0.027	110.893**	-0.155
	(0.053)	(0.053)	(46.853)	(0.121)
Flood X Treatment	0.066	0.014	-100.623*	0.513***
	(0.062)	(0.065)	(51.432)	(0.144)
Flood	-0.019	0.029	-3.086	-0.130
	(0.047)	(0.049)	(31.068)	(0.104)
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	1.47
Observations	5980	5726	5982	5982
p-value Treat + Flood X Treat	0.004	0.738	0.747	0.000

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.

Table B19: Ex-Post Outcomes with out Flood Controls

	(1) Log Cons PerCap	(2) Log Income	(3) Crop Prod. (Kg)	(4) Livestock
Treatment	0.080**	-0.019	47.896*	0.118
	(0.031)	(0.029)	(28.093)	(0.076)
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	1.51
Observations	4743	4531	4745	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. 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.

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 B20: Spillovers: Ineligible Land Farmed

	(1) Own land	(2) Rented land	(3) Sharecrop land	(4) Total land	(5) Any Cult.
Treatment branch	0.000	-0.010	-0.005	-0.013	-0.035
	(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 B21: 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	-0.78	-0.02	-0.88	1.24	-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	140.31	1.46	18.45	68.69	71.63
Observations	1271	1208	1204	1146	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 B22: Spillovers: Ineligible Ex-Post Outcomes

	(1) Log Cons PerCap	(2) Log Income	(3) Crop Prod. (Kg)	(4) Livestock
Treatment branch	0.083*	-0.028	-7.616	-0.135
	(0.048)	(0.046)	(31.866)	(0.122)
Flood X Treatment	-0.024	-0.016	-5.095	0.234
	(0.061)	(0.064)	(39.846)	(0.152)
Flood	0.082	-0.023	-28.800	-0.269**
	(0.054)	(0.059)	(33.960)	(0.135)
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	210.93	1.27
Observations	3176	3057	3177	3177
p-value Treat + Flood X Treat	0.120	0.284	0.633	0.330

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.