Credit Lines as Insurance: Evidence from Bangladesh

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October 1, 2018

[JOB MARKET PAPER]
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Abstract

When insurance markets are absent, theory suggests that households can use credit lines to insure themselves against adverse income shocks. However, in many developing countries access to credit in the aftermath of shocks is scarce as negatively affected households are frequently denied loans. In this paper I test whether a new financial product that offers guaranteed credit access after a shock, allows household to insure themselves against risk. To this end, I run a large scale RCT in Bangladesh with one of the country's largest microcredit institutions. Microfinance clients were randomly pre-approved for loans that are made available in the event of local flooding. I show that this unique type of microcredit improves household welfare through two channels: an ex-ante insurance effect where households increase investment in risky production and an ex-post effect where households are better able to maintain consumption and asset levels after a shock. I also document that households value this product, taking costly action to preserve their guaranteed access. Importantly, extension of this additional credit improves loan repayment rates and MFI profitability, suggesting that this product can be sustainably extended to households already connected to microcredit networks.

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1 Introduction

Poor households throughout the developing world struggle with income risk. They primarily rely on agriculture and small business profits, which are vulnerable to shocks including harvest failure after extreme weather events, price volatility, and a sudden loss in the family (Dercon, 2002). Research has demonstrated that these high levels of income variability prevent households from accumulating wealth and exiting poverty. Moreover, the set of risk coping and mitigation strategies that are available to households can often leave them worse off in the long run. Many turn to low-risk production technologies and under invest in inputs, which negatively affects their future returns (Donovan, 2016). Others are often forced to implement damaging coping strategies such as lowering food consumption, selling productive assets, and reducing health and educational investments (Hoddinott, 2006; Janzen and Carter, 2018). Traditional insurance markets are designed to help households cope with these risks, but they are often absent or incomplete in developing countries because of moral hazard and adverse selection, while alternative tools 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 these tools is to provide households with a credit line so they can self-insure. Credit and savings models have long highlighted the precautionary value of credit access, which can serve to insure households against income fluctuations (Deaton, 1991, 1992). However, there is little empirical evidence demonstrating that households can in fact use credit access in this way. What evidence does exists comes from developed countries (Gross and Souleles, 2002), even though the benefits of credit access will likely be larger in developing countries where insurance markets are lacking. In developing countries, the largest providers of formal credit to the poor are microfinance institutions (MFI), which severely curtail credit access in the aftermath of large aggregate income shocks (Demont, 2014). Their requirements that households be financially evaluated at the time of loan disbursal, and that households cannot borrow if they have any outstanding debt, severely restricts households' use of credit access as a buffer against risk in developing countries.[1]

This paper provides the first empirical evidence that guaranteed access to credit after negative shocks increases productive investment, improves households welfare, and ultimately, is profitable for the MFI. To this end, I partner with BRAC, a large MFI in Bangladesh, and extend a *guaranteed* credit line to poor, rural households. The product, marketed as an Emergency Loan, is a pre-approved loan that is made available to clients when an aggregate local shock (in this case a flood) occurs. I randomize the availability of the Emergency loan across 200 rural BRAC microfinance branches serving over 300,000 clients with over one million loans during the study period. Clients in the 100 treatment branches were informed, before the beginning of the planting season, that they were pre-approved to take the new loan product should a flood shock occur in their area.[2]

[1] Many MFIs have a dual mission of profit making and increasing social welfare which theoretically makes them more likely to extend credit to households after an income shock. However, the field staff responsible for approving individual loans are almost always evaluated primarily on repayment metrics, making them likely to avoid lending to risky households.

[2] The Emergency Loan was only offered to approximately 40% of clients within each treatment brach based on an

Control branches continued their normal microfinance operations. Loans were then extended upon request by eligible households after a flood had occurred (and been externally validated).

The experiment documents four primary results. First, I find that households value access to guaranteed credit and respond as theory would predict. Indeed, 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. Rough estimates suggest that these households value credit access after a shock at least 1.8 times more than credit access in the pre-period.

Second, I find that informing households that they are pre-approved for credit in the event of a flood is associated with a significant rise in risky investments. Treated households increase the amount of land dedicated to agricultural cultivation by 15% and increase non-agriculture business investments. Both of these effects are concentrated among the most risk averse households. These findings suggest that households view guaranteed liquidity access as reducing their exposure to flood risk, and respond by increasing their investment in riskier, potentially more profitable investments.

Third, I document that emergency credit, unlike many other microcredit products, improves household welfare outcomes. When there is no flood, the 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 the most severely affected households were the most likely to use this additional liquidity. This means that the largest gains associated with guaranteed credit could be 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 overall repayment rate, driven by improvements in repayment rates after a flood shock. Overall, there is suggestive evidence that branch profits weakly increases, 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. Nevertheless, it is worth highlighting that these results may not generalize to contexts where repayments rates are low to begin with.

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

individual credit score, see section 2 for more details.

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 1) credit constrained, 2) present-bias, 3) face basis risk that the index will not correspond to their own person shock, and 4) 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 drive down demand for insurance contracts where 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. This can take the form of a monopsony buyer that can credibly (and cheaply) collect payment from farmers after the fact, such 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 with 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. Like index-insurance, the availability of the additional credit is contingent on an exogenous indicator (floodwater height) to avoid high administrative costs and moral hazard. However, unlike index-insurance, no purchase (or any binding decision) is required by the household during the planting season (this is similar to the innovation explore in Casaburi and Willis (2018)). Providing coverage under a guaranteed credit scheme simply requires notifying a household that they are eligible for the product. As long as households understand the offer, and trust 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 has resolved, which means households can opt in or out depending on realized damages from the shock and any alternatives that may be available. Indeed, I see in my experiment that many households increase ex-ante investment, suggesting a reduction in perceived risk, even though ex-post take-up of the Emergency Loan is low.

There are, however, several limitations associated with using guaranteed credit as a risk management tool. Like insurance, households may be reluctant to rely on the product in times of need if they are concerned about default by the provider (this is mitigated in this context by working with BRAC Bangladesh, a well established and trusted MFI in the region). Unlike insurance, the sequence of shocks can have an impact on the usefulness of credit for income smoothing. If a household experiences multiple successive shocks under a guaranteed credit scheme, they may accumulate excess debt or exhaust their available credit line.[3] Finally, extending credit to households after a

[3]With insurance a household that experiences several shocks in a row will simply receive the fixed insurance payout

shock is inherently risky for MFIs. While I find good repayment rates in this setting, if repayment rates are lower elsewhere, providing guaranteed credit may not be sustainable from the lender's perspective. It follows that while guaranteed credit provides clear advantages to some households, it may not be a panacea.

This research also contributes to the large literature on microcredit. Developed in Bangladesh in the 1970s, microcredit institutions have since rapidly expanded, reaching over 137 million households worldwide Maes and Reed (2011). Unfortunately, despite this extensive growth and early enthusiasm for microcredit[4], the majority of research documents only modest impacts on households' well-being (Karlan and Zinman, 2011; Angelucci, Karlan, and Zinman, 2015; Banerjee et al., 2015; Banerjee, Karlan, and Zinman, 2015). This 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, early microcredit products typically featured group lending with joint liability and frequent, rigid repayment schedules designed to overcome high transaction costs and asymmetric information, but that come at the cost of making repayment difficult for those with uncertain income (Karlan, 2014). In response to these results, a 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 installment payments reduce borrower transaction costs and encourage 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 and Barboni (2017) shows that more productive borrowers opt into flexible repayment contracts even when they are more expensive. This paper builds on these results by showing that credit products that increase the flexibility of households' access to credit (not just repayment flexibility), 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) use theory and lab-in-the-field experiments to show that offering flexible repayment schedules could increase profits for lender. An advantage of this relatively large experiment is that allows 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. In this setting, I find significant positive effects on MFI profits, with significant heterogeneity among borrowers.

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 present the results of the experiment and section 7 concludes.

each period (provided they purchased the product).

[4]In 2006, Mohammad Yunus and the Grameen Bank were awarded the Nobel Prize for Peace.

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). While the country's economy has grown rapidly in recent years, GDP per capita still stands at $2,363 and approximately 43% of the population earns less than $1.25 per day (UNDP, 2015).

Many types of 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). Moreover 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 because of the high frequency of flooding across the entire country. As such, the randomized control trial was conducted in areas located close to the major rivers where frequent flooding occurs.

I work with a subset of households that are active microfinance borrowers. These households are primarily engaged in agriculture: 50% grow their own crops and 22% work as day laborers. This group is also active in starting their own businesses (27% reported owning a small shop). Education is low in these areas, and approximately two thirds of the sample have less than a primary school education.

BRAC Microcredit

BRAC was founded in 1972 in Bangladesh and is currently one of the largest NGOs in the world. Their microfinance operations began in 1974 and have expanded to serve the entire country. They operate over 2000 branches where each branch serves anywhere from 20 to 60 village organizations (VO's). These organizations are designed to facilitate coordinated activities between borrowers at the village level, including the distribution of information about new micro-finance products and creating a convenient space for BRAC loan officers to collect loan payments and instill some social pressure on borrowers to make their loan payments. VO meetings occur either weekly or monthly depending on branch policy. At each meeting the loan officer collects the scheduled loan repayments from each active borrower and answers enquiries about desired new loans from members without existing debt.

The most common loan provided by BRAC is called the *Dabi* loan, which is only given to women and is targeted at poor households[5]. Dabi loans are typically small in value (approximately 15,000 taka ($187)), and are required to be repaid within a year. Microfinance interest rates are regulated in Bangladesh and BRAC charges 25% interest on the Dabi loan, which is near the legal

[5]While the Dabi loans are given only to women, it is common that these loans are used for broader household investments such as agriculture or a business that is run by the husband of the official borrower.

maximum and similar to other MFI's. During the repayment period, borrowers are not allowed to apply for any 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 loan. The offer is only available for two months after they become eligible at the 6 month mark of their current loan cycle.[6] In every other respect, Good Loans are identical to normal Dabi loans, with the same 25% interest rate and one year repayment timeline. Taking the Good Loan does not delay the normal loan cycle, and the client can take another normal Dabi loan as soon as they have repaid their old one.

Product Description

The Emergency Loan was designed together with BRAC to improve its utility for borrowers exposed to flood risk while also 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. The credit score was created specifically for this product, and was calculated from each borrower's past repayment behavior on previously held BRAC loans. Specifically, the score was based on 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 linear weight determined by a regression of these variables on a binary indicator for loan default. This weighted sum was then normalized to a 0-100 scale. The variables themselves were chosen based on several criteria, including a) ease of calculation due to record keeping and computation limitations, b) relevance for predicting future default, and c) ease of explanation for transparency.[7] The threshold was set so that approximately 40% of borrowers were eligible at any given branch (77 out of a maximum score of 100). It is worth highlighting that targeting based on credit score does not select richer households over poorer ones. Table 1 examines differences in observables between the eligible and ineligible borrowers. The two groups look fairly similarly, 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.

Client eligibility was assessed for every borrower in April, just before planting of the Aman season and several months before the flooding season. Borrowers could retain access to their Emergency Loan eligibility for the duration of the Aman cropping season regardless of their repayment behavior in the interim. 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, a borrower who took a 10,000

[6] Good Loans are also subject to the Loan Officer and Branch Manager approval (i.e. they can be denied even if the borrower is technically eligible)

[7] 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. Only variables that were consistently predictive were kept in the final credit score. Additionally, 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.

taka loan ($125) in May from BRAC was guaranteed to borrow up to 5,000 taka ($63) should a flood occur regardless of their existing loan balance. No further evaluations of the client's ability to repay, or any other checks, were conducted before disbursing the Emergency Loan. Emergency Loans were then made available to eligible clients if flooding occurred. This was validated in two ways. First, the river gauge associated with the branch area had to be reporting water level above the pre-determined danger level for at least one day.[8] Second, a non-microfinance BRAC employee had to confirm that at least 20% of the branch service area had experienced flooding.[9] On a case by case basis, loans were also made available if the local Branch Manager notified BRAC headquarters of local floods and this report was confirmed by the BRAC employee (even if the matched river water gauge had not passed the official danger level).

Two additional features of the Emergency Loan are important to review. First, the eligibility list created by the credit score was provided directly 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.[10] The final list was then shared with BRAC headquarters. These steps were put in place to minimize the risk that BRAC would lend to borrowers that would fail to repay the loan.[11] For the purposes of the experimental results, I do not consider Branch Manager vetos and include all clients that were determined to be eligible based on the credit score alone.

Second, it is important to note how the Emergency Loan interacts with the existing Good Loan product. The Good Loan product differs from the Emergency Loan in the timing that is made available to clients (6-8 months into their normal Dabi rather than post-flood), and in how it is disbursed (by asking branch managers who can deny the request, instead of pre-approval based on credit scores). Looking through historical data this means that the Good Loans were much less likely to be disbursed in the aftermath of aggregate income shocks because most borrowers were either not in their 6-8 month timeframe and branch managers did not want to approve additional top-up loans.

Clients in the sample could be *eligible* for the Good Loan or the Emergency Loan, both, or neither. However, borrowers were informed that they could not have both a Good Loan *and* an Emergency Loan together — if they take a Good Loan they lose future eligibility for the Emergency Loan should a flood occur.[12] This limitation was introduced because of BRAC's concerns that borrowers would carry too much debt. Therefore, 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

[8]The danger level is not the water height at which the river overflows it banks, but at which there is estimated to be high probability of significant property damage in the area.

[9]This second check was deemed necessary after piloting showed that for some branch service areas, a higher river water level was necessary to cause any risk of flood damage.

[10]Branch managers in the control group performed this same veto process for a future product rather than the emergency loan itself.

[11]This is also a standard practice for every other loan.

[12]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.

Loan but not the Emergency Loan did not face this tradeoff. This creates an additional feature of the experiment that I can exploit. Namely, I can compare these two groups to determine whether households choose to preserve credit access as a buffer stock against risk. Figure 1 summarizes borrower choices related to the Good Loan and Emergency Loan.

3 Theory

Framework For Effect of Guaranteed Credit

Clients are informed about their eligibility for the Emergency Loan in April, before decisions need to be made on inputs for the coming Aman season (e.g. land to cultivate, inputs to use, business investments), and how much to borrow to finance these choices. After making these decisions, the cropping season commences and flooding either does or does not occur. If flooding does occur, each eligible borrower is informed that the Emergency Loan is available for them to access. During this period, borrowers make decisions on whether or not to take the Emergency Loan (if it is available), and whether or not to repay existing loans. Later, borrowers move into the dry season and choose to repay any loans taken after flooding.

Therefore, it is useful to categorize client decisions into three periods: choices made after being informed about their Emergency Loan eligibility but before the realization of any flooding (first period decisions), choices made after any flooding has occurred (second period decisions), and choices made in the dry season (third period decisions).

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 Aman 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 Aman season.

Second Period Decisions

1. *Emergency Loan Uptake:* In the event of a flood, borrowers will make the decision about whether to take an 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. This decision will also depend on whether or not the household defaulted in the second period.

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

Baseline Model

The model[13] has three periods that correspond to a planting, harvest, and post-harvest periods, and incorporates risky production, 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 time period two and occur with probability π_s (later defined as $\pi_B = q$ and $\pi_G = (1-q)$). Further, I assume that the only source of credit available to a household comes from the MFI. Preferences are over consumption (c) with discount factor β:

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

A household starts with exogenous cash on hand Y and also 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 (therefore positive values of b represent net borrowing while negative values 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 with interest (Rb^1) or default by paying zero. I also allow for borrowing in the bad state of the world b_B^2, which is made available with the introduction of the Emergency Loan (to simply the problem, I do not allow savings from period two to three, but this assumption does not change the core results). In period three, the household pays (or receives) return R on any period two loans, provided they have not already defaulted, and also receive an 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 then be stated as:

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

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

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

Where D and ND stand for default and no default respectively, c^t_s and b^t_s are consumption and borrowing choice in the corresponding time period and state, x is inputs, Y is exogenous first period wealth, and I is the exogenous third period income.

A household can borrow up to $\bar{B}_j$ in each period where borrowing is possible (where if $\bar{B}$ is equal to zero there would be no access to credit). To begin, I will assume $\bar{B}_2 = 0$, meaning there is no credit available in the bad state. I also make a few additional simplifying assumptions. First, I assume that it is never optimal for a household to default on their loan when the good state is realized ($s = G$). This assumption rules out households that always default and therefore took first period loans in bad faith. Second, I normalize the marginal product of x is zero in the bad state, i.e. $m_B = 0$[14].

The rest of this section is organized as follows. First, I start by separately describing the optimal borrowing and input choices assuming households do not default and then again assuming households will default in the event of a shock. Second, I compare these two scenarios and find the condition that will lead to the household to choose to repay or to default. Third, I allow for bad state borrowing and observe how the relaxation of this constraint changes household choices of inputs, borrowing, and the choice to default. Finally, given the expected effect on households' decisions, I examine the implications of extending bad state borrowing on the performance of the lending MFI.

[14]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.

No Default

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

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

Where λ_1 is the Lagrange multiplier associated with the first period borrowing constraint. Optimizing equation 1 implies that the input x is purchased until the following condition is satisfied:

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

Under a scenario without risky production or credit constraints, the agent would invest in x until the marginal product equaled the return on the risk-free asset R. The equation above shows us that there are two potential sources of distortion away from that standard result. The first term in brackets above will be greater than one and reflects the presences of the risky production technology that has a zero marginal product in the event of the bad outcome. Second, the first period credit constraint could bind in which case $\lambda_1 > 0$, which will also drive a wedge between the marginal product of the input and R. Therefore, both potential distortions will lower the choice of x relative to the unconstrained optimum.

Now, I move to examine the borrowing choice in period one. The first order condition implies that the first period borrowing is chosen such that:

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

Again, there are two potential distortions away from the optimum without risky production or credit constraints. 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 size of the second term (due to concavity), and imply reduced consumption in period one relative to a choice without risky production, which combined with the reduction in inputs purchased, implies an overall reduction in borrowing as well. Second, as before, if the first period borrowing constraint binds, λ_1 will be positive and will also imply a reduction in borrowing relative to the unconstrained optimum.

Default

In this section, I assume that the household will choose not to repay their period one loans if the bad state occurs in the second period. Under this assumption, the household problem changes to:

$$\begin{aligned}\max_{x,b^1}\ & u(Y-x+b^1)+q\beta u(0)+(1-q)\beta u\left(m_G f(x)-Rb^1\right)+\\ & q\beta^2 u(I)+(1-q)\beta^2 u(I)+\lambda_1[\bar{B}_1-b^1]+\lambda_1[0-b_B^2]\end{aligned} \tag{4}$$

The fact that the household knows they will not repay their loans in the event of a shock, changes the optimal use of inputs and borrowing in the first period. First, I can see that the optimal choice of inputs is defined by

$$m_G\frac{\partial f_G}{\partial x}=R+\frac{\lambda_1}{\beta(1-q)u'(c_G^2)} \tag{5}$$

This condition implies that households that know they will default in the bad state of the world will use inputs until the marginal return is equal to the interest rate R. The only distortion comes from the borrowing constraint in period one (λ_1). Similarly, borrowing will be chosen such that the only consideration is equalizing marginal utility in period one with discounted marginal utility in period two:

$$u'(c_1)=(1-q)\beta Ru'(c_2^G)+\lambda_1 \tag{6}$$

Repayment Decision

To examine the borrower's repayment decision, I compare the utility for the household when they choose to repay to the utility they receive under default. If a household chooses to repay, their utility under repayment must be higher than their utility under default:

$$U^{repay}\geq U^{default}$$

Which is given by:

$$\begin{aligned}& u(c_r^1)+q\beta u\left(-Rb_r^1\right)+(1-q)\beta u\left(m_G f(x_r)-Rb_r^1\right)+\\ & \quad q\beta^2 u(I)+(1-q)\beta^2 u(I)\\ & \geq\\ & u(c_d^1)+q\beta u(0)+(1-q)\beta u\left(m_G f(x_d)-Rb_d^1\right)+\\ & \quad q\beta^2 u(I)+(1-q)\beta^2 u(I)-qK\end{aligned} \tag{7}$$

Where an index of d or r signify the optimal value of the variable given repayment or default respectively. To understand this decision, I examine the switch point where a household is indifferent between repayment and default by setting these two expressions equal. In order to declutter the expression, it is useful to define new terms. First I define M as the difference in utility between default and repayment in the first period and in the second period under the good state, where $M > 0$.[15]

Using this simplification and rearranging the initial condition I can define K^*:

$$K^* = \frac{M}{q} + \beta \left[u(0) - u(-Rb_r^1) \right] \tag{8}$$

Where K^* is the cost of lost access to microfinance that would make a household indifferent between repayment and default.[16] If a household's actual K is larger than K^* they will repay and if it is lower, they will default. Therefore, if I assume that K is a random variable defined by the CDF F_K, the proportion of households that will default after shock is given by $F_K(K^*)$.

Adding Liquidity in the Bad State

I now explore how the optimal choices of x and b^1 change when the option to borrow in the bad state in period two is added. Starting with the no-default case, the household's problem is now expanded to include the choice b_B^2:

$$\begin{aligned} \max_{x,b^1,b_B^2} \quad & u(Y - x + b^1) + q\beta u\left(-Rb^1 + b_B^2\right) + (1-q)\beta u\left(m_G f(x) - Rb^1\right) + \\ & q\beta^2 u(I - Rb_B^2) + (1-q)\beta^2 u(I) + \lambda_1[\bar{B}_1 - b^1] + \lambda_2[\bar{B}_2 - b_B^2] \end{aligned} \tag{9}$$

In order to understand how the introduction of borrowing after a shock influences decisions, I assume that the first period borrowing constraint does not bind (i.e. $\lambda_1 = 0$), which allows first period choices of x and b^1 to adjust rather than being fixed at the constraint. Under this assumption, the optimal choice of x is determined by:

$$m_G \frac{\partial f_G}{\partial x} = R \left[\frac{q}{1-q} \frac{u'(c_B^2)}{u'(c_G^2)} + 1 \right] \tag{10}$$

[15]
$$M = \underbrace{\left[u(c_d^1) - u(c_r^1)\right]}_{First\ Period} + \underbrace{\left[(1-q)\beta u\left(m_G f(x_d) - Rb_d^1\right) - (1-q)\beta u\left(m_G f(x_r) - Rb_r^1\right)\right]}_{Second\ Period\ Good\ State}$$
The difference in these terms is *only* due to the different optimal choices of x and b^1 in the first period, rather than the repayment (or non-repayment) of loans. Therefore, because I know that $x_d > x_r$ and $b_d^1 > b_r^1$, the utility received when a client defaults is higher than the repayment utility. Therefore $M > 0$.

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

Allowing borrowing after a shock in the second period will increase consumption in this state (c_B^2) relative to the constrained case. Thus, $u'(c_B^2)$ decreases as does the ratio $\frac{u'(c_B^2)}{u'(c_G^2)}$ in equation 10. This implies the entire RHS of the equation falls and that therefore that optimal first period input use will rise.[17]

I use a similar argument for first period borrowing, where the gap between $u'(c_B^2)$ and $u'(c_G^2)$ is reduced in the equation 11 below, which causes the entire RHS of the equation to fall. This in turn implies and increase in period one consumption (and therefore an increase in borrowing).

$$u'(c^1) = \beta R \left[q u'(c_B^2) + (1-q) u'(c_G^2) \right] \tag{11}$$

Last, I examine what factors determine the choice of b_B^2. Because there is no uncertainty moving into the third period, the optimal choice of bad state borrowing is defined by the standard condition:

$$u'(c_B^2) = \beta R u'(c_B^3) + \lambda_2$$

Households will be more likely to borrow in the bad state if they have a particularly 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 gives four predictions that result from extending a credit line in the bad state of the world:

1. Consumption increases after a shock
2. First period investment increases
3. First period borrowing increases
4. Probability of taking the Emergency Loan will be higher among households that experience heavy damage from flooding or those with good post-Aman income opportunities

If I consider the case of households that default after a shock, it is easy to see that only prediction 1 will carry through. These households will indeed choose borrow in the bad state and therefore increase their consumption as they do not plan to repay the loan. However, because they 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. Further, I can see that the optimal bad state borrowing amount will always be to take the maximum allowed, $b_B^2 = \bar{B}_2$, as there is no cost of repayment when already under default.

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

Interaction with the Good Loan

I now consider the situation faced by clients who also have access to the Good Borrower loan. Without the Emergency Loan, these households solve the same baseline model as above, with the only difference being that their first period borrowing constraint is $1.5\bar{B}_1$.[18] However, with the introduction of the pre-approved 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:

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

Now, 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. It is for borrowers in this position that the problem of credit line preservation becomes salient - households must now consider the value of preserve their credit line for a time of need is, and whether or not this is worth forgoing current period investment. The constrained maximization problem changes to:

$$\begin{aligned} \max_{x, b^1, b^2_B} \quad & u(Y - x + b^1) + q\beta u(-Rb^1 + b^2_B) + (1-q)\beta u(m_G f(x) - Rb^1) + \\ & q\beta^2 u(I - Rb^2_B) + (1-q)\beta^2 u(I) + \lambda_1[1.5\bar{B} - b^1] + \\ & \lambda_2[0.5\bar{B} - b^2_b] + \lambda_3[1.5\bar{B} - b^1 - b^2_B] \end{aligned}$$

To simplify expressions, I assume that the Emergency Loan credit availability ($0.5\bar{B}$) would be enough so that the borrower will not be credit constrained in the bad state of the world if they maintain their full credit line (i.e. $\lambda_2 = 0$). Under this assumption, the ex-ante input choice optimality is now determined by:

$$\frac{\partial f_G}{\partial x} = R\left[\frac{q}{1-q}\frac{u'(c^2_B)}{u'(c^2_G)} + 1\right] + \frac{\lambda_1}{\beta(1-q)u'(c^2_G)} + \frac{q}{1-q}\left[\frac{u'(c^2_B) - \beta u'(c^3_B)}{u'(c^2_G)}\right] \tag{12}$$

The first two terms of the equation are the same as we have seen previously in equation 2. However, the last term is new and reflects that fact that with the combined constraint, any bor-

[18] Note that this result relies on the implicit model restriction that households cannot both borrowing and save in the same period.

rowing in period one now limits the ability to smooth consumption in the future bad state by using some of the household's credit line. 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. This has the effect of increasing the value of the right hand side of the equation implying 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 is now:[19]

$$u'(c^1) = \beta R\left[qu'(c_B^2) + (1-q)u'(c_G^2)\right] + \lambda_1 + q\beta\left[u'(c_B^2) - \beta u'(c_B^3)\right] \tag{13}$$

Here, 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 then the third term will be positive and this will imply that the increase first period borrowing will be lower relative to a Good Loan eligible client that does not have access to the Emergency Loan.

These results imply that when we consider the impact of the new product, we should see on average a *stronger* effect of the Emergency Loan product on ex-ante input use and borrowing among clients that are *not* eligible for the good borrower loan than among those who are. Additionally, the emergency loan product will *reduce* the probability that eligible clients actually take the Good Loan if they expect to be credit constrained in the bad state of the world.[20] Therefore, we get two further predictions:

5. The treatment effect on first period investment will be lower among Good Loan eligible clients.
6. The offer of the Emergency Loan will reduce the probability that eligible clients take the Good Loan.

Repayment Decision with Guaranteed Credit

The goal here is to understand how allowing second period borrowing in the bad state changes borrowers' loan repayment decisions. Recall equation 8 that defined the value K^*, which is the benefit of future access to microfinance that would make a households indifferent between repayment and default. With the introduction of the Emergency Loan, this expression expands to include the option to borrow in the second period bad state and therefore also repay, or not, in the third period:

$$K^* = \frac{M}{q} + \beta\left[u(b_B^2) - u(-Rb_r^1 + b_B^2)\right] + \beta^2\left[u(I) - u(I - Rb_b^2)\right] \tag{14}$$

[19] Again, assuming $\lambda_2 = 0$

[20] Because in reality the uptake of the Good Loan is a binary choice, the effect of the Emergency Loan on Good Loan uptake will be weakly negative.

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 $b_B^2 = 0$.

$$\frac{\partial K^*}{\partial b_B^2} = \underbrace{\frac{1}{q}\frac{\partial M}{\partial b_B^2}}_{-} + \beta \underbrace{\left[u'(0) - u'(-Rb_r^1)\left(1 - R\frac{\partial b_r^1}{\partial b_B^2}\right)\right]}_{-} + \underbrace{\beta^2 Ru'(I)}_{+} \tag{15}$$

The first and second term above are negative, which 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 default when given more credit. Therefore, the overall effect on repayment is ambiguous.

MFI Problem

I now move beyond the household and consider the implications of offering guaranteed credit after a shock from the MFI's perspective. 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 $b(R-1)$ in interest), or lost completely costing the branch the full loan amount b. When a shock occurs, $F(K^*)$ gives 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:

$$\Pi = q\left[(1 - F(K^*))(R-1)b - F(K^*)b\right] + (1-q)(R-1)b \tag{16}$$

We are interested in whether it is profitable for the MFI to extend additional, guaranteed liquidity to borrowers after a shock has occurred. To explore what happens to expected profits with this policy change, we can simple explore how equation 16 changes when the amount borrowed b, is allowed to move from b^1 to $(b^1 + b_B^2)$.[21] 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

$$\begin{aligned} &q\left[(1 - F(K_E^*))(R-1)(b_E^1 + b_B^2) - F(K_E^*)(b_E^1 + b_B^2)\right] + (1-q)(R-1)b_E^1 \\ \geq &q\left[(1 - F(K_{NE}^*))(R-1)(b_{NE}^1) - F(K_E^*)(b_E^1)\right] + (1-q)(R-1)b_{NE}^1 \end{aligned} \tag{17}$$

Where K_E^*, K_{NE}^* and b_E^1, b_{NE}^1 represent the indifference points for repayment and optimal first period borrowing choice with and without the Emergency Loan respectively. Rearranging equation

[21] I assume households will take the Emergency Loan when offered, as otherwise the expected profits do not change

17, we can write that profits will increase if

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

In equation 18, term A captures the change in profits from repayments. Because we know that b_E^1 is at least as large as b_{NE}^1, then $b_E^1+b_B^2 \geq b_{NE}^1$ unambiguously.[22] However, as we saw in equation 15, the effect of the Emergency Loan on K^* is ambiguous, therefore 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 clearly positive. However, the offer worsens repayment rate, 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 $F(K*_E)$. Therefore, as before, the sign of term B depends on what the effect of the Emergency Loan is on repayment rate (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, is $\frac{\partial K^*}{\partial b_B^2}$ is negative, then the overall sign of B is ambiguous.

Finally, term 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 term C. Taking all three terms together, the overall effect on MFI profits from offering the Emergency Loan is ambiguous, and will be determined by i) the extent that the Emergency Loan changes households repayment rates positively and ii) how the number of loans the MFI extends (including Dabi, Good, and Emergency Loans) changes as a result.

4 Research Design

The impact of the Emergency Loan was tested 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

[22] 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.

sample to branches that were located within 15 kilometers of a river gauge run by the government's Flood Forecasting and Warning Center (FFWC) so that flooding could be monitored remotely. Next, 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. Last, I consulted the Bangladeshi branch of the International Rice Research Institute (IRRI) and the BRAC branches themselves to confirm that each branch's service area had experienced flood damage in the past six years. Figure 2 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. A total of 100 branches were assigned to the treatment group, and the remaining 100 branches were placed in the control group stratified by district. Table 3 provides descriptive statistics from households sampled from the treatment and control branches and p-values for the differences between these groups. The table shows that the randomized branches are largely balanced on baseline observables.

The experiment began in April 2016 when the Emergency Loan eligibility lists were created in each of the 200 experimental branches. Each branch manager could then review the lists and remove up to 10% of the eligible borrowers based on their knowledge of borrowers' behavior. The final eligibility lists were then sent to BRAC headquarters for data keeping and to verify that no more than 10% of borrowers had been removed from the original lists. Once finalized, referral slips (see Figure 3) were created for each eligible borrower in the branch. Each slip contained the borrower's name, BRAC identification numbers, and details on the Emergency Loan 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 if they took a Good Loan. The top half of the slip was kept by the borrowers to serve as "proof" of their eligibility status and to serve as a reference about the details of the loan. The bottom half of the slip was filled out with the borrower's information and phone number to help the branch management contact eligible borrowers after a flood.

The referral slips were distributed throughout the month of April during the normal VO meetings for each branch. At the end of each meeting the loan officer distributed the referral slips to each eligible borrower and read a script that explained the purpose and the key features of the product. The concept of pre-approval was emphasized repeatedly because the idea was new within BRAC microfinance operations. Borrowers were asked questions about the Emergency Loan to confirm their understanding and time was given to answer any questions that eligible clients had about the product. Random branch visits during June of 2016 confirmed relatively good execution of pre-approval notification. Almost all borrowers had received the referral slips and understood that the Emergency Loan was available in case of flooding. There was some heterogeneity in borrowers understanding of the more nuanced details of the loan, including pre-approval and conflict with the Good Loan. This was largely driven by difference in the quality of branch management.

During the Aman season, the FFWC flood water gauges were monitored every day for high water levels. When a gauge showed water levels crossing the danger level, a BRAC research employee (designated a “sector specialist”) was asked visit the branches matched with the gauge. They mapped the area within each branch that had been affected by flooding based on conversations with local officials. If the reported amount exceeded 20%, the branch was activated (importantly, the sector specialists did not know about the 20% threshold needed to activate each branch). The branch manager was instructed from headquarters to notify all eligible borrowers that Emergency Loans were available. Borrowers were notified through their normally scheduled VO meetings or, in cases where VO meetings were suspended because of flooding, by calling clients directly and passing information through BRAC’s social network. Additionally, eligible clients were reminded about the Emergency Loan’s availability at every subsequent VO meeting until the expiration of the offer in November.

Over the course of the 2016 Aman season 92 branches were activated, 40 control and 51 treatment.[23] 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. However, 14 branches (7 treatment, 7 control) were removed from the experiment from 2016 to 2017 due to changes in the local topography (new dams and roads) that reduced the probability of local flooding in these regions to almost zero. These 14 branches were replaced with back-up branches that had been already pre-selected in the initial selection process described above. The new branches were randomized into treatment and control in February 2017. In 2017, 136 branches were activated, 73 control and 63 treatment. Flooding in 2017 was in general more severe than the previous year, and several locations suffered significant damage to crop land and physical structures.

5 Data

The data used in this analysis comes from two primary sources. First, I use BRAC’s administrative loans and savings records for all clients in the experimental branches. This dataset reveals every client’s borrowing behavior, including decisions to take loans, loan repayments and savings activities. Detailed repayment and savings data are available from April 2016 until January 2018, while loan disbursals data extends back for 1-7 years depending on the branch.[24] Within the loans data set, we observe approximately 350,000 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

[23]The discrepancy in activation rates is likely due to random chance (the difference in means is not statistically significant). Much effort was put in to ensure that control and treatment branches flood activation procedure was followed in the same way, and this policy way reinforced when the difference in activation rates emerged early in 2016.

[24]Certain BRAC branches began digitizing data earlier than others and 2) some branches in the experiment were founded relatively recently.

the purposes of this research.[25] Figure 4 shows a timeline of uptake of the three loan types studies in this research (Dabi Loan, Good Loan, and Emergency Loan) over the periods for which data is available, with the Aman growing season in 2016 and 2017 shaded in gray.

Second, I use survey data collected from 4,000 BRAC clients and 800 BRAC staff drawn from the 200 experimental branches. For the borrower survey, three village organizations (VOs) were randomly selected from each branch. Fifteen eligible borrowers and five ineligible borrowers were randomly selected within each VO. Three rounds of data collection took place: a baseline survey was conducted in April 2016 before borrowers in treatment branches were informed about their eligibility status; a follow-up survey was implemented in December 2016 after the first flooding season, and a second follow-up took place in December 2017 after the second flooding season. Survey rates were very good, 99% at the first follow-up and 98.9% at the second follow-up.[26] The household surveys focused on both agricultural and non-agriculture business investments and outputs, consumption, asset holdings, and household perceptions of and response to any flooding that occurred in the area. The surveys of BRAC's administrative staff included 4 branch-level managers (both in and outside of microfinance operations) and asked about their perceptions of flood risk, the most important local income generating activities, and their perceptions of overall local flood damage in the branch service area.

6 Results

Emergency Loan Take Up

I first examine the decision to take the Emergency Loan after a flood shock. In both years uptake of the Emergency Loan among eligible households was quite low. In 2016, only 2.9% of households chose to take the loan, likely because the floods that year were not particularly severe 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 these low take-up rates do not necessarily imply that households did not value or benefit from the Emergency loan's availability. While I address this point in more detail below, households can respond to the offer of a loan before flooding has even occurred. Indeed, the Emergency Loan stimulates higher investments and greater output, suggesting it offers important protection in the pre-period against low probability 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 others villages within the same branch will not be hit at all.

Table 5 reports which household characteristics correlate with take-up among the set of households that were offered the Emergency Loan (i.e. those that were in a treatment branch after a flood). Considering first baseline characteristics, column 1 shows that households that took the

[25] Due to uncertainty about whether the project would continue for a second year, this data is missing for five months between November 2016 and March 2017 while the decision to extend the experiment was being made.

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

Emergency Loan are observably quite similar to households that did not on most dimensions (risk aversion, time preferences, flooding history and income). Column 2 explores correlations between uptake and households status after a flood. I see higher take-up among households that were less well prepared for a flood and among those that experienced higher levels of distress. Furthermore, figure 5 highlights lower yields among households that took the Emergency Loan. Finally, figure 6 shows that there is no significant difference in the probability of Emergency Loan uptake by borrower credit score. Overall, the results suggest that the more vulnerable and worst affected households are more likely to take advantage of the guaranteed credit offer, results that are largely consistent with the theory.

Estimation Strategy

To estimate the effects of guaranteed credit lines on household level outcomes, I will compare *eligible* BRAC microfinance members across treatment and control branches. Eligible clients in control branches are those who had credit scores 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.[27] Data from both years of the experiment are pooled together (unless noted otherwise) and standard errors are always clustered at the branch level.[28] 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.

The same basic procedure is largely followed for MFI level outcomes (e.g. loan uptake decisions, repayments) but with a few modifications. Because I examine observations at the branch-month level, and thus add month m fixed effects in addition to year and district fixed effects.[29]

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

Credit Line Preservation

As mentioned above, low take-up does not necessarily reflect the value that households attribute to the Emergency Loan. Gains from the loan can be reaped even if households decide not to take the loan after the uncertainty about the flood is resolved. Access to the loan improves welfare by reducing households exposure to the downside risks associated with severe flooding. To test whether

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

[28]Appendix B 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.

[29]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

households recognize this crucial feature of the Emergency loan, I investigate two phenomenon. 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 have a recourse 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, 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 among Good Loan eligible clients in control branches compared to treatment branches in the pre-flood period. For this analysis I use BRAC's administrative data that captures loan disbursals and repayments.

Table 6 shows the results from the cross branch comparison of Good Loan eligible borrowers (the regressions are run at the branch MFI level). Column 1 shows that the availability of the Emergency Loan reduces the probability of taking a Good Loan by 2 percentage points, or 15% in treatment branches. Column 2 and 3 examine the extent to which this effect changes based on a measure of the need for liquidity, and by the perceived risk of local flooding. I proxy the need for liquidity by areas that report farming as the primary occupation, where significant investments are needed in the pre-period to prepare the seedbeds for cultivation. I do not see any significant change in the treatment effect in areas where the primary occupation is farming. However, areas that have a higher perceived flood risk are even less likely to take the good loan. Together these results shows that a significant number of households that would have exhausted their available credit absent the Emergency Loan, choose instead to preserve it. Furthermore, areas that face higher risk are more likely to preserve their credit access, confirming that at least some households view guaranteed credit access as offering effective insurance against shocks.

The fact that households are willing to give up investment in the pre-period suggests that the value of preserving the guarantee is substantial for at least this subset of households. Those that forgo the Good Loan in order to preserve access to the Emergency Loan are giving up certain credit today in order maintain credit in the future that will only be made available with some probability. If I assume that households were able to correctly predict the probability a loan would be offered (54% over the two years of the study), this implies that households value access to credit in the event of a flood at a minimum of 1.85 times the value of certain credit in the pre-period.

In order to understand which borrowers are more likely to actively preserve their credit access, I estimate a local average treatment effect across bins of the Emergency Loan credit score. Figure 8 plots the treatment effect on Good Loan uptake by credit score bin for eligible clients. There appears to be some evidence of heterogenous treatment effects: the reduction in the probability of taking a good loan among the eligible population is highest among those with especially high credit scores. Column 1 of Table 18 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 they are less present biased. Such households would likely make more timely payments (hence the higher credit scores) and be willing to preserve credit access.

Ex-Ante Household Investment

Recall from theory that the extension of a guaranteed credit line is designed to mitigate the adverse consequences of a shock, thereby encouraging households to invest more in the pre-period. 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 sensitive to interventions that reduce household flood risk. I also investigate the impacts on non-agricultural business investments because the sample is drawn from microfinance clients that are more likely to be business owners and less likely to own land than the general rural population (48% of surveyed households planted crops during the 2015 Aman season).

I begin with Table 7, which shows 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, namely 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 season. Households that knew they were eligible for the loan increased the amount of land they rented by 30%, and overall cultivation 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 straight forward. Conversely, expanding the cultivation of owned land would require farming previously fallow land or purchasing additional crop land, which is more costly and requires more planning. Similarly, sharecropping contracts become relatively less attractive because farmers ability to reduce their exposure to risk can now be fulfilled by the Emergency loan. Finally, along the extensive margin, the number of eligible households planting crops increased by approximately 4 percentage points. This represents a 10% increase in the probability that a household cultivates crops during the Aman season.

With an expansion in cultivated land, total input use is likely to increase mechanically. However, households might also increase the intensity of input usage in response to reduced exposure to risk. The first four columns of Table 8 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 increase but remain 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 8 examines the amount of investments in non-agriculture business. We see a marginally significant increase of 29% ($11 USD) over the control group.[30] However, this last result is sensitive to the regression specification and only becomes significant in the second year of the experiment.

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).[31] 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. Table 9 and 10 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 9 we see that all the point estimates on the interaction terms between risk aversion and treatment are positive. However, they are only significant for rented and total land cultivated (which is where I documented the strongest impacts previously). I also investigate the impact for risk averse households specifically by running a joint test on the treatment and interaction terms. Here I find significance for the treatment effect on rented land in addition to total land. Similarly, in Table 10 the interaction term is positive for fertilizer, pesticide, and for non-agricultural investment. The joint tests indicate that pesticide application and non-agricultural investment have increased significantly for most risk averse households. Overall these results suggest that guaranteed credit lines are encouraging investments by reducing households exposure to risk. The fact that risk averse households tend to undervest in general suggests this product is particularly valuable at correcting a negative distortion for this subgroup.

The results on increased investment and credit preservation suggest that households perceive the Emergency Loan as reducing their exposure to risk. However it is possible that households choose not to take the Emergency Loan because they learn ex-post that it would never be useful to them (in this season or in any future one). This might be driving the low take-up results we saw above. If households are learning this, we would to expect see their 2017 Aman season investments decrease to pre-treatment levels because their choice not to adopt in the future eliminates the risk reduction benefit of 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 households learn that the Emergency Loan does not insure them against negative outcomes, these households should have a smaller treatment effect on investment relative to treatment households that did not experience a flood shock. However, if households still perceive the offer of guaranteed credit as reducing the downside risk of flooding, then investment should be the same (or larger) when compared to households that were not flooded in the first year.[32]

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

[31]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.

[32]A possible confounding factor is that the extra credit afforded by access to the Emergency Loan in the first year could itself impact investment decisions in year two. However, this effect will have a minimal role due to the fact

Table 11 demonstrates how flooding in the first year affects different investment categories. First, we can see that being flooded in the previous year does seem to have negative consequences for control households' investments in the current year. In particular, control households are ten percentage points less likely to cultivate crops in areas that were flooded in 2016. However, the treatment effect on investments does not appear to be different for treatment households that were flooded in the first year relative to treatment 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 some flood risk.

Ex-Post Household Outcomes

Next I turn to 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. If a flood does not a occur, increases in investment before the Aman season will translate into improved output.

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.[33] Table 12 shows the results of regressing these outcomes on an indicator for treatment, an indicator for experiencing a flood shock during the growing season, and an interaction between the two.[34] The coefficient on treated captures the effects on household outcomes from increases in ex-ante investment only. Absent a flood the only difference in outcomes between treatment and control households will stem from changes in investment in the pre-period. In contrast, the interaction term will capture the effect of *both* channels on household outcomes. 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, treated households display the same levels of consumption, income, and livestock ownership as control households (Table 12). However, there is a significant 28% increase in crop production which aligns with the pre-period results documenting additional crops being sown by treatment 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 experience a rather large 10% increase in consumption compared to control households.[35] However, their production is affected by the flood, losing almost 80% of the gains they reap when

that only 2.9% of eligible households took the Emergency Loan when offered in the first year.

[33]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.

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

[35]The p-value for the joint test is found in the bottom row of table 12

a flood does not occur (Column 3). These losses are proportionally much larger than those observed in the control group, suggesting that treatment households expand cultivation on land that is particularly susceptible to floods. Finally, we see a large increase in the number of livestock among treatment households (Column 4). This suggests that the availability of the Emergency Loan allows households to maintain their asset levels after an income shock.

There is a concern that multiple shocks may reduce the usefulness of credit as a risk mitigation tool if households use their entire available credit line, thereby eliminating the products consumption smoothing benefits. Table 13 examines this hypothesis. To do so, I expand the regression specification from Table 12 to include an indicator for wether the household experienced flooding in both years, and an interaction of this indicator with treatment. The experiment was only conducted over two years, so multiple shocks can only be picked up for households that experience flooding in both 2016 and 2017. The results confirm that experiencing successive shocks reduces food consumption by 19%, but has little observable impact on the other three outcomes. This suggests that multiple shocks are indeed harmful to households well being, even if the channels through which this occurs are unclear. Next, 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.

Finally, Table 14 explores how the availability of the Emergency Loan changes outcomes for households that earn income through the labor market rather than (or in addition to) agriculture or a small business. The first column shows that laborers' daily wage does not change in flooded or non-flooded areas. In non-flooded areas however, the number of days employed elsewhere as a day laborer decreases by 10%, likely a result of more households spending time on their own fields. In flooded areas, we see a 30% reduction in day labor, which is substantially reversed in treatment households (by approximately 20%). This result could be consistent with the fact that households often use the Emergency Loan to re-plant the fields destroyed by floods, increasing the number of opportunities for other laborers to find work. However, given the low rates of Emergency Loan take-up, this channel is unlikely to explain the entirety of this effect.

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. 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 increases the likelihood that borrowers take an initial loan from BRAC. To do so, I examine the probability that a normal dabi loan is taken in the pre-flood period among all members of the branch.[36] The results in Table 15 show that treatment causes the probability of taking a dabi loan to increase by 11% (0.7 percentage points) in the pre-period. However, it is possible that the increase in loan disbursement during the pre-period came at the expense of future loans (for example, if households simply move up their previously planned investment timeline). Figure 9 examines whether this is occurring by plotting 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. Finally, as with the Good Loan analysis, I examine whether the increase in Dabi Loan uptake differs across credit scores. Figure 10 and column 2 in Table 18 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 16 shows how the probability of a missed payment differs between treatment and control branches in the pre-period and after a flood. The coefficient on treatment shows that access to the Emergency Loan has no effect on repayment rates in the absence of a shock. Looking at the coefficient on flooding, we see that flooding increases the number of missed payments by approximately 3.9 percentage points (40% percent) in control branches. 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 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 borrower credit score. Figure 11 and 12 illustrate how repayment rates differ by credit score and by treatment status. First, Figure 11 shows that the treatment effect on repayment rates[37] is largest among clients with scores that are close to the eligibility threshold of 77. The effect falls quickly at higher credit scores (column 3 of Table 18 shows that this heterogeneity is statistically significant). This decrease is likely explained by the fact that borrowers with high credit scores already repay at such high rates that further improvements are difficult. In Figure 12, we see that approximately 6% of payments are

[36] 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.

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

missed among those with high credit scores, which is low enough that it may be difficult to improve repayment rates significantly.

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 17 shows the estimated effects of treatment on three measures of MFI profitability: the net present value of each loan disbursed, the monthly profitability of the branch in aggregate, and the per-member monthly profitability of each branch.[38] 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 allow us to say that branch profitability was likely not harmed.

We can examine the extent to which the effects on profitability vary by borrower credit score. Figure 13 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 18 show that this heterogeneity is statistically significant). These results are consistent with the effects I have shown previously. Clients with scores near the cutoff both have the highest improvements on repayment rates and the lowest reductions in the probability of taking a Good Loan. In contrast, high credit score clients make only modest improvements to their repayment rates while experiencing the largest reductions in the probability of taking a Good Loan.

These results have interesting implications for the targeting of the Emergency Loan. The Emergency Loan was targeted at the top 40% of borrowers based on a credit score reflecting 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.

As a final check on MFI performance we can look at saving rates. BRAC benefits directly from the amount of savings stored by clients at the branch. Table 19 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 a draw down in liquid assets, savings rates do not differ between the two branches. However, column 2 shows that in the aftermath of

[38]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.

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[39].

7 Conclusion

Millions of households across the world are exposed to severe income risk. In many cases, these households live in areas where insurance markets are non-existent and they have to resort to 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. I build on recent literature, which suggests that uninsured risk is an important constraint and that existing insurance products are inadequate, by offering a guaranteed credit line as a potential solution. I run a large scale RCT to investigate whether guaranteed credit can successfully function as insurance 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. Household that were informed about their guaranteed credit access also increased their investments in productive (but risky) activities in the pre-period. These effects were concentrated among more risk-averse households. This increase in investments translated into more production absent a flood, and higher consumption and asset levels when a shock did occur.

I also show that the extension of a guaranteed credit line after a shock has modest, but largely positive effects for MFIs. More members take loans in the pre-period in response to the added security, repayment rates after a shock are improved, and savings rates increase. Therefore, at least in this context, a product like the Emergency Loan slightly improves branch performance in addition to benefiting clients. Provided that loan repayment rates remain similar in other settings, this suggests that guaranteed credit can be offered by MFIs and does not require any third party subsidies. This is appealing because MFIs are ubiquitous in low income countries and can easily offer the product to many households using their existing infrastructure.

One question raised by the results is why a product like the Emergency Loan that seems to benefit both households and the MFI has not already been adopted by the microfinance industry. I suggest two obstacles that may prevent adoption. First, many MFIs do not keep adequate records and lack the lending history necessary to create a credit score to target responsible borrowers. The results are unlikely to generalize to lower performing clients and it is important to be able to identify who these households are. Second, a guaranteed credit product does not necessary align with the incentives facing branch level officials. Branch managers are commonly incentivized to disburse a certain number of loans and to maximize repayment rates. However, in the aftermath

[39]Flood damage at the branch level was only collected in 2017, therefore column 3 only uses data from this year.

of an aggregate shock, a branch manager may be concerned that households are going to miss payments on their existing loans, and a product like the Emergency loan will compound these losses. This would increase the downside risk facing the branch, and could potentially jeopardize the manager's job. Therefore, there is likely be resistance from branch level staff to adopt similar guaranteed products.

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. With the growing frequency and severity of weather shock due to climate change, adding an easily accessible tool that helps households reduce exposure to risk is important. The tool I explore here (guaranteed credit) is appealing because it is already understood in these environments and it widely used worldwide. While the household impacts are similar to those documented in the index-insurance literature, pre-approved credit has the advantage that it can be extended without requiring any commitment from the beneficiary, bypassing many of the drivers of low demand for insurance. Moreover, because the decision to utilize the additional credit is made after any shock damages have been realized, households can optimally opt-in based on the 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 flood.

References

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

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

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

Banerjee, Abhijit, Esther Duflo, and Richard Hornbeck. 2014. "Bundling Health Insurance and Microfinance in India: There Cannot Be Adverse Selection If There Is No Demand." *American Economic Review* 104 (5):291–297.

Banerjee, Abhijit, Dean Karlan, and Jonathan Zinman. 2015. "Six Randomized Evaluations of Microcredit: Introduction and Further Steps." *American Economic Journal: Applied Economics* 7 (1):1–21.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Dehejia, Rajeev, Heather Montgomery, and Jonathan Morduch. 2012. "Do Interest Rates Matter? Credit Demand in the Dhaka Slums." *Journal of Development Economics* 97 (2):437–449.

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

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

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

Emerick, Kyle, Alain de Janvry, Elisabeth Sadoulet, and Manzoor H. Dar. 2016. "Technological Innovations, Downside Risk, and the Modernization of Agriculture." *American Economic Review* 106 (6):1537–1561.

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

Field, Erica and Rohini Pande. 2010. "Repayment Frequency and Default in Microfinance: Evidence from India." *Journal of the European Economic Association* 6 (2-3):501–509.

Field, Erica, Rohini Pande, John Papp, and Natalia Rigol. 2013. "Does the Classic Microfinance Model Discourage Entrepreneurship among the Poor? Experimental Evidence from India." *American Economic Review* 103 (6):2196–2226.

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

Giné, Xavier and Dean S. Karlan. 2014. "Group versus Individual Liability: Short and Long Term Evidence from Philippine Microcredit Lending Groups." *Journal of Development Economics* 107:65–83.

Giné, Xavier and Dean Yang. 2009. "Insurance, Credit, and Technology Adoption: Field Experimental Evidencefrom Malawi." *Journal of Development Economics* 89 (1):1–11.

Giné, Xavier, X. 2009. "Innovations Insuring the Poor: Experience with Weather Index-Based Insurance in India and Malawi — FARMD: Forum for Agricultural Risk Management in Development." Tech. rep., International Food Policy Research Institute.

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

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

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

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

Janzen, Sarah A and Michael R Carter. 2018. "After the Drought: The Impact of Microinsurance on Consumption Smoothing and Asset Protection." Working Paper 19702, National Bureau of Economic Research.

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

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

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

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

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

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

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

Khandker, Shahidur R., M. Abdul Khaleque, and Hussain A. Samad. 2011. *Can Social Safety Nets Alleviate Seasonal Deprivation? Evidence from Northwest Bangladesh.* Policy Research Working Papers. The World Bank.

Knutson, Thomas R., Joseph J. Sirutis, Gabriel A. Vecchi, Stephen Garner, Ming Zhao, Hyeong-Seog Kim, Morris Bender, Robert E. Tuleya, Isaac M. Held, and Gabriele Villarini. 2013. "Dynamical Downscaling Projections of Twenty-First-Century Atlantic Hurricane Activity: CMIP3 and CMIP5 Model-Based Scenarios." *Journal of Climate* 26 (17):6591–6617.

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

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

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

Mel, Suresh De, David McKenzie, and Christopher Woodruff. 2011. "Enterprise Recovery Following Natural Disasters." *The Economic Journal* 122 (559):64–91.

Miranda, Mario J. and Katie Farrin. 2012. "Index Insurance for Developing Countries." *Applied Economic Perspectives and Policy* 34 (3):391–427.

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

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

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

Navajas, Sergio, Mark Schreiner, Richard L. Meyer, Claudio Gonzalez-vega, and Jorge Rodriguez-meza. 2000. "Microcredit and the Poorest of the Poor: Theory and Evidence from Bolivia." *World Development* 28 (2):333–346.

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

Rosenzweig, Mark R. and Hans P. Binswanger. 1993. "Wealth, Weather Risk and the Composition and Profitability of Agricultural Investments." *The Economic Journal* 103 (416):56–78.

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

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

Tedeschi, Gwendolyn Alexander. 2006. "Here Today, Gone Tomorrow: Can Dynamic Incentives Make Microfinance More Flexible?" *Journal of Development Economics* 80 (1):84–105.

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

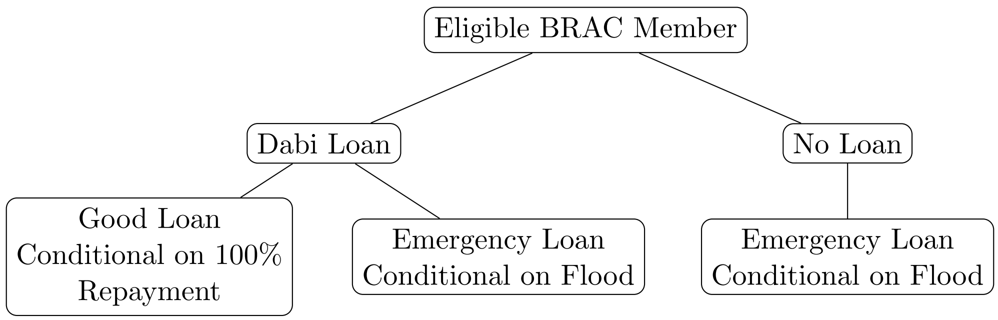
———. 1995. "Risk and Saving in Northern Nigeria." *The American Economic Review* 85 (5):1287–1300.

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

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

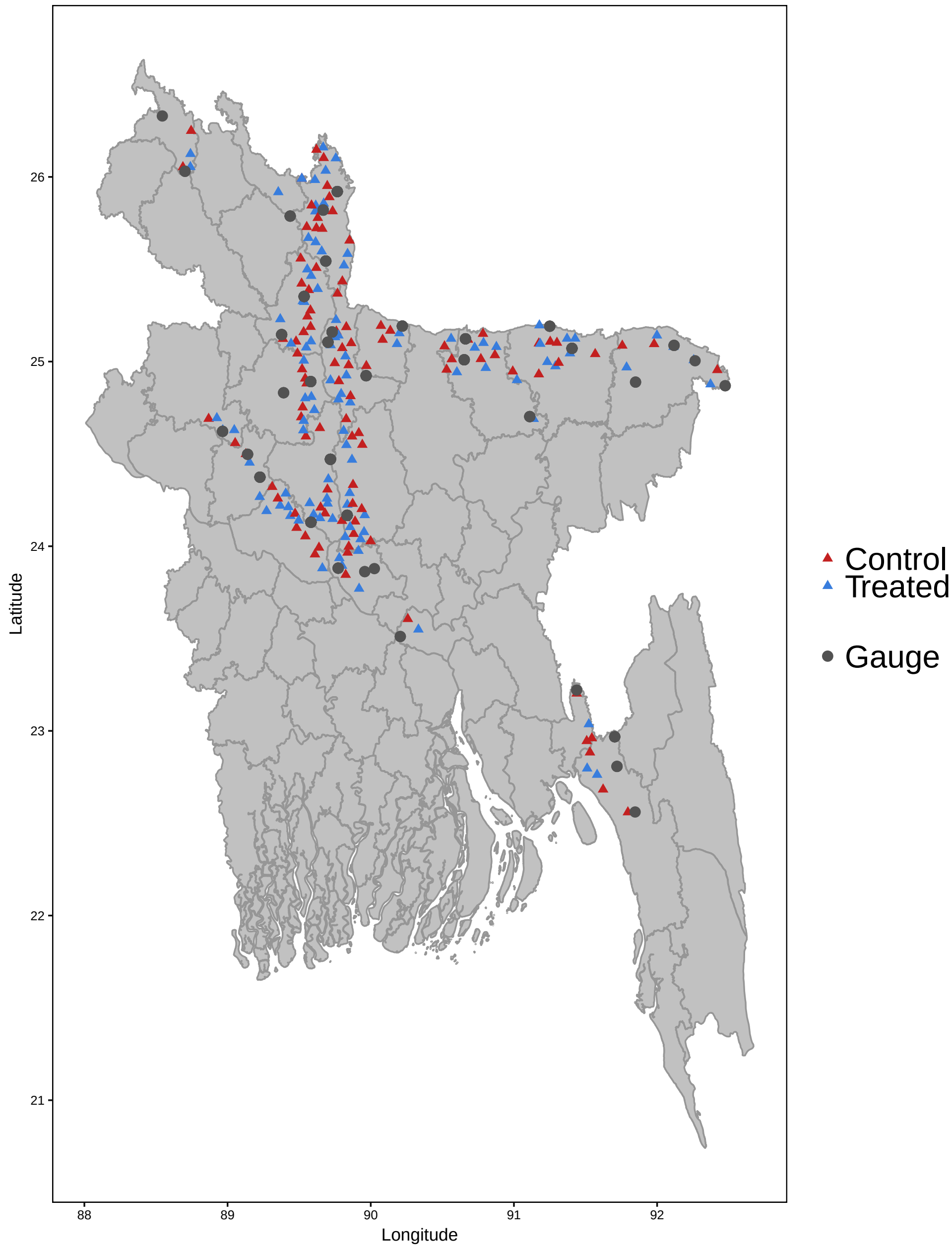
Figures

Figure 1: Loan Choices for Eligible Members



Notes: Figures 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 and vice versa.

Figure 2: 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 3: 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

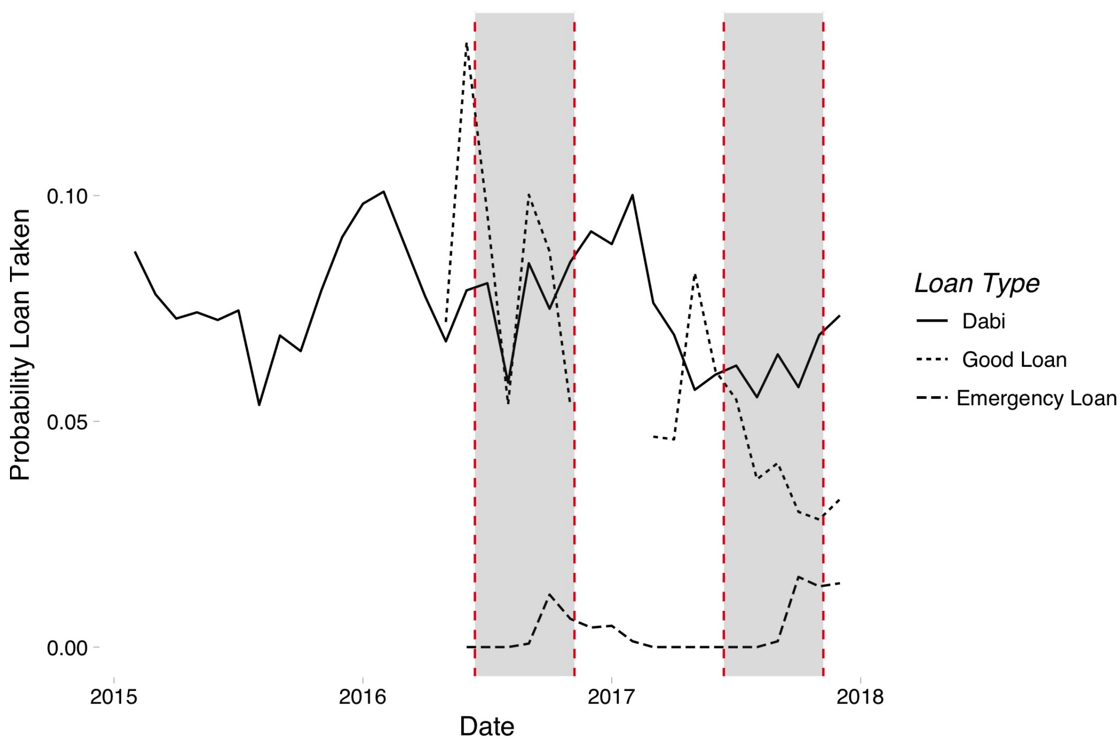
Referral Slip – Emergency Loan

Office Copy: Please keep

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

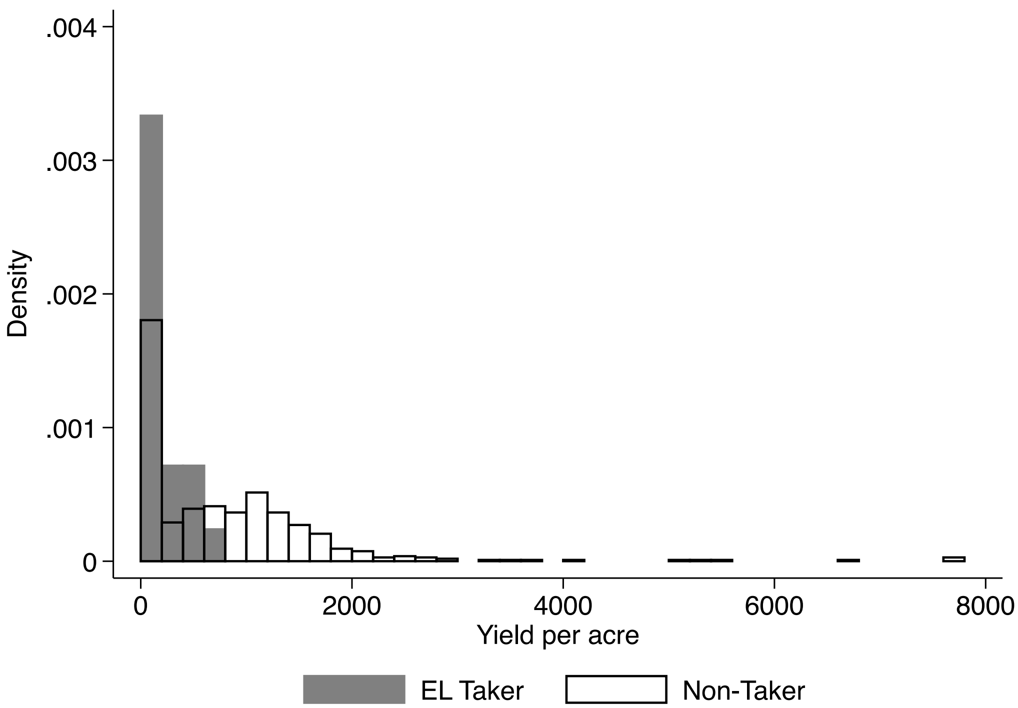
Notes: Shows the referral slip (translated from Bangla) given to BRAC microfinance members eligible for the Emergency Loan. The slip records clients name and BRAC identifiers, the maximum pre-approved loan size, as well as a brief description of the loan product. The bottom of the slip also contained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

Figure 4: BRAC Loans



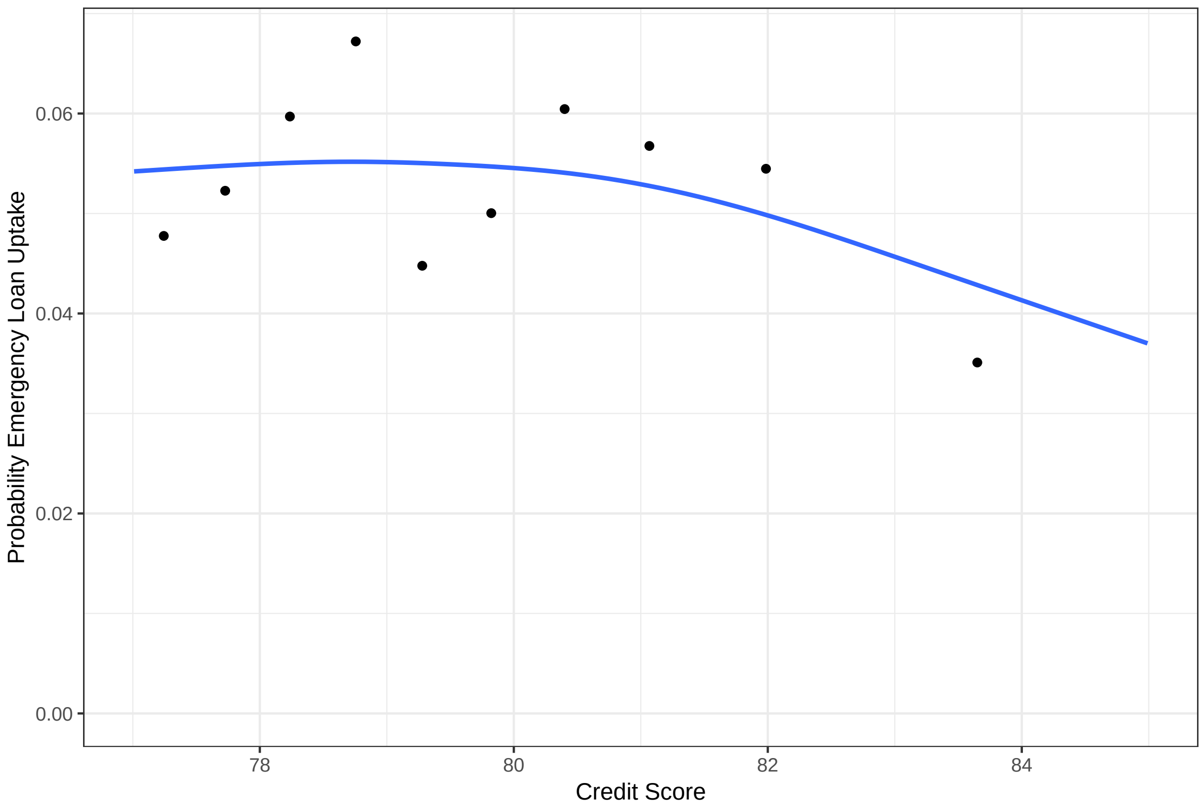
Notes: Figure shows the uptake of the three different BRAC loan products examined in the experiment. The solid line shows Dabi loan uptake as a proportion of overall branch membership. The Short-dashed line shows Good Loan uptake as a proportion of Good Loan eligible clients. The long-dashed line shows Emergency Loan uptake as a proportion of eligible clients offered the loan. 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 5: Yield Per Acre by Emergency Loan Uptake



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

Figure 6: Emergency Loan Uptake by Credit Score



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

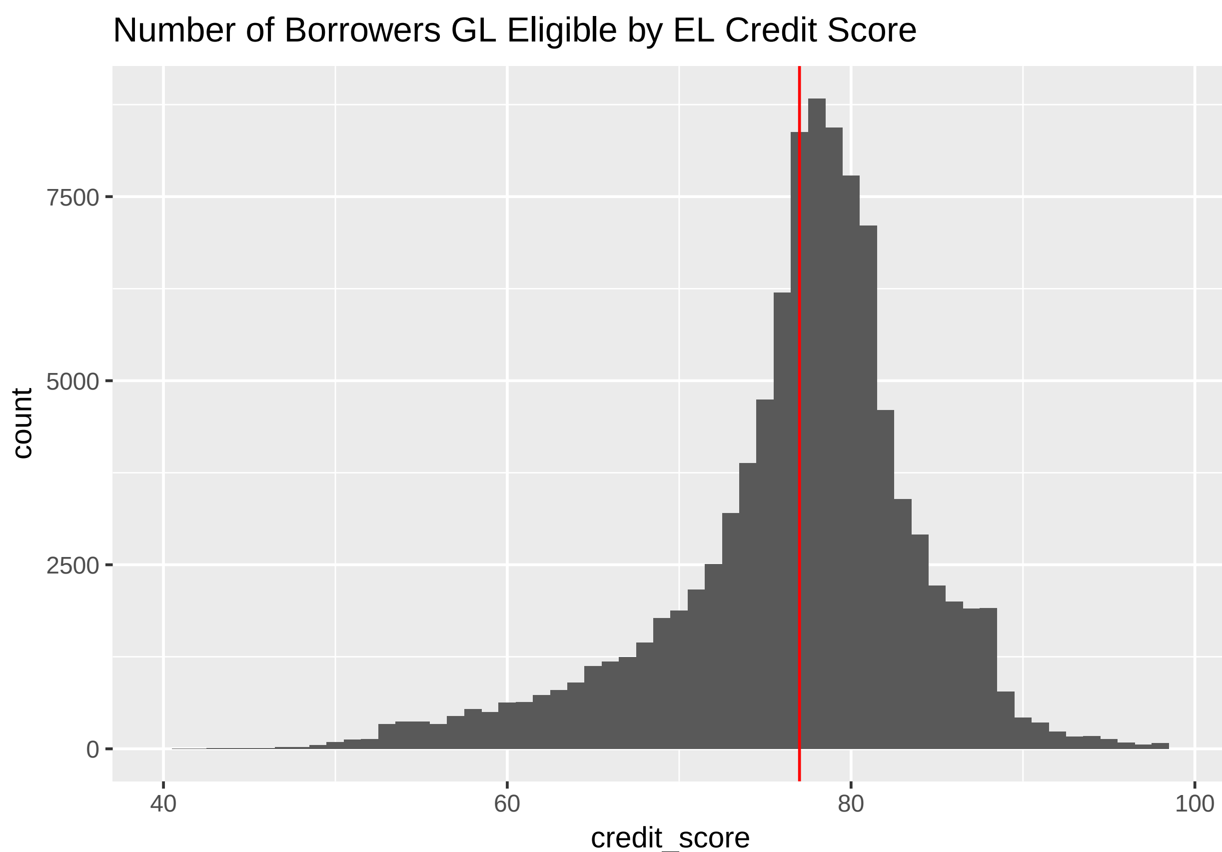
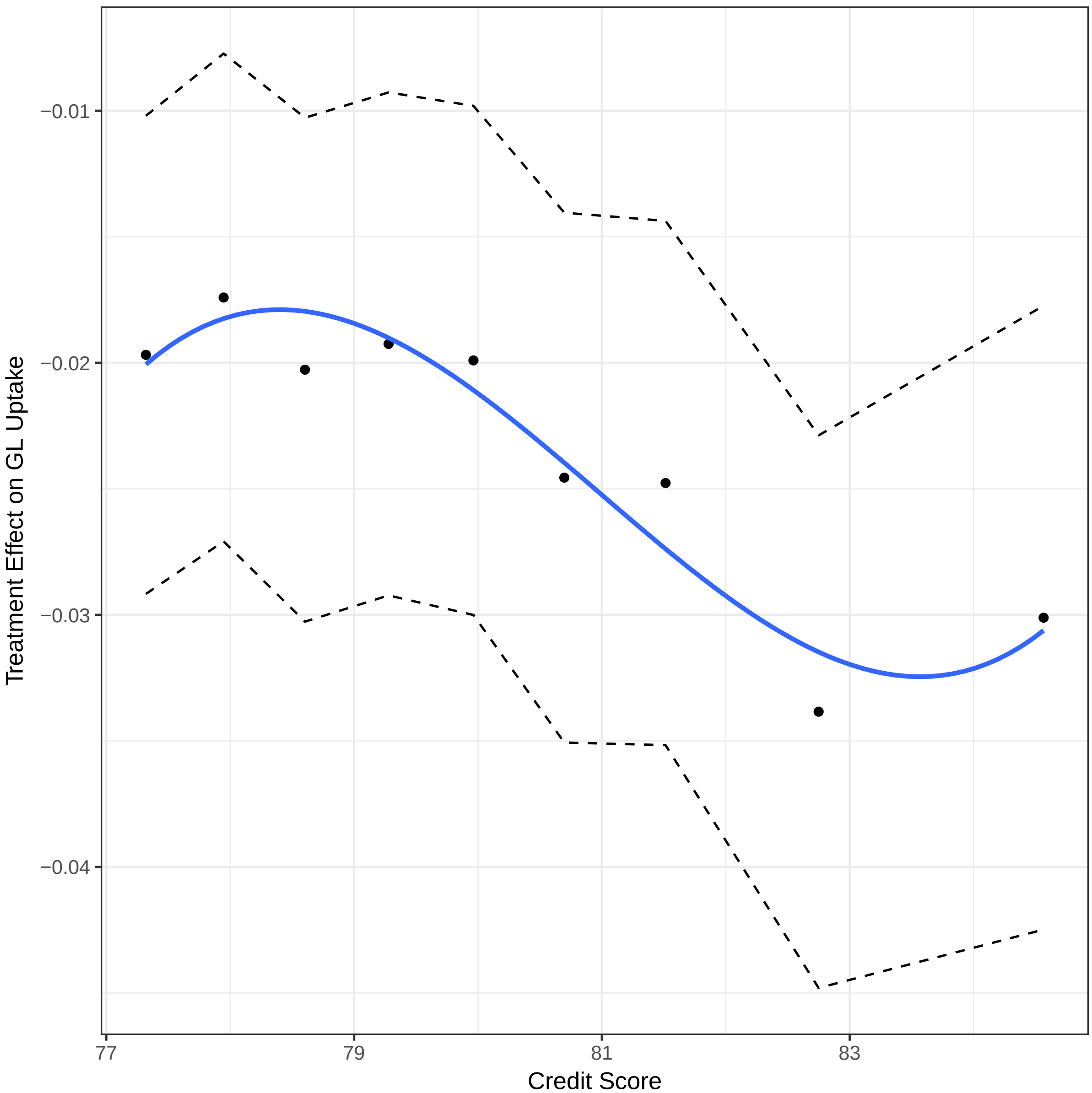


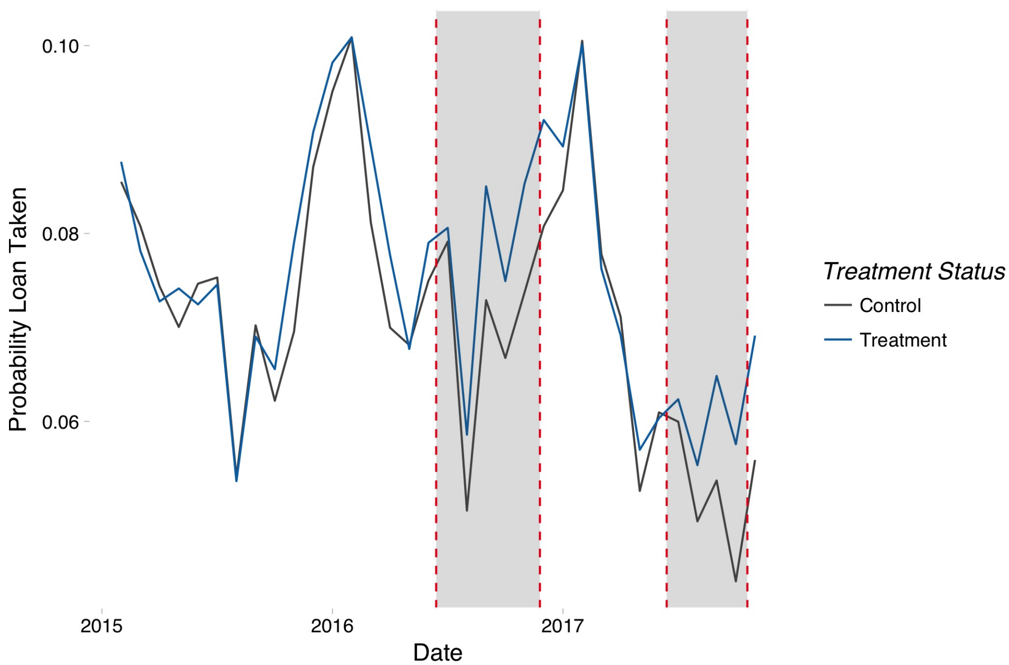
Figure 7: Plots the distribution of Good Loan eligible borrowers across all treatment branches by their Emergency Loan credit score. The eligibility threshold for the Emergency Loan (77) is shown in red.

Figure 8: Good Loan Uptake Heterogeneity



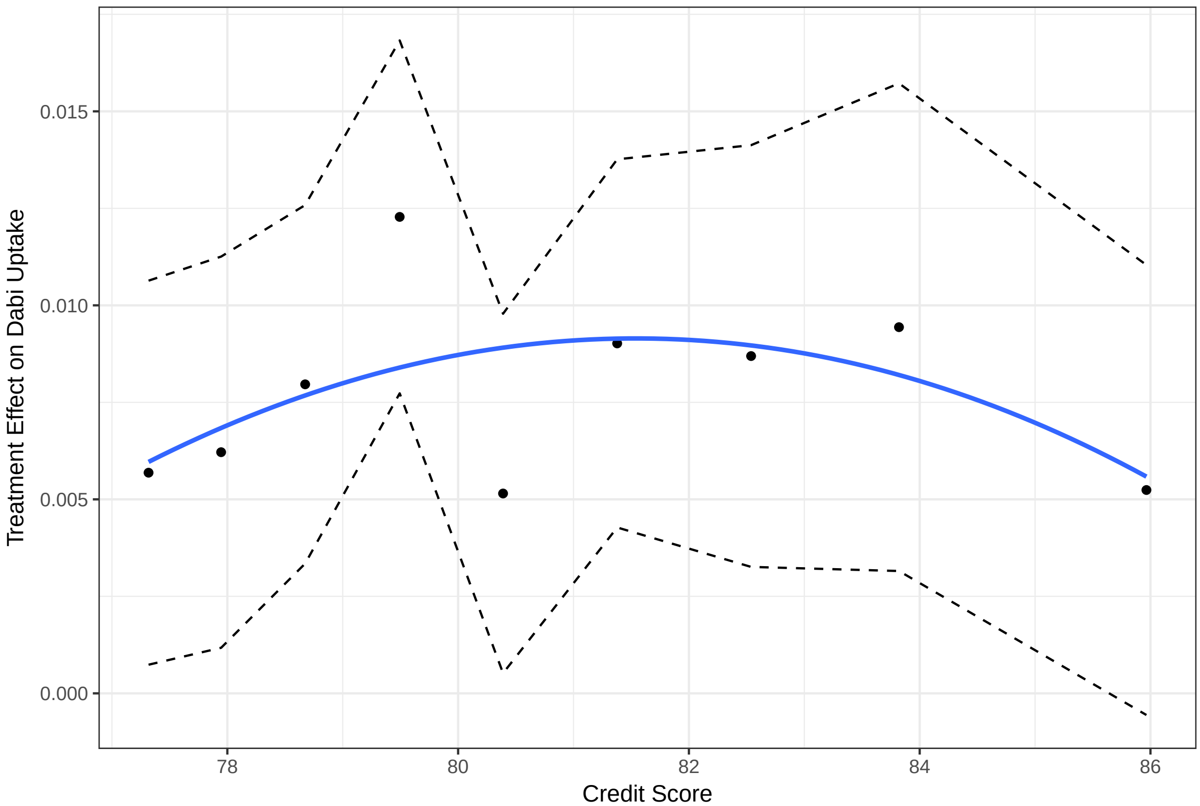
Notes: Plots the treatment effect on the uptake of the Good Loan in treatment branches by decile of borrower credit score. The regression run on each decile includes year and district fixed effects. Sample is comprised of Emergency Loan eligible borrowers who were also eligible for a Good Loan in the pre-flood period. Standard errors are clustered at the branch level. Table 18 tests whether the treatment effect heterogeneity is significant.

Figure 9: Dabi Loan Uptake Over Time



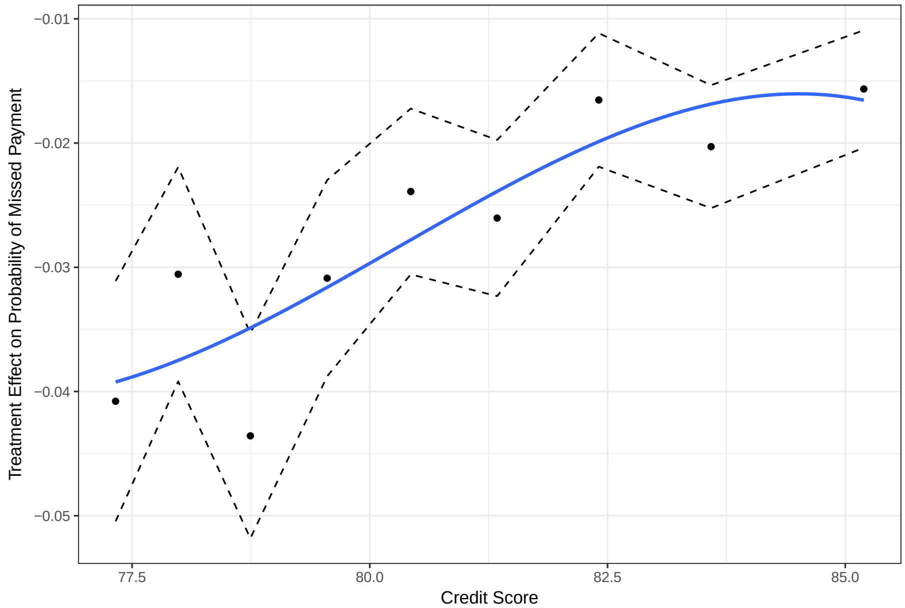
Notes: Plots the probability that an Emergency Loan eligible BRAC member takes a dabi loan in a given month. Probability of loan uptake is calculated using the complete number of BRAC members in each branch, regardless of whether or not they have a current dabi loan. This is to ensure that the denominator 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. This graph corresponds to regression table 16.

Figure 10: Dabi Loan Uptake Heterogeneity



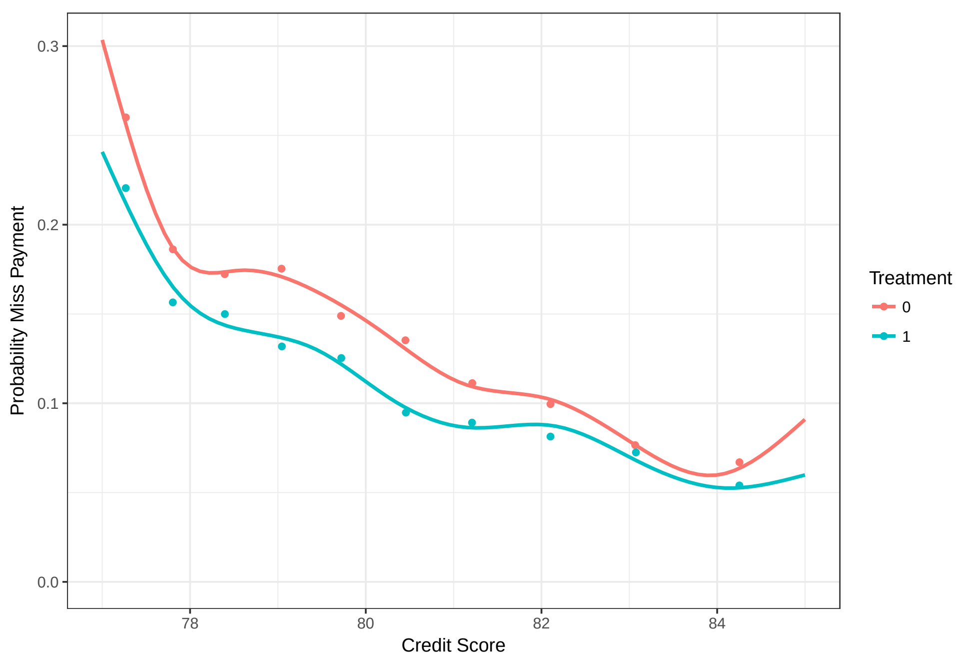
Notes: Plots the treatment effect on the uptake of the Dabi Loan by decile of borrower credit score. The regression run on each decile includes year, month, and district fixed effects. The sample includes only Emergency Loan eligible borrowers. Standard errors are clustered at the branch level. Table 18 tests whether the treatment effect heterogeneity is significant.

Figure 11: Missed Payment Treatment Effect Heterogeneity



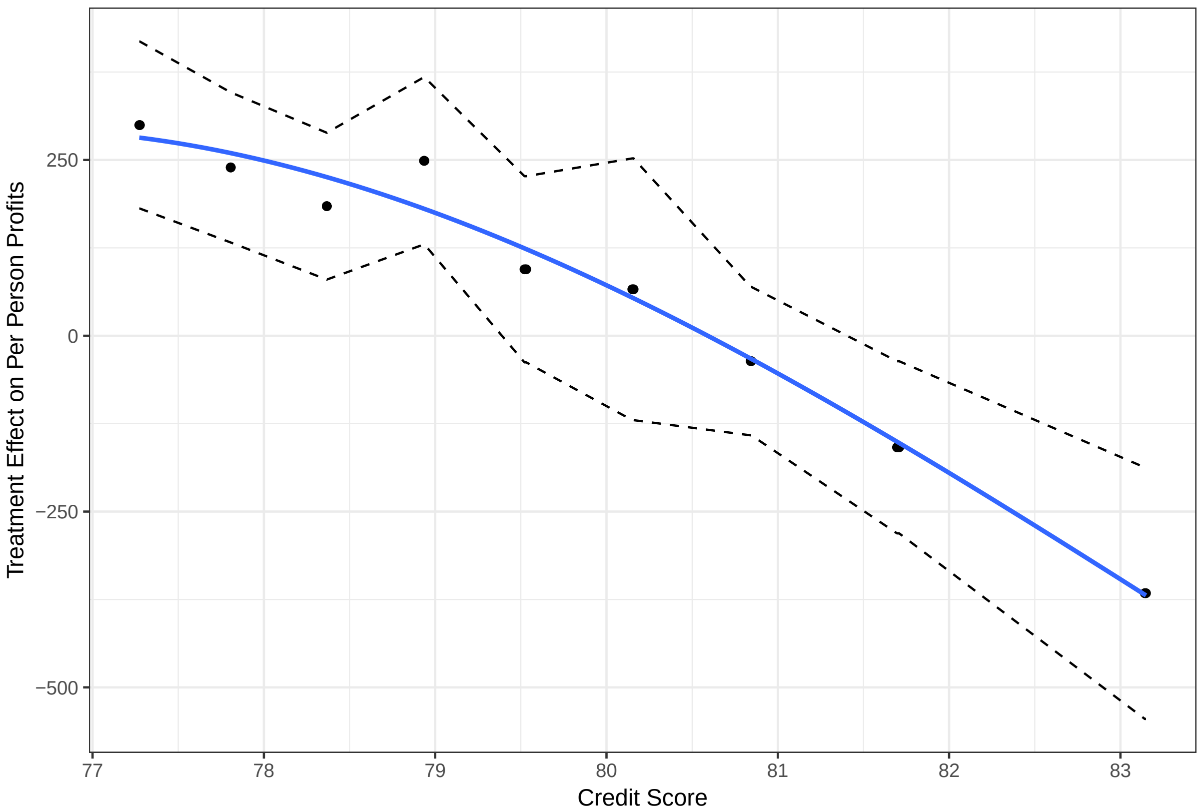
Notes: Plots the treatment effect on the probability of a missed payment by decile of borrower credit score. The estimated treatment effect is the average change in repayment rate across both flooded and non-flooded branches. The regression run on each decile includes year, month, and district fixed effects. The sample includes only Emergency Loan eligible borrowers. Standard errors are clustered at the branch level. Table 18 tests whether the treatment effect heterogeneity is significant.

Figure 12: 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.

Figure 13: Per-Person Profits Heterogeneity



Notes: Plots the treatment effect on per-person profits by decile of borrower credit score. Profits are measured in Bangladeshi taka ($1 = 84tk). The sample includes only Emergency Loan eligible borrowers. Standard errors are clustered at the branch level. Table 18 tests whether the treatment effect heterogeneity is significant.

Table 1: 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 conducted 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 2: 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 3: 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	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 4: Flood Summary

	2016	
Treatment	Flooded	Branches
No	No	60
No	Yes	40
Yes	No	49
Yes	Yes	51

	2017	
Treatment	Flooded	Branches
No	No	27
No	Yes	73
Yes	No	37
Yes	Yes	63

Table 5: 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 6: 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 7: 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 8: 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 measured in dollars.

Table 9: 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 10: 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 11: Investment After Shock

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

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

Table 12: Ex-Post Outcomes

	(1) Log Cons PerCap	(2) Log Income	(3) Crop Prod. (Kg)	(4) Livestock
Treatment	0.050	-0.024	92.104**	-0.075
	(0.046)	(0.044)	(41.259)	(0.106)
Flood X Treatment	0.058	0.002	-83.157	0.353**
	(0.062)	(0.063)	(51.968)	(0.144)
Flood	-0.046	0.030	-0.831	0.058
	(0.059)	(0.057)	(38.074)	(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 13: 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 that also experienced flooding in 2016.

Table 14: Day Labor

	(1) Daily Wage	(2) Days Worked
Treatment	0.45	-1.57**
	(9.77)	(0.78)
Flood X Treatment	-0.90	2.02*
	(11.76)	(1.17)
Flood	0.91	-4.50***
	(8.40)	(0.94)
Controls	Yes	Yes
District FE	Yes	Yes
Mean Dep. Var	306.75	14.79
Observations	928	2776
p-value Treat + Flood X Treat	0.941	0.573

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. Daily wage is in taka per day. Days worked is the number of days working for others providing farm labor or construction (construction was often for agriculture related infrastructure such as repairing irrigation channels).

Table 15: 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 16: 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 17: Branch Profit by Emergency Loan Availability

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

Notes: Sample for column 1 includes loans made only to Emergency Loan eligible clients. Standard errors clustered at branch level. The outcome for column 1 is the measured profit in Bangladeshi taka (\$1 = 84 taka) for a given loan assuming an annual cost of capital of 6% for the MFI. The outcome for column 2 is overall branch profitability. The outcome in column 3 is overall branch profitability divided by the number of branch members. Observations in column 1 are at the loan level and for column 2 and 3 are at the branch-month level.

Table 18: MFI Outcomes by Credit Score

	Good Loan Uptake	Dabi Uptake	Missed Payment	Per Person Profit
	(1)	(2)	(3)	(4)
Treatment	-0.020^{*}	0.008^{***}	-0.027^{**}	169^{**}
	(0.011)	(0.002)	(0.013)	(78.034)
Credit Score x Treatment	-0.003^{*}	0.000	0.004^{*}	-25^{*}
	(0.002)	(0.0002)	(0.002)	(14.7)
Credit Score	0.004^{***}	-0.0001	-0.010^{***}	13^{**}
	(0.001)	(0.0002)	(0.002)	(5.740)
District F.E.	Yes	Yes	Yes	Yes
Month F.E.	No	Yes	Yes	No
Year F.E.	Yes	Yes	Yes	No
Mean of Dep. Var.	0.13	0.062	0.096	2202
Observations	37,392	396,228	910,862	40,514

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.

Table 19: 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.

Appendix A: Comparative Statics

In this section 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^2_B. Starting with the maximization problem defined in equation 9:

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

Where the FOCs are given by:

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

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 $\frac{\partial x}{\partial b^2_B}$ and $\frac{\partial b^1}{\partial b^2_B}$ by:

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

Calculating each term separately:

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

Inverting the matrix

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

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.

Appendix B

In this appendix 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 20 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 20: 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 21: 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 22: 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 23: 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 24: 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 25: 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 26: 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	-3.29	0.20	-1.57	-1.89	3.58
Treatment	(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 27: 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 28: 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	17.52	0.55	-1.01	4.76	29.34
Treatment	(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 29: 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 30: 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 31: 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.