Adapting to Floods with Guaranteed Credit: Evidence from Bangladesh

Gregory Lane*

September 20, 2022

Abstract

As the effects of climate change worsen for households in low-income countries, policy solutions need to be developed at-scale. I estimate the impact of a product that helps households cope with floods, while overcoming existing market frictions that have limited the use of other adaptation measures. I find that a loan product that *guarantees* credit access to agricultural households following a flood increases their welfare through two channels: an ex-ante insurance effect, whereby households increase investments in risky but profitable production; and an ex-post effect, whereby households use the loan to smooth consumption. Repayment is high and the loan is profitable for the lender – demonstrating that guaranteed credit is a sustainable tool that institutions can supply to households vulnerable to climate shocks.

*University of Chicago (email: laneg@uchicago.edu). I gratefully acknowledge the financial support of BASIS and Feed the Future. I would like to thank my partner BRAC for their collaboration, and in particular Hitoishi Chakma, Monirul Hoque, and Faiza Farah Tuba for their invaluable assistance. I thank Fiona Burlig, Tamma Carleton, Kyle Emerick, Fred Finan, Sylvan Herskowitz, Alain de Janvry, Amir Jina, Erin Kelley, Florence Kondylis, John Loeser, Jeremy Magruder, Aprajit Mahajan, Edward Miguel, Edward Rubin, and Elisabeth Sadoulet for their advice and comments. All errors are my own. AEA RCT identification number: 0001287. This project received IRB approval from UC Berkeley (#2015-12-8181)

1 Introduction

Households in low income countries face climate shocks that make it difficult to escape poverty. The World Bank estimates that 1.47 billion people are directly exposed to flooding, 90% of whom live in low- and middle-income countries (Rentschler and Salhab, 2020). The frequency of floods is predicted to increase in the next decade, exacerbating the risks that poor households face (Hirabayashi et al., 2013). When governments lack the technical and financial means to prevent floods or provide emergency relief, households adopt costly coping strategies. In particular, they skew their investments towards lower-risk activities that limit their long-run earning potential (Karlan et al., 2014; Emerick et al., 2016; Hsiang and Jina, 2020; Donovan, 2020). As a consequence, developing adaptation measures to climate change and including them in policies for poverty reduction is critical for development. However, a host of market failures challenge efforts to implement effective adaptation strategies to respond to these environmental risks. For example, investing in infrastructure that mitigates the impact of floods is expensive and difficult to implement in rural areas (Brooks and Donovan, 2020), while the use of climate resistant technologies (drought or flood resistant seeds) is hampered by their variable returns (Emerick et al., 2016). The viability of financial products has also been explored, but their dissemination has been threatened by weak institutions and a lack of demand (Fafchamps and Lund, 2003; Mobarak and Rosenzweig, 2013). Therefore, adapting to more frequent flooding requires developing and evaluating new tools that can overcome these frictions.

In this paper, I design and study the impact of a tool that has the potential to mitigate the negative impacts of floods among vulnerable households, while overcoming the pitfalls that have limited the efficacy of other interventions. Specifically, I offer households living in flood-prone areas a credit line when they are hit by a shock, and thus when the marginal utility of additional consumption is high. I am able to do this at scale by working with BRAC, one of world's largest NGOs. We randomize the availability of the credit-line (the "Emergency Loan") across 200 BRAC branches located in flood-prone areas. We contacted over 300,000 clients in 100 treatment branches one month before planting, and informed them that they had been pre-approved to take the Emergency Loan should a flood occur in their area during the rest of the agricultural season. This notice was delivered well before any cropping decisions were made to give households enough time to consider investing in higher-risk, higher-return opportunities. These investments could lead to benefits from the loan even if no additional credit was disbursed. Treatment households could choose to take the loan provided a validated flood occurred in their area. Control branches continued their normal micro-finance operations.

The Emergency Loan overcomes a host of market frictions that have limited the supply and use of other climate adaptation measures. First, it overcomes market failures in credit and insurance markets. Typically, credit products have not been used to respond to shocks because financial institutions do not want to lend to vulnerable households for fear of losing money (Demont, 2014; McCulloch et al., 2016; Labie, Laureti, and Szafarz, 2017). Similarly, the demand for insurance products remains low because farmers do not not want to pay up-front premiums for uncertain benefits (Cole and Xiong, 2017; Casaburi and Willis, 2018). In contrast, the Emergency Loan commits institutions to evaluating borrowers' creditworthiness prior to the shock, thereby overcoming their reluctance to lend when a shock in fact occurs. Moreover, it does not require any up-front payments from households. Second, the Emergency Loan overcomes failures in the markets for new climate-resistant agricultural technologies. These technologies (e.g. irrigation, drought or flood resistant seeds) are not always adapted to the most extreme weather conditions, they can be expensive, and they are under-supplied in local markets (Fishman, Gine, and Jacoby, 2021; Emerick et al., 2016; Dar et al., 2021). They often require costly changes to farmers' crop and input choices, while often lowering average yield if the extreme weather event does not occur (Lybbert and Sumner, 2012; Lobell, Deines, and Tommaso, 2020). This means that it may take longer for farmers to learn about the benefits of these technologies, and some may decide to disadopt if they do not see any returns in the first year (Dar et al., 2022). In contrast, the Emergency Loan does not require any up-front investments, and benefits households even if they ultimately choose not to take the loan by providing the necessary assurances that make higher risk-higher return investments more appealing. Finally, it overcomes limitations with large-scale infrastructure programs (e.g. flood barriers, embankments), that are difficult to extend reliably to households because they require substantial investments and coordinated efforts by institutions that are often absent in rural markets (Brooks and Donovan, 2020). The Emergency Loan by contrast can be disseminated by local MFI's, without necessarily compromising the provider's bottom line, and it is a financial product that is well understood by most households in low-income countries.

The results of this paper demonstrate that the Emergency Loan can be an effective adaptation tool by lowering the impact of flood shocks. Moreover, by insuring households against this event, the Emergency Loan encourages households to make profitable investments that boost their average returns. I document these benefits in three steps. First, I find that guaranteed credit encourages households to make investments they may have otherwise avoided. Specifically, I find that treated households increase the amount of land dedicated to agricultural cultivation by 15%, with suggestive evidence that they increase per-acre input use as well. This suggests that households recognize guaranteed liquidity access can reduce their exposure to flood risk, which encourages them to invest more in production.

Second, I find this improves household outcomes by increasing the number of crops they produce, and consume. Pre-approval for the Emergency Loan leads to a 17% increase in crop production and an 8% increase in per-capita consumption. There are two potential channels that can explain these results: households' ex-ante investments can translate into higher production, and households can activate their loans in the event of a flood and use the additional credit to support consumption. I find strong evidence for the former, and suggestive evidence of the later. In the absence of a flood, when no additional liquidity is disbursed, I find that crop production increases by 33% and per capita consumption is weakly higher among treated households. This confirms that farmers respond to BRAC's guarantee by finding new investment opportunities that yield substantial returns, even though no additional credit was made available. In the presence of a flood, when households have the option to activate their loans, I find increased levels of consumption (10%) relative to control areas that also experienced a flood. While some of this effect could be driven by ex-ante investments' continued payoffs, we find that households who suffered more from a flood are also more likely to activate the option for additional liquidity. This suggests that the Emergency Loan is used to boost consumption post-flood – though I interpret this result with some caution because the number of households that took the loan is relatively small.

Finally, I show that the Emergency Loan is attractive to both sides of the market – a necessity for a climate adaptation measure to be scaled in the marketplace. On the supply side, I find that the extension of guaranteed credit in the aftermath of shocks marginally improves overall MFI performance. Borrowers with access to the Emergency Loan improve their repayment rates after a flood shock, thereby improving their repayment rates overall. Branch profits increase, with the largest increases in profits coming from "marginal" clients. This result is encouraging for MFIs, which have traditionally withheld credit in the aftermath of aggregate shocks. In particular, it shows there need not be a tension between borrower welfare and lenders' incentives to minimize default risk.

On the demand side, I rely on a subset of my sample (15%) to show that households value this product as well. This sub-sample of borrowers had access to a more traditional BRAC loan called the Good Borrower Loan when they were informed about their eligibility for the Emergency Loan. The Good Borrower Loan offered the same amount of credit as the Emergency Loan, but it was only available for the next two months (the planting season), rather than being triggered by a flood (which typically occur between planting and harvest). Any client who chose to take the Good Borrower Loan would then lose their access to the Emergency Loan. I find that a significant share of these borrowers are willing to forgo taking credit in the pre-period through the Good Borrower Loan in order to preserve access to Emergency Loan in the post-period, suggesting they value the precautionary benefits of credit access (Deaton, 1991, 1992). Estimates suggest that these households value credit access after a shock approximately 1.8 more times than credit access in the pre-period.

This paper makes two primary contributions. First, I show that financial products like the Emergency Loan can be an effective adaptation tool. In doing so, I provide some of the first evidence that low levels of adaptation reflect constrained sub-optimal investments. While regions frequently exposed to climate shocks show signs of adapting to these extreme weather events (Carleton et al., 2022; Hsiang and Jina, 2020), Carleton and Hsiang (2016) shows that large adaptation gaps remain, and poor countries remain disproportionately exposed to climate shocks. They highlight the need to generate new evidence on whether these adaptation gaps reflect optimal investments or constrained suboptimal adaptation attributable to persistent market frictions. My paper provides evidence of the latter by studying an intervention that solves a market failure that is preventing optimal adaptation. My paper shows that the Emergency Loan effectively mitigates the direct effects of financial market failures while also enhancing adaptation. Moreover, I provide evidence for the Emergency Loan's viability at scale, which is important for governments and institutions seeking to provide households with a set of tools that will help them in the face of climate shocks.

Additionally, I contribute to a growing literature that examines how specific interventions can improve households' resilience in the face of climate change. Brooks and Donovan (2020) show that building bridges in rural Nicaragua to help households stay connected to markets when flash floods occur significantly improves farmers' income. Similarly, Jones et al. (2022) and Emerick et al. (2016) document the benefits of risk-reducing technologies (irrigation and flood resistant seeds, respectively), both of which can help farmers cope with the consequences of climate change. The Emergency Loan adds to this literature by identifying a tool that mitigates the impacts of climate shocks and overcomes the constraints that have limited the widespread use of these other adaptation measures. Unlike large infrastructure projects, the Emergency Loan is relatively cheap and relies on existing institutions. Unlike climate resistant technologies, the Emergency Loan does not require any up-front payments or costly behavioral adjustments to learn about the technologies' benefits.

Second, this research speaks to a large literature on the efficacy of financial services that can be used by low-income households to overcome shocks and stressors (Rosenzweig and Binswanger, 1993; Conning and Udry, 2007). Generally, this literature has focused on insurance products that are designed to reduce households' exposure to risk, and credit products that have the goal of encouraging productive investments. The Emergency Loan I develop combines aspects of microcredit and insurance, resolving some of the key limitations that both products have faced.

The Emergency Loan provides similar risk reducing benefits to index-insurance while largely overcoming the problem of low demand (Cole and Xiong, 2017). Similar to index insurance, it avoids high administrative costs and moral hazard by making the availability of the additional credit contingent on an exogenous indicator (floodwater height). Unlike index insurance, households are not required to purchase the product during the planting season. Households can benefit from the security of the credit line even if they choose not to take a loan after a shock. My experiment confirms that many households who do not take the Emergency Loan increase their ex-ante investment in response to the offer, suggesting a reduction in perceived risk. This makes the product more appealing among households that are potentially credit constrained, present-biased, face basis risk, and lack trust in institutions' ability make pay-outs (Cole et al., 2013; Clarke, 2016). While other papers have found that allowing insurance premiums to be paid after harvest improves demand for index insurance, this solution is only feasible when there is the possibility of an interlinked transaction. This can take the form of a monopsony buyer that can credibly collect payments from farmers after the fact (Casaburi and Willis, 2018), or tying insurance payments to credit contracts (McIntosh, Sarris, and Papadopoulos, 2013).

The Emergency Loan also provides more flexibility than traditional micro-loans. The strict repayment schedules, and group lending features associated with traditional loans make it difficult for households to optimally invest in more risky (but more profitable) opportunities, limiting its overall impact on household welfare (Karlan and Zinman, 2011; Karlan et al., 2014; Crépon et al., 2015; Angelucci, Karlan, and Zinman, 2015; Banerjee et al., 2015; Banerjee, Karlan, and Zinman, 2015). This paper joins an active literature documenting how introducing additional flexibility to credit schemes can improve outcomes. Field and Pande (2010), Field et al. (2013), and Beaman et al. (2014) show that delaying the start of repayment installments, reducing payment frequency and allowing lump sum re-payments post-harvest reduces borrower transaction costs, and boosts investments and profits. More recently, Battaglia, Gulesci, and Madestam (2021) and Barboni and Agarwal (2022) show that allowing borrowers to delay repayments improves business outcomes without harming repayment rates; while Aragón, Karaivanov, and Krishnaswamy (2020) show that a fully flexible credit line improves small business profits by allowing borrowers to quickly respond to changes in the market. The Emergency Loan builds on this movement towards more flexible credit by changing the timing of when credit is made available rather than changing when payments are due. Specifically, it offers more credit after income shocks when this liquidity is likely to be most beneficial. This is similar to the insights explored by Fink, Jack, and Masiye (2020) and Burke, Bergquist, and Miguel (2018) where loans are offered during the lean and post-harvest season respectively, enabling households to optimize labor and storage decisions.

Finally, the Emergency Loan is profitable for the lender — a fact that more papers are trying to document as they recognize that only financial tools that boost MFI profits are sustainable long term. Field et al. (2013) develop a structural model to show that longer grace periods are not sustainable for MFIs, while Barboni (2017) uses lab-in-the-field experiments to show that flexible repayment schedules could increase profits for lenders. An advantage of my setting is the partnership with BRAC, which allows for an empirical examination of the impact of this new product on overall MFI profitability. This has been difficult to pin-down because MFIs are typically risk-averse and hesitant to experiment (Karlan and Zinman, 2018). However, I find that BRAC derives positive profits from the product, a result that could induce more lending institutions to extend credit after an income shock when the marginal utility of consumption is high.

The rest of the paper is organized as follows: Section 2 and Section 3 describe the context and the new credit product in detail. Section 4 describes the main research design and execution of the experiment. Finally, section 5 presents the results of the experiment and section 6 concludes.

2 Context: Floods and Costly Coping Strategies

Extreme weather events are frequent, and are projected to worsen with the advent of climate change. This includes flooding, which is a global threat but most prevalent in South and East Asia (Rentschler and Salhab, 2020). Approximately 80% of Bangladesh is located on floodplains, and floods occur yearly with varying degrees of severity. In normal years, approximately 20% of the country is flood affected, while in extreme years, up to 60% of the country can be submerged by flood water (Brammer, 1990). Furthermore, recent projections estimate that flood areas could increase by as much as 29% in Bangladesh due to climate change (World Bank, 2016). As 70% of Bangladesh's population lives in rural areas and more than 80% of rural households depend on agriculture (World Bank, 2016), the impact of floods are devastating. They destroy crops, livestock, productive assets, and homes, in addition to the direct threats to health and human life. For example, the catastrophic 1998 flood is estimated to have cost Bangladesh 8% of its GDP (Haque et al., 2022). The severity of flood risk is confirmed in my baseline data where 85% of the sample reports having been affected by a flood in the past five years, and average agricultural losses hover around 70% when flooding occurs.

In most low-income countries, including Bangladesh, households cannot rely on social safety net programs. While informal networks in Bangladesh are strong, they are unreliable during flooding events because other members of the network are often hit by the same shock (Will et al., 2021). Without access to such social safety nets, households have to adopt costly coping strategies to self-insure – lowering their food consumption, selling productive assets, and pulling children out of school – which ultimately lowers household income over time. They also adopt ex-ante avoidance strategies that limit their vulnerability to floods but also lowers average returns. This includes reducing their investment in agricultural production, choosing production techniques that are less susceptible to shocks but also less profitable, and investing in alternative low-return activities (Few, 2003; Brouwer et al., 2007; Donovan, 2020).

Existing tools that could help households adapt to the threat of flooding are hindered by market frictions. First, financial institutions are reluctant to lend to households after a shock, and no MFIs prior to this study were offering guaranteed credit in Bangladesh. Similarly, insurance products suffer from low demand because they require households to make up-front payments in the planting season when liquidity is tight. Work by Hill et al. (2019) shows that significant subsidies are required to induce households to buy a single unit of index-insurance. Second, the use of climate resistant technologies (irrigation, flood and drought resistant seeds) is limited by their cost, their low-supply and their uncertain returns. For example, Dar et al. (2022) show that the adoption of a new drought-resistant rice variety was mixed because it required significant changes in cropping patterns while providing uncertain benefits. Finally, Bangladesh's government often lacks the technical and financial means to provide large scale emergency relief post-flood, or invest in large-scale infrastructure projects to control floodwaters. Research in Bangladesh confirms that villages want to invest in flood infrastructure such as embankments, but cannot afford to do so (Brouwer et al., 2007).

3 The Emergency Loan

3.1 Product Description

I worked with Bangladesh's largest MFI (BRAC) to design a tool that would help households cope with the risks of climate shocks (floods), without resorting to costly and inefficient practices. Specifically, we developed the Emergency Loan – a product that guarantees credit access to households who suffer a flood shock. The product was designed to help households make more profitable ex-ante investments and improve their consumption ex-post. It was also structured with the potential to be profitable for the MFI to supply, a fundamental requirement for policies to build resilience in the long-term.

Clients were eligible for the Emergency Loan provided they had a credit score above a fixed threshold. We created this new credit score for each borrower based on their past repayment behavior (including past percentage of missed payments, average percent behind on loan payments, maximum percent behind on any loan, and the number of months as an active BRAC microfinance member).[1] We assessed each client's eligibility in April, before the Aman planting season and several months before the flooding season. By assessing creditworthiness before flood shocks occur, we overcome MFI's hesitancy to lend to households after a flood shock – a friction that has limited the use of credit in the past. Borrowers retained their eligibility for the Emergency Loan for the duration of the Aman cropping season. Approximately 40% of borrowers within a BRAC branch were eligible to receive the loan. Targeting based on credit score did not result in richer households being selected over poorer ones. Eligible and ineligible borrowers are fairly similar along most dimensions (see Table A.1), although eligible borrowers are a few years older, and have slightly less annual income, livestock and savings.

We informed borrowers that they were pre-approved for this loan in April by distributing referral slips to eligible clients (see Appendix Figure A.1). Each slip contained the borrower's name, BRAC ID, and details of the Emergency Loan they were eligible to take – including the amount they were pre-approved to borrow and the conditions when the loan would be made available. BRAC loan officers read a script that explained how the institution was extending a guaranteed credit line to eligible borrowers should a flood occur. They communicated to borrowers that they did not have to make any upfront payments, and could choose to take the loan when the floods occurred. In doing so, the Emergency Loan was designed to overcome households' aversion to making upfront payments for uncertain returns – a common constraint that insurance products have faced. Loan officers emphasized borrowers' pre-approval status repeatedly because this concept was new. Random branch visits conducted in June confirmed that borrowers received the referral slips, and understood what *guaranteed* credit meant. Eligible households were approved to borrow up to 50% of the total principal amount of their last regularly approved loan. An eligible borrower who took a 10,000 taka loan ($125) for example was guaranteed to borrow up to 5,000 taka ($63) should a flood occur regardless of her existing loan balance at the time of disbursal. Clients were eligible for the Emergency Loan regardless of whether or not they currently had an

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

active loan.[2]

Eligible clients could then request an Emergency Loan if flooding occurred in their branch service area. Flooding was validated in two ways. First, a government maintained river gauge associated with the branch area had to report water levels above the pre-determined danger level for at least one day.[3] Second, a non-microfinance BRAC employee had to confirm that the branch had experienced flooding. Once these checks were completed, *all* eligible clients within a treatment branch were informed they could take the Emergency Loan. It is worth noting that the activation threshold for a flood was relatively low, and the branch service area was relatively large, which meant that many eligible households within a branch did not suffer damages from a flood. This implies that the Emergency Loan's take-up rate could be low when calculated as the fraction of households who were eligible.[4]

Working with BRAC was beneficial for a number of reasons. First, BRAC has over 2000 branches throughout the country, where each branch serves 20 to 60 village organizations (VO's).[5] This allowed us to focus on areas bordering the major rivers, where productive investments are frequently exposed to flooding. Second, BRAC's clients are familiar with credit and have high repayment rates. Loan officers visit each village organization weekly to collect scheduled loan repayments from active borrowers, and answer inquiries about new loans. This provided a robust platform for introducing a new loan product. The fact the Emergency Loan could be disseminated by MFI's without necessarily compromising their bottom line, and was well-understood by rural households, was particularly appealing in light of our motivation to find a sustainable tool that could help households cope with the consequences of climate change. Other measures such as large-scale infrastructure projects or climate-resistant technologies often require coordination between different external actors, and can be costly to supply.

Finally, it is important to review how the Emergency Loan interacts with existing BRAC

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

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

[4]Low-take up rates do not necessarily detract from the Emergency Loan's value for two reasons. First, the loan can provide ex-ante investment benefits even in the household does not take the loan. Second, it means the loan is "self-targeting" because the only households that choose to take it are the ones that have determined that paying the loan's interest rate is the best option available to them (instead of relying on informal risk sharing networks for example). One of the main attractions of this risk-reducing tool is that it protects households against relatively rare, but extreme outcomes, without detracting from their ability to rely on coping strategies that may be less expensive than loans when the shock is less severe. This also means that the cost of providing the Emergency Loan is sustainable for an MFI (where the cost of false positive – providing insurance payouts to farmers that don't need them – is a large contributor to the prohibitively high costs of providing index-insurance. For example Elabed et al. (2013) estimate that 33% of the premium is used to pay for false positive payouts.)

[5]Village organizations represent 16 to 33% of households in the village.

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

Eligibility for the Emergency Loan did not depend on whether clients had an open Dabi loan. However, the Emergency Loan and Good Loan were mutually exclusive. The Emergency Loan resembled the Good Loan in the amount disbursed, the interest rate, and the repayment period. However, it differed in two key ways. First, it was offered 6-8 months into the normal Dabi Loan cycle rather than after a flood. Second, Good Loans had to be requested from branch managers who could deny the request, while the Emergency Loan was guaranteed to borrowers based on their credit score. Historical data confirms that Good Loans were much less likely to be disbursed after aggregate income shocks. Clients could be *eligible* for the Good Loan and the Emergency Loan. However, if they took a Good Loan they would lose the ability to withdraw an Emergency Loan should a flood occur. Figure A.2 summarizes borrower choices related to the Good Loan and Emergency Loan. Clients who were *eligible* for the Emergency Loan and the Good Loan in the planting season (15% of the total sample) then faced a tradeoff: they could take the Good Loan immediately and forgo the option of accessing additional liquidity in the event of a flood in the rest of agricultural season; or they could preserve their credit access as a buffer against future flood risk.

3.2 Theoretical Framework For the Effect of Guaranteed Credit

This section provides a simple theoretical framework for thinking about the effect of guaranteed credit. It builds on Karlan et al. (2014), where MFI clients make decisions about investments, borrowing, and repayment in a risky environment. I briefly lay out the model's predictions for how the Emergency Loan should affect borrowers, and the MFI offering the loan. Examining both sides of the market is critical for evaluating the sustainability of this product as a risk-management tool in the face of climate shocks. The model is discussed in detail in Appendix B,

The status-quo scenario is one where households have access to a risky production technology (e.g agriculture) that requires upfront investments in the pre-period (planting) that

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

may not yield any return in the post-period (harvest) with some exogenous probability. These households have access to imperfect capital markets and no insurance markets. Capital markets are imperfect because households can access credit to invest, but they do not have access to credit in the event of a bad outcome. Under this scenario, we obtain the standard theoretical result that households will reduce their investments and borrowing at planting (relative to a risk-free world) in order to hedge against a shock in the future. On the lender's side, expected profits will depend on the types of households in the market and the probability of a shock occurring. There are two types of households: those who are able to repay whether or not they suffer a shock and those that choose (or are forced) to default after a shock. Expected profits for the MFI will increase if the share of households who are able to pay is high and the probability of a shock occurring is low.

The introduction of the Emergency Loan changes outcomes for borrowers and lenders. Borrowers can now access extra liquidity in the aftermath of a shock, thereby increasing consumption in this post-period. This reduces the marginal benefit of savings during this post-period, which means households can save less and increase their investments in the pre-period. Larger ex-ante investments will boost production levels and consumption when no shock occurs.

Lenders profits may change through two main channels. First the total amount of credit disbursed by the MFI may change. This amount is likely to rise as i) households will now demand more credit at planting, and ii) some households will take the Emergency Loan after a shock.[7] Second, the number of households that choose (or can) repay their loans after a shock may change, and the direction of this effect is unclear. On the one hand, the cost of repaying the loan is lower now that households have extra liquidity from the Emergency Loan. On the other hand, the value of a one-time default has increased due to the no-questions-asked loan offer. Therefore, the overall effect on the lender is unclear — it could improve or harm overall profitability.

[7]For borrowers with access to the Good Loan, this may not be true. Some households may choose to forgo the Good Loan that they would have otherwise taken in order to preserve access to the Emergency Loan. For these households the total amount of credit they take will decrease after the introduction of the Emergency Loan. Given that a subset of borrowers are eligible for both the Good Loan and the Emergency loan, in aggregate the net increase in loans given is likely to be positive. However, it is important to note that the direction of this effect could be negative for certain sub-populations.

4 Research Design and Data

4.1 Research Design

I measure the impact of the Emergency Loan using a randomized control trial with a sample of 200 BRAC branches. These branches were randomly selected from a larger group that satisfied several criteria. First, I only included branches located in flood-prone areas. Second, I limited the sample to branches that were located within 15 kilometers of a river gauge run by the government's Flood Forecasting and Warning Center (FFWC) so that flooding could be monitored remotely. Last, I analyzed 15 years of historical data from the FFWC river gauges and selected areas of the country where flooding had exceeded the danger height levels at least twice (Figure A.3). It is important to highlight that households in these flood-prone areas may have partially adapted to flood shocks already, and the impact of any one shock may be less severe as a result. This would not limit the value of the Emergency Loan, which is designed to encourage households to invest in new opportunities. I assigned 100 branches to the treatment group, and the remaining 100 branches to the control group, stratified by district. Appendix table A.2 provides descriptive statistics from households sampled from the treatment and control branches and shows that the randomized branches are balanced on baseline observable characteristics.[8]

The experiment began in April 2016 when I created the Emergency Loan eligibility lists across the 200 experimental branches. BRAC then notified eligible borrowers in *treatment* branches that they were pre-approved for a loan should a validated flood occur in their area. This additional credit was guaranteed for the rest of the agricultural season. We communicated pre-approval status to borrowers one month before the planting season to provide households enough time to change their investment decisions (see Section 3 for further details about the Emergency Loan).

We also needed to inform eligible clients when a validated flood occurred so they could request a loan. I scraped the FFWC's website and generated alerts whenever measured water levels exceeded the pre-determined flood-danger threshold. A BRAC research employee visited the branches that were matched to gauges exhibiting these dangerous water levels, and met with local officials within these branches to collect information on the extent of flooding at that branch. If we confirmed that more than 20% of the branch's catchment area was flooded from their reports, the branch was "activated".[9] The branch manager received

[8] Appendix table A.3 shows balance for the Good Loan eligible sub-sample.

[9] Importantly, neither the BRAC research employee nor the branch officials knew about the 20% threshold needed to activate each branch. The research employee was not aware of the branch's treatment status either. It is important to highlight that the information collected by the research employee only 'disagreed' with the FFWC in 12 out of the 200 branches (5%), and these were exactly balanced across treatment and control.

instructions from headquarters to notify all eligible borrowers that Emergency Loans were available through their normally scheduled village organization (VO) meetings or by calling clients directly. Eligible clients were reminded about the Emergency Loan's availability at every subsequent VO meeting until the expiration of the offer in November.

Over the course of the 2016 Aman season, 92 branches were activated: 40 control and 51 treatment.[10] However, 2016 was not a major flooding year and the water levels in the majority of activated branches did not cause widespread damage. As a result, BRAC decided to continue piloting the Emergency Loan for a second year in 2017. From 2016 to 2017, the experimental protocol remained the same. Only small improvements were made to the loan officers' description of the product. New credit scores were created for all branches, which meant that some previously eligible households lost their eligibility.[11] In 2017, 136 branches were activated, 73 control and 63 treatment. Flooding in 2017 was more severe than in 2016, and several locations suffered significant damages to crop land and physical structures.

4.2 Data

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

Second, I use survey data collected from 4,000 BRAC clients, and 800 BRAC staff, across the 200 experimental branches. Branch staff surveys document the most important income generating activities in the area, perceptions of flood risk, and aggregate flood damage at the branch level. For the borrower survey, I sampled three village organizations at random from each branch. I then randomly selected fifteen eligible borrowers and five ineligible borrowers from these VOs. Three rounds of data collection took place: a baseline survey in April 2016 before borrowers in treatment branches were informed about their eligibility status; a follow-up survey in December 2016 after the first rainy season; and a second follow-up in December 2017 after the second rainy season. Re-survey rates were high at 99% due to BRAC's strong

Finally, to the extent that any concern about strategic misreporting by the research employee remains, I reproduce the main ex-post tables using an alternative flooding definition based only on FFWC's danger level, which shows consistent results (Appendix Tables A.5 to A.7.)

[10] The difference is not statistically significant.

[11] Appendix Tables A.8 to A.14 account for possible differential selection into eligibility in 2017. Results are stable when excluding 2017 data or when instrumenting for eligibility using branch treatment status.

network.[12]

To capture ex-ante investments, the survey asks farmers about the amount of land dedicated to crop cultivation during the Aman season, and the amount of inputs applied to those plots.[13] Land area is split into three cultivation categories: land that farmers own themselves, land that is rented in, and land that is under a sharecropping contract. These categories are collected separately because farmers' response to the Emergency Loan may differ across these land types. Specifically, expanding cultivation of land owned may be difficult in the short time frame between when the offer of the Emergency Loan is made and planting. Next, sharecropping contracts are designed to reduce risk exposure, which may make them *less* attractive to farmers offered the Emergency Loan. In contrast, it may be relatively easier for farmers to expand land rented in this short timeframe. Finally, I also collect data on the amount of non-agriculture business investments made by households, which is the value of any newly purchased or repaired business assets.

To capture ex-post outcomes, I focus on per-capita (food) consumption, crop production, overall income and business performance. Consumption is measured as the sum of the past week's expenditure on a set of household food items and cellphone airtime. Household income is the sum of earnings from crop sales, livestock, wages, business, and remittances. Business outcomes were measure in two ways: by the total value of the current business stock, and by business profits accrued in the past month.

5 Results

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

$$Y_{ibdt} = treatment_{ibd}\beta + \phi_t + \varepsilon_{ibdt}$$

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 and a year fixed effect. Data from both years of the experiment are pooled together (unless noted otherwise) and standard errors are always clustered at the district level (Burlig, Preonas, and Woerman,

[12] Table A.4 formally tests for differential attrition between treatment and control groups. The treatment group has slightly less attrition than the control group and this small difference is not statistically significant.

[13] Inputs include fertilizer, pesticide, and seeds to focus on items that need to be purchased and applied ex-ante.

2020). All outcomes are winsorized at the 99.5% level to account for outliers.

For "ex-post" outcomes that occur after the flood season, I run an additional regression with an indicator for weather a flood occurred during the growing season, and its interaction with treatment.

$$Y_{ibdt} = treatment_{ibd}\beta + treatment_{ibd} \times flood_{bdt}\gamma + \phi_t + \varepsilon_{ibdt}$$

Where "flood" is an indicator for whether a flood occurred at the branch-year level, as the Emergency Loan's activation happened at the branch level; "treatment" is an indicator for being in a treated branch that was not flooded, and isolates the benefits of the Emergency Loan resulting from differences in ex-ante investment (because the loans were not offered in non-flooded areas). The interaction term captures the additional impact of the Emergency Loan's availability in branches where floods occurred. It is important to highlight that not all households within a branch suffered flood damage. Therefore, the interaction effect is a lower bound on the impact of the Emergency Loan for households that suffer *damages* from floods.

A similar approach is followed for MFI level outcomes (e.g. loan uptake decisions, repayment rates), with a few notable exceptions. Because I examine observations at the branch-month level, I add month m fixed effects in addition to year and district fixed effects to the estimating equation.[14]

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

5.1 Ex-Ante Household Investment

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

Table 1 presents the amount of land devoted to agriculture, and whether any crops were planted, during the Aman season. Households that knew they were eligible for the loan increase the amount of land they *rent* by 27% (Column 2), and the *total* land they cultivate by 15% (Column 4). Neither owned nor sharecropped land show any significant change. Along the extensive margin, the number of households planting crops also increases by approxi-

[14]Some regressions have only a single observation per year, in which case month fixed effects are dropped.

mately 3.6 percentage points (Column 5). This represents an 8% increase in the probability that a household cultivates crops during the Aman season. While households could have adjusted their pre-period investments along different dimensions, we would expect changes in land allocation and crop production to be most prominent because households' income depends primarily on agriculture. Moreover, we would expect households to increase the amount of land they rent because it is the easiest margin of adjustment in the time-frame they have. Indeed, expanding the cultivation of owned land requires purchasing additional crop land, which is costly and requires more planning; while expanding the amount of share-cropped land is less appealing now that farmers can reduce their exposure to risk with the Emergency Loan. Furthermore land rental payments can often be delayed until after the harvest period, which means the Emergency Loan can be used to cover these payments if required.

Next, we investigate whether households increase the intensity of input usage now that they are less exposed to risk.[15] Columns 1 and 2 in Table 2 show that the amount of fertilizer and pesticides applied per acre of land increases, although only pesticide application is statistically significant. Column 3 shows that the total amount of money spent on all inputs per acre also increases. These result should be interpreted with some caution as the reported randomization inference p-values show lower levels of statistical significance that those calculated from the regression. Nevertheless, these results confirm that treatment households are maintaining normal levels of input usage per acre despite the overall expansion of cultivated land. Finally, column 4 of Table 2 shows that non-agricultural business investments increase by 36% ($14 USD) over the control group (albeit not statistically significant).

It is possible that these effects could dissipate over time if households that experience a flood in 2016 decide that the Emergency Loan is no longer useful. In this case we would expect to see 2017 Aman season investments among flooded households decrease to pre-treatment levels because they no longer perceive any risk reduction benefits from accessing guaranteed credit. To test this, I examine how investment decisions change in the second year of the experiment based on whether households experienced a flood shock in the first season. If flood-afflicted treatment households decide that the Emergency Loan is not useful anymore, we should see smaller treatment effects among these households relative to treatment households that did not experience a flood shock in 2016. Appendix Table A.15 illustrates how flooding in the first year affects different investment categories. The treatment effect

[15] There are a few reasons why we may expect less adjustments to input use than land use. First, with only 6% of farmers in my sample using no fertilizer at all, there may be less scope to move from farmer's baseline input choice to the "optimal" level. Moreover, the Emergency Loan does not provide extra liquidity ex-ante when input purchases need to be made. Therefore, liquidity constraints may limit the extent of increased input use.

on investments does not appear to differ for treated households that were flooded in the first year relative to treated households that were not. This suggests that households that experienced a flood in 2016 still perceive the Emergency Loan as offering viable protection against flood risk.

5.2 Ex-Post Household Outcomes

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

The model suggests there are two potential channels driving these ex-post results. First, increases in investment in the planting season can translate into improved outputs. Second, treatment households that take the loan will have additional liquidity. I can explore these mechanisms further by separately estimating the impact of the Emergency Loan for households that experienced a flood and those that do not. Specifically, I regress the household outcomes listed above on an indicator for treatment, an indicator for experiencing a flood shock, and an interaction between the two. The coefficient on treatment captures the impact of increases in ex-ante investments. Absent a flood, the only difference in outcomes between treatment and control households stems from changes in investments in the pre-period. In contrast, the sum of the coefficients on treatment and the interaction between treatment and flood will capture the payoffs of pre-period investments (i.e. those that were not destroyed by the shock) *and* improved liquidity access post-flooding.

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

The second channel is more difficult to isolate on its own. The effect of treatment on ex-post outcomes in branches that *did* experience a flood will include any returns to investment that were not damaged by a flood, *and* the impact of any additional liquidity that treated households choose to take. Overall, we see that treated households lose 90% of the crop production gains they experience when a flood does not occur (Column 2). These losses are larger than those observed in the control group, suggesting that treatment households expand cultivation on land that is particularly susceptible to floods. Nevertheless, treated households experience a rather large 10% increase in consumption compared to control households that also experienced a flood. This suggests that the availability of the Emergency Loan allows households to preserve some consumption, and maintain their asset levels after an income shock.[16]

These higher consumption levels for treated households affected by a flood could stem from the fact that not all of their new investments were destroyed, or that households took the Emergency Loan. We can use data on Emergency Loan take-up rates to investigate this further. In 2016, only 2.9% of households chose to take the loan, which likely reflects the lack of severe flooding in most locations. In 2017, floods were much more damaging and uptake of the Emergency Loan increased to 5.4%. Low ex-post uptake of this product is not entirely unexpected because flood damage is highly idiosyncratic within these large branch service areas, such that certain households may be dramatically affected while others may not be.[17] Table 4 further explores which types of households are most likely to take the Emergency Loan. I find higher take-up rates among households that were less well prepared for a flood, and among those that experienced higher levels of distress in the event of a flood (see Appendix Figures A.4 and A.5). These results suggest that the most vulnerable and worst affected households are the most likely to take advantage of the guaranteed credit offer. This result provides some rational for why consumption rates might have been higher in the treatment group: vulnerable households' marginal propensity to consume will be high post-flood, and they are likely to rely on the additional liquidity from the Emergency Loan

[16]There is a concern that multiple shocks may reduce the usefulness of credit as a risk mitigation tool if households accumulate excessive debt or exhaust their credit line. Appendix Table A.16 examines this hypothesis. I expand the regression specification from Table 3 to include an indicator for whether households experience flooding in both years, and an interaction of this indicator with treatment. To determine whether the usefulness of guaranteed credit is reduced after successive shocks, I examine the interaction of the double flood indicator and the treatment indicator. These coefficients are all statistically insignificant, but a sum of all the treatment coefficients shows that treatment households are still weakly better off after a double shock. Overall, this suggests that the gains in consumption 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.

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

to boost their consumption. Nevertheless, the low take-up rates we observe overall suggest that the pre-period investments households were making in response to the availability of the loan remain a driving force behind the results on consumption.

Finally, I explore whether the Emergency Loan affects household use of other traditional coping strategies, which include livestock sales, day labor, savings, migration rates, and cash transfers (see Appendix Tables A.17 and A.18). I find suggestive evidence that treatment households are able to maintain the amount of livestock they own after a flood (significant at the 10% level). They also provide less day labor, which could be because they spend more time on their own farms when a flood hits. Additionally, using BRAC's administrative data, I find that savings levels in treatment households are higher in the aftermath of flooding. I find no change in the number of migrants that leave the house or the amount of transfers households receive. Taken together, these results suggest that the Emergency Loan provides a new strategy for households to cope with floods which substitutes for others they once used (some of which were more costly).

5.3 Spillovers to Ineligible Households

While eligible households in treatment branches largely benefit from the Emergency Loan, it is also important to examine whether the availability of this product affects *ineligible* households in those same branches. These households are members of the same BRAC village organizations, and it is reasonable to expect that pre-existing social and business connections could be affected by the availability of the Emergency Loan. To determine whether ineligible households are adversely impacted, I focus the analysis on downstream ex-post outcomes. Table 5 Panel A shows that consumption for ineligible households in treatment branches increases by 6% relative to ineligible households in non-treatment branches. I find this effect is concentrated in branches that did not experience a flood shock - with consumption increasing by 9% in non-flooded areas (Panel B). While the point estimate on consumption in flooded branches remains positive (4%), it is insignificant. Table 5 shows no significant changes to ineligible households' income, crop production, business stock value or business profits.

There are several ways the Emergency Loan could affect ineligible households' consumption including land re-allocations, employment and transfers between households. I find suggestive evidence that the employment channel matters most. In theory, ineligible households may be able to consume more if they are hired more frequently by eligible households as agricultural day-laborers and earn additional income. Table 6 reports treatment effects for ineligible households on the number of days worked (Column 1) and their earnings from day labor (Column 2), by non-flooded and flooded branches. I find some evidence that in non-flooded branches, ineligible households work 1.7 more days as day laborers and earn 9.5 more dollars in wages (the latter is imprecise and insignificant). These effects are not present in flooded branches. This provides suggestive evidence that ineligible households are hired more frequently to work on the larger plots of land that eligible households have cultivated in locations where flooding does not occur.

I also explore whether land reallocations or cash transfers can explain the results on consumption for ineligible households. In theory, ineligible households could decide to rent-out more of their land now that treated households are insured against a flood, and consume the additional income. Appendix Table A.19 shows that ineligible households decrease the amount of land they rent-in by 0.025 acres (19% decrease), which is consistent with eligible households' higher propensity to rent-in. Nevertheless, the total amount of land that ineligible households farm remains unaffected because they cultivate slightly more of their own land (0.02 acres – 15% increase), a margin of adjustment that is feasible for most farmers who typically leave some of their land fallow every year.[18] Similarly, I do not find evidence that the Emergency Loan changed the amount of transfers to ineligible households in non-flood or flooded locations. While the Emergency Loan could have induced treated households to be more generous with their transfers, or disrupted these informal relationships, Table 6 shows no changes in the total value of cash and in-kind transfers received by ineligible households.

In light of this suggestive evidence of spillovers on consumption to the ineligible sample, I report the "total" estimated average treatment effects on the entire sample population of both eligible and ineligible households. As the sample was drawn to include 40% ineligible households, and 60% eligible households, I re-weight the sample accordingly. I find that the total average effect on consumption at the branch level remains large (8% increase) and statistically significant, reflecting the Emergency Loan's positive impact for both eligible and ineligible households (Table A.21). While no other ex-post outcomes change significantly, the point estimate on crop production of 30.89 Kg ($t = 1.54$) represents a non-negligible 11% increase. Decomposing these effects into flooded and non-flooded areas, I find that the total average effect on consumption is roughly similar in both flooded and non-flooded areas. As we've seen above, consumption impacts on eligible households are largest in flooded areas while ineligible households benefit most in non-flooded areas.

I conclude this section by investigating how ex-ante investment outcomes change overall. I find that the effect on total land cultivated remains positive (0.03 acres, $t = 1.48$), and represents a 10% increase in cultivated land (see Table A.22). This provides suggestive

[18] I also investigate whether ineligible households use different amounts of inputs, which could happen if ineligible households farm lower quality land. I find no evidence of this (Appendix Table A.20)

evidence that the introduction of the Emergency Loan brings new land into cultivation rather than reallocating land across households. Finally, I examine total average effects on per-acre input use. All point estimates remain positive, and the effect on pesticide use per acre remains statistically significant at the 5% level (though all other point estimates are insignificant – Table A.23).

5.4 Value of Guaranteed Credit

We have seen that the Emergency Loan improves household outcomes by reducing their exposure to the downside risks associated with severe flooding, thereby encouraging profitable investment. This suggests that households should value the product. However, it is unclear if borrowers recognize these benefits and are willing to take costly actions to preserve their access to guaranteed credit. Moreover, the sustainability of the Emergency loan as an adaptation measure for grappling with the consequences of climate change depends on whether institutions are willing to supply it on the market. The purpose of this section is to assess whether this product is appealing to both sides of the market – a necessity for it to become an effective adaptation strategy that policy-makers can rely on in low-income countries.

Value for Borrowers - Credit Line Preservation

To shed light on this question, I work with a subset of my sample (15%) that were eligible to take a Good borrower Loan when they were informed about their eligibility for the Emergency Loan.[19] These loans were mutually exclusive, which meant these borrowers faced a tradeoff. They could take the Good Loan in the planting season and forgo the Emergency Loan should a flood occur, or decline the Good Loan in order to preserve the option to take the Emergency Loan should a flood occur in the post-planting season. According to the theoretical model presented in the Appendix, forward looking households will want to preserve credit access as a buffer against this risk. I test this prediction by comparing the probability of taking a Good Loan in the pre-period among Good Loan eligible clients in treatment branches, where the Emergency Loan *was* available, to Good Loan eligible clients in control branches, where the Emergency Loan *was not* available.

Table 7 shows the results from comparing Good Loan eligible borrowers across treatment and control branches (where the regressions are run at the branch level). Column 1 shows that the availability of the Emergency Loan reduces the probability of taking a Good Loan by two percentage points, or 15% in treatment branches. Column 2 and 3 examine the extent

[19] Appendix Table A.3 reports balance between treatment and control among this sub-group. There are no large differences between the two treatment arms.

to which this effect varies based on branch clients' need for liquidity, and their perceived risk of local flooding.[20] While I do not see any significant differences by liquidity needs, I do find that branches are even less likely to take the Good Loan when the perceived risk of flooding is higher. This confirms our theoretical prediction that some households view guaranteed credit as offering effective insurance against shocks and want to preserve their access to it.

Households that forgo the Good Loan in order to preserve their access to the Emergency Loan are giving up certain credit today in order maintain credit access in the future (should a flood occur). I calculate what this implies about the value households' assign to the Emergency Loan relative to credit in the pre-period under conservative and more realistic assumptions. First, I estimate that households' marginal utility of accessing credit after a flood is at least 1.85 times more than the marginal utility of certain credit in the pre-period. This assumes that households can correctly predict the probability that a loan will be offered (54% over the two years of the study), that they will take the loan if it is made available, and that they do not discount the future. However, under more realistic assumptions, I calculate that the marginal utility of a loan after a flood is 20.5 times greater than in the pre-period. This assumes that households expect to use the Emergency Loan at the same rates observed in the experiment (5%), and they have an annual discount rate of 6%.[21]

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

Value for MFI Operations

MFIs have hesitated to provide credit to households in the aftermath of a shock because they are concerned with default risk. The Emergency Loan overcomes this constraint by requiring that MFIs assess borrowers' eligibility before the shock occurs. Whether or not

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

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

institutions will then include this type of product in their climate adaptation responses depends on whether it is cost-effective to do so. Theoretically, the impact on MFI profitability is ambiguous, and therefore I empirically investigate the effect on BRAC branch profitability.

Overall branch profitability is derived from the number of loans disbursed, the size of those loans, and the overall repayment rate. To capture the effect of all of these factors on branch profits, we can directly compare the overall profitability of branches that offered the Emergency Loan to those that did not, including in the analysis *both* eligible and ineligible branch members.[22]Table 9 shows the estimated effects of treatment on three measures of MFI profitability: the net present value (NPV) of each loan disbursed to eligible clients, the monthly profitability of the branch in aggregate, and the per-member monthly profitability of each branch.[23] The first two results show positive point estimates, but neither is statistically significant. However, column 3 shows a 4% increase in the per-person profits in treatment branches. In sum, these results suggest a modest increase in branch profitability, and rule out large MFI losses.

Finally, in column 4 of Table 9 I examine the effect of treatment on the expected NPV of the branch portfolio as a whole. I estimate the NPV of the branch following Karlan and Zinman (2018). I estimate the average profitability of clients grouped by treatment status and ex-ante credit score. I then assign these values to the stock of clients that existed in each branch at the beginning of the experiment. I then aggregate up to the branch credit-score level:

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

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

I can also examine the extent to which the effects on profitability vary by borrower credit score. Figure 1d plots the treatment effect on per-person profitability by credit score

[22]Note, that for this exercise I do not attempt to include BRAC administrative costs into the profit calculation due to lack of good information on their magnitude. Anecdotally, BRAC did not hire any new staff to implement this project and material costs were low. Nevertheless, this does not account for whether staff felt burdened with additional work. To the extent that such costs are substantial, the profit results below should be thought of as an upper-bound.

[23]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.

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 8 show that this heterogeneity is statistically significant). These results have interesting implications for the targeting of the Emergency Loan. The Emergency Loan was targeted to the top 40% of borrowers based on a credit score that reflected their past loan behavior. This system was designed to reduce the downside risk for the MFI in case repayment rates from the Emergency Loan were low. However, the results suggest that BRAC could do even better by lowering the eligibility threshold. Assuming the measured treatment effects are continuous across the threshold, this would extend access to clients who are most likely to improve MFI profitability.

I further investigate two key outcomes that determine branch profitability: the number of loans disbursed, and repayment rates to determine which of these two measures may be responsible for the modest improvements we observe in MFI profitability.[24] In the absence of a shock, I find that access to the Emergency Loan has no effect on repayment rates for all loans (Appendix Table A.24). In the presence of a flood, the number of missed payments across all loans increases by approximately 3.9 percentage points (40% percent) in control branches. In treatment branches this effect is overcome by a reduction in missed payments of 4 percentage points, thereby returning repayment rates to approximately normal rates. Furthermore, the repayment rate of the Emergency Loan itself is almost identical to other loans during the same period (10% missed payments for the Emergency Loan as compared with 9.6% on all loans). This result is even more meaningful when we remember that households that took the Emergency Loan experienced greater damages from the flood. Overall, these results demonstrate that the availability of the Emergency Loan improves repayment for the MFI in the aftermath of the flood (on a branch wide basis).

I also look for heterogeneity in repayments rates by borrowers' credit score. Figure 1c plots repayment rates by treatment status across credit scores. This shows that the effect of treatment on repayment rates is largest among clients with scores that are closest to the eligibility threshold. The treatment effect is much smaller at higher credit scores (column 3 of Table 8 shows that this heterogeneity is statistically significant), and explains some of the heterogenous effects on profits above.[25] The repayment heterogeneity likely stems from the fact that borrowers with high credit scores already repay at such high rates that further

[24] I also investigate whether the size of disbursed loans changes and I find no change, perhaps reflecting the formulaic nature of loans sizes offered by BRAC.

[25] The other factor likely driving the heterogeneity in profits is the reduction in the number of Good Loans given out to borrowers with the highest credit scores, as seen in Table 7. This results in fewer loans going to borrowers who are most likely to repay, lowering overall profits among this cohort.

improvements are difficult to make.[26]

Finally I investigate whether the number of loans BRAC disburses changes. We have already seen that the number of Emergency Loans increases, while the number of Good Borrower Loans falls. Therefore, I also test how the Emergency Loan affects the likelihood that borrowers take a regular Dabi loan in the pre-period, where my model shows that treated households should be more willing to make risky investments, and borrow to do so. I find that treatment causes the probability of taking a Dabi loan to increase by 11% (0.5 percentage points) in the pre-period (see Appendix Table A.25) – and does not differ by borrower credit score (Figure 1b and Table 8 Column 2). In sum, offering the Emergency Loan leads to small increases in Dabi loans and deceases for Good Loans, leading to an overall effect on the total loans disbursed that is close to zero.

6 Conclusion

Rising global temperatures will lead to more extreme weather, and the number of medium to large scale disasters is predicted to increase by 40% from 2015 to 2030. The UN also estimates that climate financing is falling 20% short of the 100 billion yearly commitment by wealthy nations (United Nations, 2020). Under these circumstances it is critical to find sustainable and cost-effective solutions that will help low-income households cope with the consequences of climate change. This can be difficult to achieve in countries where the use of more commonly used adaptation measures (infrastructure, insurance schemes, and social safety net programs) is limited by market frictions.

One solution is to provide households with a guaranteed credit line in the event of a shock. While theory suggests this should improve household welfare, MFI's concerns about default risk could limit supply. To test this empirically, I run a large scale RCT offering guaranteed credit in rural regions of Bangladesh where annual flood risk is high. First, I show that households that were informed about their guaranteed credit access increase their investments in productive activities in the pre-period. This increase in investments yields higher production levels absent a flood, and higher consumption levels when a shock occurs.

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

[26] Appendix Figure A.6 plots the levels of repayment rate.

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

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

From a policy perspective, this research suggests that credit represents a scaleable and effective policy adaptation tool that organizations can use in low-income countries. As the frequency and severity of weather shocks increases with climate change, providing households with an easily accessible tool that reduces their exposure to extreme weather is important. While the product investigated in this experiment targets flood shocks, similar products could likely be designed to address other types of climate shocks (e.g. droughts, cyclones). Furthermore, the tool I explore here is appealing because it overcomes market frictions that have limited the utility of other adaptation measures. MFI loans are already understood in many rural areas worldwide. Moreover, MFIs make decisions about who is eligible for the loan before a shock occurs, which overcomes lenders' hesitation to lend after a shock. From the borrower's side, guaranteed credit does not require any up-front commitments from the beneficiary, bypassing one of the main drivers of low demand for insurance. Additionally, because the decision to utilize additional credit is made after shock damages are realized, households can opt-in after assessing ex-post costs and benefits. Therefore, guaranteed credit can crowd-in ex-ante investment even if households choose not to use the product in the aftermath of a shocks.

References

Angelucci, Manuela, Dean Karlan, and Jonathan Zinman. 2015. "Microcredit Impacts: Evidence from a Randomized Microcredit Program Placement Experiment by Compartamos Banco." *American Economic Journal: Applied Economics* 7 (1):151–182.

Aragón, Fernando M., Alexander Karaivanov, and Karuna Krishnaswamy. 2020. "Credit lines in microcredit: Short-term evidence from a randomized controlled trial in India." *Journal of Development Economics* 146:102497.

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

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

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

Barboni, Giorgia and Parul Agarwal. 2022. "How do flexible microfinance contracts improve repayment rates and business outcomes? Experimental Evidence from India." *Working Paper* .

Battaglia, Marianna, Selim Gulesci, and Andreas Madestam. 2021. "Repayment Flexibility and Risk Taking: Experimental Evidence from Credit Contracts." *CEPR Working Paper* .

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.

Brooks, Wyatt and Kevin Donovan. 2020. "Eliminating Uncertainty in Market Access: The Impact of New Bridges in Rural Nicaragua." *Econometrica* 88 (5):1965–1997. URL `https://onlinelibrary.wiley.com/doi/abs/10.3982/ECTA15828`.

Brouwer, Roy, Sonia Akter, Luke Brander, and Enamul Haque. 2007. "Socioeconomic vulnerability and adaptation to environmental risk: A case study of climate change and flooding in Bangladesh." *Risk Analysis* 27 (2):313–326.

Burke, Marshall, Lauren Falcao Bergquist, and Edward Miguel. 2018. "Sell Low and Buy High: Arbitrage and Local Price Effects in Kenyan Markets*." *The Quarterly Journal of Economics* 134 (2):785–842.

Burlig, Fiona, Louis Preonas, and Matt Woerman. 2020. "Panel data and experimental design." *Journal of Development Economics* 144:102458. URL `https://www.sciencedirect.com/science/article/pii/S030438782030033X`.

Carleton, Tamma, Amir Jina, Michael Delgado, Michael Greenstone, Trevor Houser, Solomon Hsiang, Andrew Hultgren, Robert E Kopp, Kelly E McCusker, Ishan Nath, James Rising, Ashwin Rode, Hee Kwon Seo, Arvid Viaene, Jiacan Yuan, and Alice Tianbo Zhang. 2022. "Valuing the Global Mortality Consequences of Climate Change Accounting for Adaptation Costs and Benefits*." *The Quarterly Journal of Economics* URL `https://doi.org/10.1093/qje/qjac020`. Qjac020.

Carleton, Tamma A. and Solomon M. Hsiang. 2016. "Social and economic impacts of climate." *Science* 353 (6304):aad9837. URL `https://www.science.org/doi/abs/10.1126/science.aad9837`.

Casaburi, Lorenzo and Jack Willis. 2018. "Time versus State in Insurance: Experimental Evidence from Contract Farming in Kenya." *American Economic Review* 108 (12):3778–3813.

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

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

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

Dar, Manzoor H, Alain de Janvry, Kyle Emerick, Erin M Kelley, and Elisabeth Sadoulet. 2022. "Casting a Wider Net: Sharing Information Beyond Social Networks." *Working Paper* :62.

Dar, Manzoor H, Kyle Emerick, Elisabeth Sadoulet, Alain de Janvry, and Eleanor Wiseman. 2021. "Private Input Suppliers as Information Agents for Technology Adoption in Agriculture." *Unpublished Working Paper* .

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

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

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

Donovan, Kevin. 2020. “The Equilibrium Impact of Agricultural Risk on Intermediate Inputs and Aggregate Productivity.” *The Review of Economic Studies* 88 (5):2275–2307.

Elabed, Ghada, Marc F. Bellemare, Michael R. Carter, and Catherine Guirkinger. 2013. “Managing basis risk with multiscale index insurance.” *Agricultural Economics* 44 (4-5):419–431.

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):1537–61.

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

Few, Roger. 2003. “Flooding, vulnerability and coping strategies: local responses to a global threat.” *Progress in Development Studies* 3 (1):43–58.

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

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

Fink, Günther, B. Kelsey Jack, and Felix Masiye. 2020. “Seasonal Liquidity, Rural Labor Markets, and Agricultural Production.” *The American Economic Review* 110 (11):42.

Fishman, Ram, Xavier Gine, and Hanan G. Jacoby. 2021. “Efficient Irrigation and Water Conservation: Evidence from South India.” Working Paper, World Bank, Washington, DC. Accepted: 2021-06-03T20:00:52Z.

Haque, Md Munjurul, Sabina Islam, Md Bahuddin Sikder, and Md Saiful Islam. 2022. “Community flood resilience assessment in Jamuna floodplain: A case study in Jamalpur District Bangladesh.” *International Journal of Disaster Risk Reduction* 72:102861.

Hill, Ruth Vargas, Neha Kumar, Nicholas Magnan, Simrin Makhija, Francesca de Nicola, David J. Spielman, and Patrick S. Ward. 2019. “Ex ante and ex post effects of hybrid index insurance in Bangladesh.” *Journal of Development Economics* 136:1–17.

Hirabayashi, Yukiko, Roobavannan Mahendran, Sujan Koirala, Lisako Konoshima, Dai Yamazaki, Satoshi Watanabe, Hyungjun Kim, and Shinjiro Kanae. 2013. “Global flood risk under climate change.” *Nature Climate Change* 3 (9):816–821. Number: 9 Publisher: Nature Publishing Group.

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

Jones, Maria, Florence Kondylis, John Loeser, and Jeremy Magruder. 2022. "Factor Market Failures and the Adoption of Irrigation in Rwanda." *American Economic Review* 112 (7):2316–52.

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

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

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

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

Lobell, David B., Jillian M. Deines, and Stefania Di Tommaso. 2020. "Changes in the drought sensitivity of US maize yields." *Nature Food* 1 (11):729–735. URL https://www.nature.com/articles/s43016-020-00165-w. Number: 11 Publisher: Nature Publishing Group.

Lybbert, Travis J. and Daniel A. Sumner. 2012. "Agricultural technologies for climate change in developing countries: Policy options for innovation and technology diffusion." *Food Policy* 37 (1):114–123.

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

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

Mobarak, Ahmed Mushfiq and Mark R. Rosenzweig. 2013. "Informal Risk Sharing, Index Insurance, and Risk Taking in Developing Countries." *American Economic Review* 103 (3):375–80.

Rentschler, Jun and Melda Salhab. 2020. "People in Harm's Way : Flood Exposure and Poverty in 189 Countries." *World Bank Policy Research Working Paper, No. 9447* .

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.

United Nations. 2020. "The Sustainable Development Goals Report 2022." URL https://unstats.un.org/sdgs/report/2022/The-Sustainable-Development-Goals-Report-2022.pdf.

Will, Meike, Jürgen Groeneveld, Karin Frank, and Birgit Müller. 2021. "Informal risk-sharing between smallholders may be threatened by formal insurance: Lessons from a stylized agent-based model." *PLOS ONE* 16 (3):e0248757. Publisher: Public Library of Science.

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.

Tables

Table 1: Land Farmed

	(1) Own land	(2) Rented land	(3) Sharecrop land	(4) Total land	(5) Any Cult.
Treatment	0.004	0.053***	-0.004	0.052**	0.036*
	(0.009)	(0.014)	(0.004)	(0.020)	(0.019)
Rand. Inf. p-val	0.812	0.003	0.298	0.088	0.158
Mean Dep. Var	0.13	0.20	0.02	0.35	0.46
Observations	4759	4755	4758	4754	4760

Notes: Sample includes only eligible BRAC members from both treatment and control groups. Data is pooled from both the 2016 and 2017 Aman season. Standard errors clustered at the district level. Land measured in acres. Total land is the sum of own land, rented land, and sharecropped land. Any Cult. is an indicator for whether or not a household planted any crops during the season.

Table 2: Ex-Ante Investments

	(1) Fert. Applied	(2) Pest. Applied	(3) Input Cost per Acre	(4) Non-Ag Invest
Treatment	6.50	0.25**	2.38*	14.88
	(5.12)	(0.10)	(1.33)	(9.25)
Rand. Inf. p-val	0.242	0.169	0.382	0.050
Mean Dep. Var	140.71	1.58	65.87	38.57
Observations	2186	2143	2019	4760

Notes: Sample includes only eligible BRAC members from both treatment and control groups. Data is pooled from both the 2016 and 2017 Aman season. Standard errors clustered at the district level. Fertilizer and pesticide measured in kg/L per acre. Input cost per acre is the sum of the cost of fertilizer, pesticide, and seeds (measured in dollars) divided by the total number of acres cultivated. Non-Ag Invest is non-agriculture business investment measured by the total value in dollars of newly purchased (or repaired) business assets.

Table 3: Ex-Post Outcomes

Panel A: Ex-Post Outcomes by Treatment

	(1) Log Cons PerCap	(2) Crop Prod. (Kg)	(3) Log Income	(4) Bus. Stock Value	(5) Business Profit
Treatment	0.088**	49.723**	-0.017	142.618	7.853
	(0.037)	(22.151)	(0.026)	(129.161)	(30.373)
Rand. Inf. p-val	0.008	0.079	0.542	0.280	0.722
Mean Dep. Var	5.93	275.30	10.77	863.83	229.42
Observations	4758	4760	4546	800	800

Panel B: Ex-Post Outcomes by Treatment and Flood Realization

	(1) Log Cons PerCap	(2) Crop Prod. (Kg)	(3) Log Income	(4) Bus. Stock Value	(5) Business Profit
Treatment	0.055	87.691**	-0.067	133.259	-8.814
	(0.041)	(37.423)	(0.042)	(175.353)	(28.829)
Flood X Treatment	0.061	-65.127	0.093	28.394	34.378
	(0.056)	(41.689)	(0.060)	(269.205)	(43.952)
Flood	-0.069	-86.802**	-0.065	-131.620	-56.963
	(0.052)	(38.787)	(0.058)	(149.026)	(36.933)
Rand. Inf. p-val Treat	0.259	0.049	0.202	0.537	0.809
Rand. Inf. p-val Inter.	0.368	0.240	0.251	0.913	0.492
Treat + Flood X Trt	0.026	0.331	0.546	0.425	0.572
Mean Dep. Var	5.93	275.30	10.77	863.83	229.42
Observations	4758	4760	4546	800	800

Notes: Sample includes only eligible BRAC members from both treatment and control groups. Data is pooled from both the 2016 and 2017 Aman season. Standard errors clustered at the district level. Log Cons PerCap is household log per capita expenditure in the past week across a range of food products and cell phone credit. Crop Prod. (Kg) is total crop production measured in kilograms. Log income is log household earnings from crop sales, livestock, wages, business, and remittances measured in dollars. Bus. Stock Value is the total value of the current business stock measured in dollars. Business profits is the total profits earned by in the past month in dollars. Flood is an indicator that equals one if flooding occurred and the Emergency Loan was activated. The row Treat + Flood X Treat reports p-values for the null hypothesis that the sum of the two treatment coefficients is equal to zero.

Table 4: Emergency Loan Uptake

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

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

Table 5: Spillovers: Ineligible Ex-Post Outcomes

	Panel A: Ex-Post Outcomes by Treatment				
	(1) Log Cons PerCap	(2) Log Income	(3) Crop Prod. (Kg)	(4) Bus. Stock Value	(5) Business Profit
Treatment branch	0.060**	-0.015	-1.115	-54.130	3.158
	(0.025)	(0.033)	(24.945)	(100.498)	(42.388)
Rand. Inf. p-val	0.100	0.620	0.990	0.670	0.950
Mean Dep. Var	6.00	10.83	224.51	643.81	229.04
Observations	1916	1843	1917	269	269

	Panel B: Ex-Post Outcomes by Treatment and Flood Realization				
	(1) Log Cons PerCap	(2) Log Income	(3) Crop Prod. (Kg)	(4) Bus. Stock Value	(5) Business Profit
Treatment branch	0.094***	-0.041	-13.747	-156.825	46.990
	(0.028)	(0.060)	(35.940)	(153.483)	(55.605)
Flood X Treatment	-0.049	0.047	23.301	208.523	-85.672
	(0.046)	(0.076)	(39.233)	(215.052)	(54.322)
Flood	-0.020	-0.112*	-68.793*	43.549	50.826
	(0.044)	(0.064)	(39.488)	(120.011)	(42.333)
Rand. Inf. p-val Treat	0.170	0.540	0.800	0.420	0.380
Rand. Inf. p-val Inter.	0.620	0.650	0.720	0.430	0.300
Treat + Flood X Trt	0.247	0.880	0.750	0.692	0.290
Mean Dep. Var	6.00	10.83	224.51	643.81	229.04
Observations	1916	1843	1917	269	269

Notes: Sample includes only ineligible BRAC members from both treatment and control groups. Data is pooled from both the 2016 and 2017 Aman season. Standard errors clustered at the district level. Log Cons PerCap is household log per capita expenditure in the past week across a range of food products and cell phone credit. Crop Prod. (Kg) is total crop production measured in kilograms. Log income is log household earnings from crop sales, livestock, wages, business, and remittances measured in dollars. Bus. Stock Value is the total value of the current business stock measured in dollars. Business profits is the total profits earned by in the past month in dollars. Flood is an indicator that equals one if flooding occurred and the Emergency Loan was activated. The row Treat + Flood X Treat reports p-values for the null hypothesis that the sum of the two treatment coefficients is equal to zero.

Table 6: Spillovers: Labor and Transfers

	(1) Days Worked	(2) Day Labor Earnings	(3) Cash Transfer	(4) In-Kind Transfer
Treatment branch	1.715*	9.447	1.233	0.205
	(0.982)	(16.292)	(4.237)	(0.275)
Flood X Treatment	-2.272	-5.892	-2.452	-0.438
	(1.442)	(23.159)	(9.841)	(0.622)
Flood	2.353**	2.091	15.570**	1.316***
	(0.982)	(17.390)	(7.225)	(0.444)
Rand. Inf. p-val Treat	0.250	0.750	0.750	0.990
Rand. Inf. p-val Inter.	0.220	0.930	0.760	0.940
Treat + Flood X Trt	0.576	0.830	0.891	0.677
Mean Dep. Var	9.75	129.86	10.98	0.97
Observations	1917	1917	1917	1917

Notes: Sample includes only ineligible BRAC members from both treatment and control groups. Data is pooled from both the 2016 and 2017 Aman season. Standard errors clustered at the district level. Days Worked is the number of days worked as a day laborer during the Aman season. Day Labor earnings is the income reported from day labor in dollars. Cash Transfer is the amount of cash assistance received by the household in dollars. In-Kind transfer is the value in dollars of any in-kind assistance received by the household. Flood is an indicator that equals one if flooding occurred and the Emergency Loan was activated. The row Treat + Flood X Treat reports p-values for the null hypothesis that the sum of the two treatment coefficients is equal to zero.

Table 7: Uptake of Good Loan by Emergency Loan Availability

	Took Good Loan		
Treatment	-0.027^{***}	-0.030^{***}	-0.033^{***}
	(0.008)	(0.010)	(0.008)
Farming x Treatment		0.005	
		(0.017)	
Farming Main Activity		-0.013	
		(0.011)	
Flood Risk x Treatment			-0.015^{**}
			(0.006)
Flood Risk			0.020^{***}
			(0.004)
Rand Inf. p-val Treatment	0.01	0.00	0.00
Rand Inf. p-val Interaction	-	0.77	0.02
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 the district 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 8: Effect MFI Outcomes by Credit Score

	Good Loan Uptake	Dabi Uptake	Missed Payment	Per Person Profit	NPV
	(1)	(2)	(3)	(4)	(5)
Treatment	-0.020^{*}	0.006^{***}	-0.038^{**}	107.75	$26,670,704^{*}$
	(0.011)	(0.002)	(0.017)	(78.83)	(15,818,664)
Credit Score x Treatment	-0.003^{*}	0.000	0.005^{**}	-29.47^{*}	$-301,927$
	(0.002)	(0.000)	(0.002)	(17.13)	(192,639)
Credit Score	0.004^{***}	0.0001	-0.016^{***}	15.40^{**}	$3,401,245^{***}$
	(0.001)	(0.0002)	(0.002)	(6.17)	(139,930)
Rand Inf. p-value Treatment	0.02	0.00	0.01	0.2	0.07
Rand Inf. p-value Interaction	0.04	0.90	0.08	0.11	0.47
Month F.E.	No	Yes	Yes	No	No
Mean of Dep. Var.	0.13	0.062	0.096	2202	26,061,643
Observations	37,392	396,228	466,028	42,402	3,845

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

Table 9: Branch Profit by Emergency Loan Availability

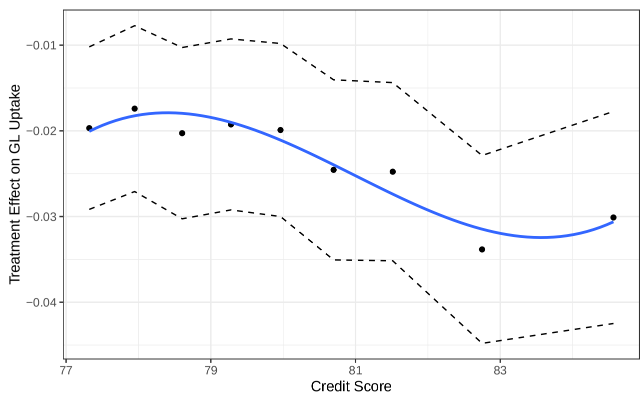
	Profit (Taka)			NPV
	Per Loan	Monthly Branch	Monthly Per Person	
	(1)	(2)	(3)	(4)
Treatment	245	109,090	97**	2,575,218**
	(244)	(130,593)	(46)	(1,065,260)
Rand Inf. p-value	0.82	0.63	0.00	0.09
Month F.E.	No	Yes	Yes	No
Mean of Dep. Var.	2,823	1,745,794	2202	26,061,643
Observations	103,571	3,736	3,706	3,845

Notes: The sample for column 1 includes loans made only to Emergency Loan eligible clients. The sample in columns 2-4 includes data from both eligible and ineligible clients. Standard errors clustered at the district 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. The outcome in column 4 is branch NPV in taka as measured at the start of the experiment.

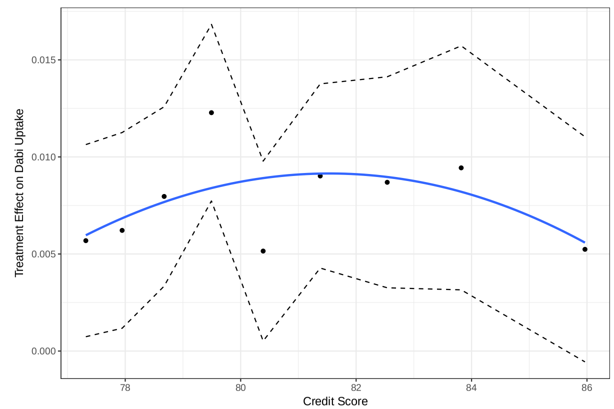
Figures

Figure 1: Heterogeneity by Credit Score

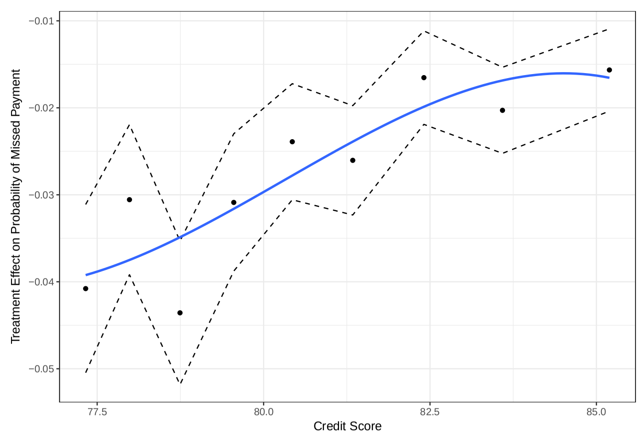
(a) Good Loan Uptake



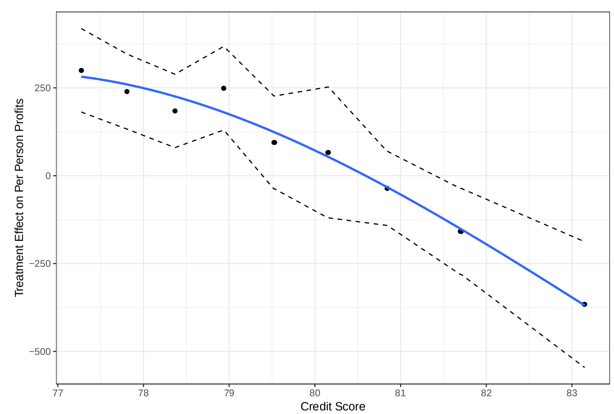
(b) Dabi Loan Uptake



(c) Missed Payment



(d) Per-Person Profits



Notes: Plots the treatment effect on the outcome in treatment branches by decile of borrower credit score. The sample is comprised of Emergency Loan eligible borrowers. Data is pooled from both 2016 and 2017. For Good Loan Uptake, the sample is limited to those who were also eligible for a Good Loan in the pre-flood period. Standard errors are clustered at the district level. Table 8 tests whether the treatment effect heterogeneity is significant.

Online Appendix

Contents

A Tables and Figures

A.1 Tables

A.1.1 Balance Checks

Table A.1: Eligible Compared to Ineligible

	(1) Ineligible	(2) Eligible	(3) p-value of equality test
Household Size	4.740	4.873	0.042
	(0.055)	(0.033)	
Age Head of Household	39.499	40.627	0.031
	(0.423)	(0.267)	
Educ. Head of Household	2.904	2.509	0.004
	(0.127)	(0.068)	
Married	0.952	0.933	0.033
	(0.007)	(0.005)	
Acres of Land Owned	0.509	0.448	0.376
	(0.044)	(0.037)	
Land Owned Cult. Last Season	0.221	0.177	0.050
	(0.026)	(0.010)	
Land Rented Last Season	0.230	0.259	0.182
	(0.015)	(0.012)	
Land Sharecropped Last Season	0.032	0.047	0.289
	(0.006)	(0.008)	
Any Cultivation	0.504	0.513	0.609
	(0.016)	(0.009)	
Household Income	20.916	19.591	0.045
	(0.661)	(0.310)	
Weekly Expenditure	0.286	0.276	0.265
	(0.008)	(0.005)	
BRAC Loan Last Year	0.889	0.887	0.887
	(0.010)	(0.006)	
Migrants In Household	0.136	0.142	0.695
	(0.012)	(0.007)	
Flooded in Past	0.540	0.538	0.878
	(0.016)	(0.009)	
Electricity Access	0.709	0.716	0.672
	(0.014)	(0.008)	
Asset Count	1.649	1.690	0.266
	(0.031)	(0.019)	
Cows Owned	0.665	0.905	0.000
	(0.037)	(0.026)	
Risk Aversion	0.508	0.511	0.866
	(0.013)	(0.007)	
Time Preference	6.120	5.939	0.094
	(0.092)	(0.054)	

Notes: Table compares households that were eligible for the Emergency Loan to those who were ineligible in both treatment and control branches at baseline in April 2016. Asset count is the number of items a household reported owning of a gas or electric stove, radio, television, refrigerator, bicycle, and motorcycle. Risk aversion was measured by asking households to choose between a certain payoff and a lottery with increasing odds. Risk aversion is a continuous measure but has been rescaled so that it ranges from 0 to 1, where 0=most risk loving and 1=most risk averse. Note that some agricultural outcomes analyzed at endline such as fertilizer and pesticide applied were not captured at baseline due to survey time constraints and so cannot be reported here.

Table A.2: Balance Table

	(1) Control	(2) Treatment	(3) p-value of equality test
Household Size	4.867	4.881	0.826
	(0.047)	(0.046)	
Age Head of Household	40.869	40.390	0.369
	(0.374)	(0.380)	
Educ. Head of Household	2.538	2.477	0.653
	(0.095)	(0.096)	
Married	0.937	0.928	0.302
	(0.006)	(0.007)	
Acres of Land Owned	0.392	0.437	0.166
	(0.021)	(0.025)	
Land Owned Cult. Last Season	0.168	0.172	0.811
	(0.011)	(0.013)	
Land Rented Last Season	0.239	0.254	0.438
	(0.013)	(0.015)	
Land Sharecropped Last Season	0.056	0.038	0.277
	(0.014)	(0.008)	
Total Land Cultivated	0.463	0.464	0.974
	(0.022)	(0.021)	
Any Cultivation	0.515	0.510	0.807
	(0.013)	(0.013)	
Household Income	1588.780	1545.711	0.386
	(34.130)	(36.028)	
Weekly Expenditure	22.003	22.216	0.769
	(0.489)	(0.532)	
BRAC Loan Last Year	0.876	0.899	0.053
	(0.009)	(0.008)	
Migrants In Household	0.147	0.135	0.404
	(0.010)	(0.010)	
Flooded in Past	0.526	0.548	0.226
	(0.013)	(0.013)	
Electricity Access	0.707	0.723	0.337
	(0.012)	(0.012)	
Asset Count	1.717	1.664	0.149
	(0.026)	(0.027)	
Cows Owned	0.892	0.921	0.571
	(0.035)	(0.039)	
Risk Aversion	0.509	0.513	0.769
	(0.011)	(0.010)	
Time Preference	5.933	5.947	0.903
	(0.077)	(0.076)	
Loan Principal	28106	26916	0.446
	(18908)	(17387)	
Loans Repaid Late	0.03	0.03	0.466
	(0.05)	(0.055)	
Credit Score	76.91	77.06	0.942
	(8.75)	(8.5)	
Savings (Taka)	7131	6784	0.179
	(7006)	(6845)	

Notes: Table compares households in treatment and control branches using data from baseline or from BRAC's administrative data set. The sample is comprised only of households who did not drop out of the sample for future surveys. Asset count is the number of items a household reported owning of a gas or electric stove, radio, television, refrigerator, bicycle, and motorcycle. Risk aversion was measured by asking households to choose between a certain payoff and a lottery with increasing odds. The variable is a continuous measure but has been rescaled so that it ranges from 0 to 1, where 0=most risk loving and 1=most risk averse. Note that some agricultural outcomes analyzed at endline such as fertilizer and pesticide applied were not captured at baseline due to survey time constraints and so cannot reported here.

Table A.3: Good Loan Eligible Sample: Balance Table

	(1) Control	(2) Treatment	(3) p-value of equality test
Household Size	4.913	4.965	0.665
	(0.085)	(0.083)	
Age Head of Household	41.539	40.824	0.441
	(0.640)	(0.670)	
Educ. Head of Household	2.410	2.490	0.733
	(0.159)	(0.170)	
Married	0.953	0.932	0.150
	(0.010)	(0.011)	
Acres of Land Owned	0.437	0.486	0.431
	(0.041)	(0.047)	
Land Owned Cult. Last Season	0.158	0.220	0.093
	(0.018)	(0.031)	
Land Rented Last Season	0.225	0.248	0.459
	(0.020)	(0.024)	
Land Sharecropped Last Season	0.056	0.021	0.136
	(0.023)	(0.006)	
Any Cultivation	0.495	0.519	0.461
	(0.023)	(0.023)	
Household Income	19.662	20.109	0.684
	(0.674)	(0.864)	
Weekly Expenditure	0.265	0.257	0.519
	(0.008)	(0.008)	
BRAC Loan Last Year	0.920	0.948	0.074
	(0.013)	(0.010)	
Migrants In Household	0.167	0.134	0.211
	(0.020)	(0.017)	
Flooded in Past	0.512	0.568	0.079
	(0.023)	(0.023)	
Electricity Access	0.702	0.727	0.385
	(0.021)	(0.020)	
Asset Count	1.672	1.614	0.333
	(0.044)	(0.041)	
Cows Owned	0.873	0.979	0.285
	(0.061)	(0.078)	
Risk Aversion	0.503	0.516	0.625
	(0.018)	(0.019)	
Time Preference	5.810	5.907	0.617
	(0.139)	(0.136)	
Loan Principal	13874	13305	0.621
	(9869)	(8657)	
Loans Repaid Late	0	0	1
	(0)	(0)	
Credit Score	77.2	77.72	0.299
	(7.47)	(7.21)	
Savings	7293	7032	0.279
	(6181)	(5777)	

Notes: Table compares households in treatment and control branches at baseline conducted only among the Good Loan Eligible sample and households who did not drop out of the sample for future surveys. Asset count is the number of items a household reported owning of a gas or electric stove, radio, television, refrigerator, bicycle, and motorcycle. Risk aversion was measured by asking households to choose between a certain payoff and a lottery with increasing odds. The variable is a continuous measure but has been rescaled so that it ranges from 0 to 1, where 0=most risk loving and 1=most risk averse. Note that some agricultural outcomes analyzed at endline such as fertilizer and pesticide applied were not captured at baseline due to survey time constraints and so cannot be reported here. There are no late payments in this sample of Good Loan eligible clients because by definition did could not have late payments on current loans.

A.1.2 Attrition

Table A.4: Attrition Rate

	(1) Attrition
Treatment	-0.003
	(0.002)
Mean Dep.	0.01
Observations	4001

Notes: Table shows the difference in attrition rates between the treated and control group from those surveyed at baseline.

A.1.3 Flood Definition

In this subsection I examine whether the flood activation was potentially compromised due to the BRAC research employee (whose job was to gather information on flooding in areas where the Flood Forecasting and Warning Center (FFWC) indicated flooding) differentially activating treatment or control branches. I perform two checks for this concern.

First, I compare branches that were officially activated via the full procedure with new flood indicator based *only* on the FFWC danger level. This occurred only a total of 12 times in the entire experiment, or for 5% of all potentially activated branches. Nine of these instances occurred in 2016 and three of them in 2017. Importantly, instances of this disagreement are balanced between treatment and control branches for both 2016 and 2017:

Table A.5: FFWC Triggered but Non-Activated Branches

	Treatment Status	
	No	Yes
2016	4	5
2017	2	1
Total	6	6

Notes: Table shows the number of branches, split by treatment status and year, where the linked FFWC flood monitoring station passed the danger threshold but were not activated based on the report supplied by the research employee.

Second, I create a new flood indicator which is defined only based on the FFWC trigger and re-run the ex-post analysis reported in Table 3. Table A.6 shows below that the results remain qualitatively the same. The two main differences are that the coefficient on interaction between flooding and treatment is smaller (but still negative) for crop production and larger (and now weakly statistically significant) on Log Income.

Similarly, Table A.7 reproduces the loan repayment results using the new FFWC based flood indicator. These results are qualitatively similar to Table A.24. The base negative effect of flooding on missed payments is smaller than previously estimated by 0.027 percentage points, however the interaction effect between flooding and treatment of -0.040 is nearly identical to the previously estimated treatment effect of -0.044 (both being significant at the 10% level).

Table A.6: Ex-post with Alternative Flood Definition

	(1) Log Cons PerCap	(2) Crop Prod. (Kg)	(3) Log Income	(4) Bus. Stock Value	(5) Business Profit
Treatment	0.059	88.819*	-0.092**	115.962	8.076
	(0.042)	(49.224)	(0.044)	(208.505)	(37.040)
FFWC Flood X Treat	0.052	-29.153	0.128*	11.539	13.144
	(0.054)	(54.945)	(0.065)	(251.282)	(45.529)
FFWC Flood	-0.086	-80.613**	-0.068	-165.910	-49.364
	(0.053)	(34.217)	(0.053)	(187.067)	(37.862)
Mean Dep. Var	5.93	290.70	10.77	882.58	232.54
Observations	4758	4760	4546	800	800
Treat + Flood X Trt	0.03	0.01	0.45	0.47	0.61
Rand. Inf. p-val Treat	0.24	0.08	0.10	0.68	0.88
Rand. Inf. p-val Inter.	0.48	0.67	0.10	0.96	0.78

Notes: Sample includes only eligible BRAC members from both treatment and control groups. Data is pooled from both the 2016 and 2017 Aman season. Standard errors clustered at the district level. Log Cons PerCap is household log per capita expenditure in the past week across a range of food products and cell phone credit. Crop Prod. (Kg) is total crop production measured in kilograms. Log income is log household earnings from crop sales, livestock, wages, business, and remittances measured in dollars. Bus. Stock Value is the total value of the current business stock measured in dollars. Business profits is the total profits earned by in the past month in dollars. FFWC Flood is an indicator that each branch was flood affected *only* according to the government run FFWC (defined as having water levels exceed the "danger" threshold).

Table A.7: Repayment with Alternative Flood Definition

	Missed Payment
Treatment	0.012
	(0.025)
Treat x FFWC Flood	-0.040^{*}
	(0.020)
FFWC Flood	0.038^{*}
	(0.023)
Rand Inf. p-val Treatment	0.46
Rand Inf. p-val Interaction	0.02
Month F.E.	Yes
Mean of Dep. Var.	0.096
Unique Borrowers	109,647
Observations	378,970

Notes: Sample includes only Emergency Loan eligible clients. Standard errors clustered at the district level. The outcome variable is an indicator for whether or not the client missed a loan payment in a given month. FFWC Flood is an indicator that each branch was flood affected *only* according to the government run FFWC (defined as having water levels exceed the danger threshold).

A.1.4 Eligibility Selection

In this section I examine whether selection into eligibility in 2017 matters for the results. First, I simply examine whether there was differential Emergency Loan eligibility in 2017 across treatment and control branches. We see in Table A.8 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.

Table A.8: 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 A.9: Land Farmed 2016

	(1) Own land	(2) Rented land	(3) Sharecrop land	(4) Total land	(5) Any Cult.
Treatment	0.002	0.062***	-0.008*	0.053**	0.027
	(0.010)	(0.018)	(0.004)	(0.025)	(0.023)
Mean Dep. Var	0.15	0.22	0.02	0.39	0.50
Observations	2986	2986	2986	2986	2986
Rand. Inf. p-val	0.880	0.020	0.080	0.140	0.260

Notes: Sample includes only eligible BRAC members from both treatment and control groups. Data is from only the 2016 Aman season. Standard errors clustered at the district 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 A.10: Ex-Ante Investments 2016

	(1) Fert. Applied	(2) Pest. Applied	(3) Input Cost per Acre	(4) Non-Ag Invest
Treatment	4.45	0.38**	1.13	0.85
	(4.98)	(0.16)	(1.80)	(3.73)
Mean Dep. Var	129.93	1.34	60.53	7.84
Observations	1479	1479	1375	2986
Rand. Inf. p-val	0.420	0.020	0.730	0.720

Notes: Sample includes only eligible BRAC members from both treatment and control groups. Data is only from the 2016 Aman season. Standard errors clustered at the district level. Fertilizer and pesticide measured in kg/L per acre. Input cost per acre is the sum of the cost of fertilizer, pesticide, and seeds (measured in dollars) divided by the total number of acres cultivated. Non-Ag Invest is non-agriculture business investment measured by the total value in dollars of newly purchased (or repaired) business assets.

Table A.11: IV Land Farmed

	(1) Own land	(2) Rented land	(3) Sharecrop land	(4) Total land	(5) Any Cult.
Treatment	0.017	0.081***	-0.006	0.091***	0.055***
	(0.011)	(0.016)	(0.004)	(0.021)	(0.021)
Mean Dep. Var	0.14	0.19	0.02	0.34	0.44
Observations	5998	5994	5997	5993	5999

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. Standard errors clustered at the district 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 A.12: IV Inputs

	(1) Fert. Applied	(2) Pest. Applied	(3) Input Cost per Acre	(4) Non-Ag Invest
Treatment	3.00	4.92	-9.89*	-66.92**
	(7.31)	(4.94)	(5.33)	(33.07)
Mean Dep. Var	146.48	5.04	72.55	84.48
Observations	2642	2563	2434	5999

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. Standard errors clustered at the district level. Fertilizer and pesticide measured in kg/L per acre. Input cost per acre is the sum of the cost of fertilizer, pesticide, and seeds (measured in dollars) divided by the total number of acres cultivated. Non-Ag Invest is non-agriculture business investment measured by the total value in dollars of newly purchased (or repaired) business assets.

Table A.13: Ex-Post Outcomes 2016

	(1) Log Cons PerCap	(2) Log Income	(3) Crop Prod. (Kg)	(4) Bus. Stock Value
Treatment	0.061	-0.026	123.504**	39.236
	(0.051)	(0.038)	(56.334)	(216.013)
Flood X Treatment	0.062	-0.011	-125.086**	80.582
	(0.058)	(0.073)	(57.559)	(324.959)
Flood	-0.026	-0.022	-117.903**	-185.782
	(0.055)	(0.089)	(43.564)	(220.115)
Mean Dep. Var	5.86	10.73	326.15	925.01
Observations	2984	2841	2986	565
p-value Treat + Flood X Treat	0.014	0.574	0.950	0.619
Rand. Inf. p-val Treat	0.260	0.680	0.010	0.840
Rand. Inf. p-val Inter.	0.480	0.860	0.120	0.830

Notes: Sample includes only eligible BRAC members from both treatment and control groups. Data is from only the 2016 Aman season. Standard errors clustered at the district level. Log Cons PerCap is household log per capita expenditure in the past week across a range of food products and cell phone credit. Crop Prod. (Kg) is total crop production measured in kilograms. Log income is log household earnings from crop sales, livestock, wages, business, and remittances measured in dollars. Bus. Stock Value is the total value of the current business stock measured in dollars. Flood is an indicator that equals one if flooding occurred and the Emergency Loan was activated. The row Treat + Flood X Treat reports p-values for the null hypothesis that the sum of the two treatment coefficients is equal to zero.

Table A.14: IV Ex-Post Outcomes

	(1) Log Cons PerCap	(2) Log Income	(3) Crop Prod. (Kg)	(4) Bus. Stock Value
Treatment	0.060	-0.056	114.142**	113.066
	(0.059)	(0.067)	(53.629)	(212.908)
Flood X Treatment	0.058	0.083	-91.948	-31.413
	(0.068)	(0.079)	(57.044)	(250.743)
Flood Current Year	-0.055	-0.056	-72.719**	-142.046
	(0.042)	(0.046)	(30.739)	(183.332)
Mean Dep. Var	5.95	10.78	258.57	905.75
Observations	5997	5743	5999	983
p-value Treat + Flood X Treat	0.004	0.570	0.513	0.624

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. Standard errors are clustered at the district level. Log Cons PerCap is household log per capita expenditure in the past week across a range of food products and cell phone credit. Crop Prod. (Kg) is total crop production measured in kilograms. Log income is log household earnings from crop sales, livestock, wages, business, and remittances measured in dollars. Bus. Stock Value is the total value of the current business stock measured in dollars. Flood is an indicator that equals one if flooding occurred and the Emergency Loan was activated. The row Treat + Flood X Treat reports p-values for the null hypothesis that the sum of the two treatment coefficients is equal to zero.

A.1.5 Successive Shocks

This section examines how ex-ante treatment effects on investments are impacted after experiencing a flood in year one and how ex-post outcomes are affected for households who experience flooding in both years.

Table A.15: Investment After Shock

	(1) Fert. Applied	(2) Pest. Applied	(3) Total land	(4) Any Cult.	(5) Non-Ag Invest
Treatment	5.210	0.227	0.049*	0.027	13.452
	(4.882)	(0.142)	(0.026)	(0.021)	(9.052)
Flood Last Year X Treat	0.030	0.117	0.046	0.075**	-5.379
	(18.178)	(0.583)	(0.027)	(0.033)	(24.535)
Flood Last Year	32.616	0.043	-0.162***	-0.173***	46.113**
	(28.702)	(0.373)	(0.021)	(0.038)	(19.028)
Mean Dep. Var	140.71	1.58	0.35	0.46	38.57
Observations	2186	2143	4754	4760	4760
p-value Treat + Interaction	0.761	0.493	0.001	0.006	0.756
Rand. Inf. p-val Treat	0.450	0.270	0.150	0.260	0.090
Rand. Inf. p-val Inter.	1.000	0.880	0.190	0.140	0.880

Notes: Sample includes only eligible BRAC members from both treatment and control groups. Data is pooled from both the 2016 and 2017 Aman season. Standard errors clustered at the district 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. Non-Ag Invest is non-agriculture business investment measured by the total value in dollars of newly purchased (or repaired) business assets.

Table A.16: Ex-post After Successive Shocks

	(1) Log Cons PerCap	(2) Log Income	(3) Crop Prod. (Kg)	(4) Bus. Stock Value
Treatment	0.049	-0.071	87.151**	136.735
	(0.052)	(0.042)	(37.724)	(174.056)
Flood X Treatment	0.101	0.089	-81.505	31.672
	(0.073)	(0.067)	(49.429)	(276.614)
Flood Current Year	-0.041	-0.049	-74.621*	-147.513
	(0.050)	(0.064)	(39.767)	(151.327)
Flood Both X Treat	-0.132	0.030	65.727	-36.192
	(0.096)	(0.074)	(42.202)	(220.357)
Flood Both Years	-0.167**	-0.082	-50.327	139.959
	(0.065)	(0.085)	(42.603)	(207.659)
Mean Dep. Var	5.93	10.77	275.30	863.83
Observations	4758	4546	4760	800
p-value Sum Treatment Coef.	0.837	0.354	0.012	0.538
Rand. Inf. p-val Treat	0.110	0.260	0.070	0.560
Rand. Inf. p-val Flood X Treat	0.420	0.400	0.300	0.830
Rand. Inf. p-val Fl. Both X Treat	0.300	0.570	0.200	0.900

Notes: Sample includes only eligible BRAC members from both treatment and control groups. Data is pooled from both the 2016 and 2017 Aman season. Standard errors clustered at the district level. Log Cons PerCap is household log per capita expenditure in the past week across a range of food products and cell phone credit. Crop Prod. (Kg) is total crop production measured in kilograms. Log income is log household earnings from crop sales, livestock, wages, business, and remittances measured in dollars. Bus. Stock Value is the total value of the current business stock measured in dollars. Flood Current Year is an indicator that equals one if flooding occurred in the current year. Flood Both Years is an indicator that captures the additional effect of successive shocks for branches that experienced flooding in 2017 and that also experienced flooding in 2016.

A.1.6 Additional Household Outcomes

Table A.17: Other Income Activities

	Panel A: Additional Ex-Post Outcomes by Treatment						
	(1) Migrants	(2) Livestock Count	(3) Livestock Income	(4) Days Worked	(5) Day Labor Earnings	(6) Cash Transfer	(7) In-Kind Transfer
Treatment	0.007	0.050	52.334	-0.605	-13.794*	6.335	0.255
	(0.009)	(0.035)	(145.920)	(0.440)	(6.799)	(5.159)	(0.269)
Rand. Inf. p-val	0.499	0.353	0.678	0.196	0.104	0.174	0.418
Mean Dep. Var	0.07	0.95	583.93	8.75	121.37	13.50	0.95
Observations	4760	4760	4760	4760	4755	4760	4757

	Panel B: Additional Ex-Post Outcomes by Treatment and Flood Realization						
	(1) Migrants	(2) Livestock Count	(3) Livestock Income	(4) Days Worked	(5) Day Labor Earnings	(6) Cash Transfer	(7) In-Kind Transfer
Treatment	-0.004	-0.071	69.532	-0.241	-3.079	-0.391	-0.049
	(0.012)	(0.083)	(209.124)	(0.804)	(12.878)	(4.312)	(0.234)
Flood X Treatment	0.020	0.221	-32.506	-0.656	-19.571	12.128	0.542
	(0.015)	(0.132)	(355.601)	(0.906)	(13.820)	(14.547)	(0.823)
Flood	-0.020	-0.071	40.737	0.008	6.731	-0.395	0.141
	(0.016)	(0.083)	(192.561)	(0.985)	(14.006)	(4.002)	(0.233)
Rand. Inf. p-val Treat	0.788	0.359	0.691	0.761	0.777	0.942	0.882
Rand. Inf. p-val Inter.	0.308	0.042	0.911	0.540	0.238	0.171	0.307
Treat + Flood X Trt	0.221	0.057	0.881	0.042	0.000	0.297	0.428
Mean Dep. Var	0.07	0.95	583.93	8.75	121.37	13.50	0.95
Observations	4760	4760	4760	4760	4755	4760	4757

Notes: Sample includes only eligible BRAC members from both treatment and control groups. Data is pooled from both the 2016 and 2017 Aman season. Standard errors clustered at the district level. Migrants is the number of migrants from the household over the entire Aman season. Livestock Count is the total number of cows and goats owned by the household. Livestock income is the reported income earned from livestock products or sales. Days Worked is the number of days worked as a day laborer during the Aman season. Day Labor earnings is the income reported from day labor in dollars. Cash Transfer is the amount of cash assistance received by the household in dollars. In-Kind transfer is the value in dollars of any in-kind assistance received by the household. Flood is an indicator that equals one if flooding occurred and the Emergency Loan was activated. The row Treat + Flood X Treat reports p-values for the null hypothesis that the sum of the two treatment coefficients is equal to zero.

Table A.18: Savings Transactions by Emergency Loan Availability

	Savings	
	Pre-Period	All
	(1)	(2)
Treatment	8.85	−14.58
	(9.34)	(18.57)
Treat x Flood		45.37**
		(20.67))
Flood		−53.75**
		(24.60))
Year & Month F.E.	Yes	Yes
Mean of Dep. Var.	82.6	71.8
Unique Accounts	108,446	109,647
Observations	622,551	1,150,895

Notes: Sample includes only Emergency Loan eligible clients. Standard errors clustered at district 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.

A.1.7 Spillover Mechanisms and Total Effects

In this section I report the spillovers on the ineligible households for the main ex-ante outcomes, explore potential channels for spillovers through the labor market and transfers, and report weighted regressions to estimate the "total effect" of the experiment for the full population of eligible and ineligible households.

Table A.19: Spillovers: Ineligible Land Farmed

	(1) Own land	(2) Rented land	(3) Sharecrop land	(4) Total land	(5) Any Cult.
Treatment branch	0.020	-0.025	-0.002	-0.005	-0.029
	(0.025)	(0.016)	(0.004)	(0.031)	(0.028)
Rand. Inf. p-val	0.380	0.260	0.610	0.870	0.260
Mean Dep. Var	0.13	0.15	0.02	0.30	0.42
Observations	1917	1917	1917	1917	1917

Notes: Sample includes only ineligible BRAC members both treatment and control groups. Data is pooled from both the 2016 and 2017 Aman season. Standard errors clustered at the district 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 A.20: Spillovers: Ineligible Inputs

	(1) Fert. Applied	(2) Pest. Applied	(3) Input Cost per Acre	(4) Non-Ag Invest
Treatment branch	1.34	0.03	1.79	4.17
	(7.52)	(0.14)	(5.17)	(7.58)
Rand. Inf. p-val	0.890	0.890	0.600	0.670
Mean Dep. Var	136.92	1.36	67.04	41.75
Observations	806	779	722	1917

Notes: Sample includes only ineligible BRAC members from both treatment and control groups. Data is pooled from both the 2016 and 2017 Aman season. Standard errors clustered at the district level. Fertilizer and pesticide measured in kg/L per acre. Input cost per acre is the sum of the cost of fertilizer, pesticide, and seeds (measured in dollars) divided by the total number of acres cultivated. Non-Ag Invest is non-agriculture business investment measured by the total value in dollars of newly purchased (or repaired) business assets.

Table A.21: Total Effect: Ex-Post Outcomes

	(1) Log Cons PerCap	(2) Log Income	(3) Crop Prod. (Kg)	(4) Bus. Stock Value	(5) Business Profit
Panel A: Ex-Post Outcomes by Treatment					
Treatment branch	0.081***	-0.020	30.893	81.106	4.521
	(0.028)	(0.023)	(20.086)	(94.717)	(30.666)
Rand. Inf. p-val	0.000	0.350	0.150	0.460	0.830
Mean Dep. Var	5.95	10.79	258.17	790.83	228.33
Observations	6526	6247	6529	1055	1055
Panel B: Ex-Post Outcomes by Treatment and Flood Realization					
	(1) Log Cons PerCap	(2) Log Income	(3) Crop Prod. (Kg)	(4) Bus. Stock Value	(5) Business Profit
Treatment branch	0.068**	-0.056	51.524	24.869	7.393
	(0.029)	(0.034)	(32.332)	(127.318)	(30.485)
Flood X Treatment	0.026	0.067	-33.587	106.543	-3.982
	(0.045)	(0.050)	(37.799)	(188.641)	(31.373)
Flood	-0.045	-0.073	-81.083**	-76.545	-21.330
	(0.041)	(0.054)	(37.654)	(103.024)	(36.768)
Rand. Inf. p-val Treat	0.220	0.290	0.130	0.770	0.940
Rand. Inf. p-val Inter.	0.550	0.320	0.390	0.670	0.890
Treat + Flood X Trt	0.038	0.752	0.455	0.361	0.927
Mean Dep. Var	5.95	10.79	258.17	790.83	228.33
Observations	6526	6247	6529	1055	1055

Notes: Sample includes both ineligible and eligible BRAC members from treatment and control groups. Data is pooled from both the 2016 and 2017 Aman season. The regression is weighted to account for relative under sampling of ineligible households. Log Cons PerCap is household log per capita expenditure in the past week across a range of food products and cell phone credit. Crop Prod. (Kg) is total crop production measured in kilograms. Log income is log household earnings from crop sales, livestock, wages, business, and remittances measured in dollars. Bus. Stock Value is the total value of the current business stock measured in dollars. Business profits is the total profits earned by in the past month in dollars. Flood is an indicator that equals one if flooding occurred and the Emergency Loan was activated. The row Treat + Flood X Treat reports p-values for the null hypothesis that the sum of the two treatment coefficients is equal to zero.

Table A.22: Total Effect: Land Farmed

	(1) Own land	(2) Rented land	(3) Sharecrop land	(4) Total land	(5) Any Cult.
Treatment branch	0.010	0.023*	-0.003	0.031	0.010
	(0.012)	(0.013)	(0.003)	(0.021)	(0.018)
Rand. Inf. p-val	0.550	0.030	0.330	0.200	0.530
Mean Dep. Var	0.13	0.18	0.02	0.33	0.45
Observations	6528	6524	6527	6523	6529

Notes: Sample includes both ineligible and eligible BRAC members from treatment and control groups. Data is pooled from both the 2016 and 2017 Aman season. Standard errors clustered at the district level. The regression is weighted to account for relative under sampling of ineligible households. 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 A.23: Total Effect: Inputs

	(1) Fert. Applied	(2) Pest. Applied	(3) Input Cost per Acre	(4) Non-Ag Invest
Treatment branch	4.30	0.19**	2.21	10.02
	(2.92)	(0.08)	(1.68)	(6.25)
Rand. Inf. p-val	0.380	0.080	0.320	0.090
Mean Dep. Var	138.97	1.49	65.97	39.34
Observations	2940	2874	2696	6529

Notes: Sample includes both ineligible and eligible BRAC members from treatment and control groups. Data is pooled from both the 2016 and 2017 Aman season. Standard errors clustered at the district level. The regression is weighted to account for relative under sampling of ineligible households. Fertilizer and pesticide measured in kg/L per acre. Input cost per acre is the sum of the cost of fertilizer, pesticide, and seeds (measured in dollars) divided by the total number of acres cultivated. Non-Ag Invest is non-agriculture business investment measured by the total value in dollars of newly purchased (or repaired) business assets.

A.1.8 Additional MFI Outcomes

Table A.24: Repayment by Emergency Loan Availability

	Missed Payment
Treatment	0.014
	(0.026)
Treat x Flood	-0.044^{*}
	(0.026)
Flood	0.065^{***}
	(0.022)
Rand Inf. p-val Treatment	0.54
Rand Inf. p-val Interaction	0.04
Month F.E.	Yes
Mean of Dep. Var.	0.096
Unique Borrowers	109,647
Observations	379,901

Notes: Sample includes only Emergency Loan eligible clients. Standard errors clustered at the district level. The outcome variable is an indicator for whether or not the client missed a loan payment in the given month. The variable flood is an indicator for whether the branch was flooded in a given year.

Table A.25: Dabi Loan Uptake by Emergency Loan Availability

	Loan Uptake
Treatment	0.005***
	(0.002)
Rand Inf. p-val Treatment	0.00
Month F.E.	Yes
Mean of Dep. Var.	0.062
Unique Borrowers	108,446
Observations	466,824

Notes: Sample is comprised of Emergency Loan eligible clients in the pre-flood period. Data is pooled from both the 2016 and 2017. Standard errors clustered at the district 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.

A.2 Figures

A.2.1 Experiment Details

Figure A.1: Referral Slip

brac

Referral Slip – Emergency Loan

Member Copy: Please keep

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

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

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

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

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

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

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

brac

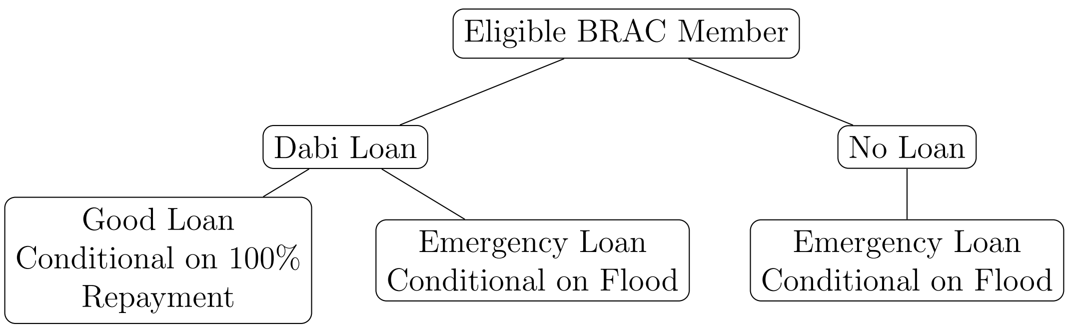
Referral Slip – Emergency Loan

Office Copy: Please keep

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

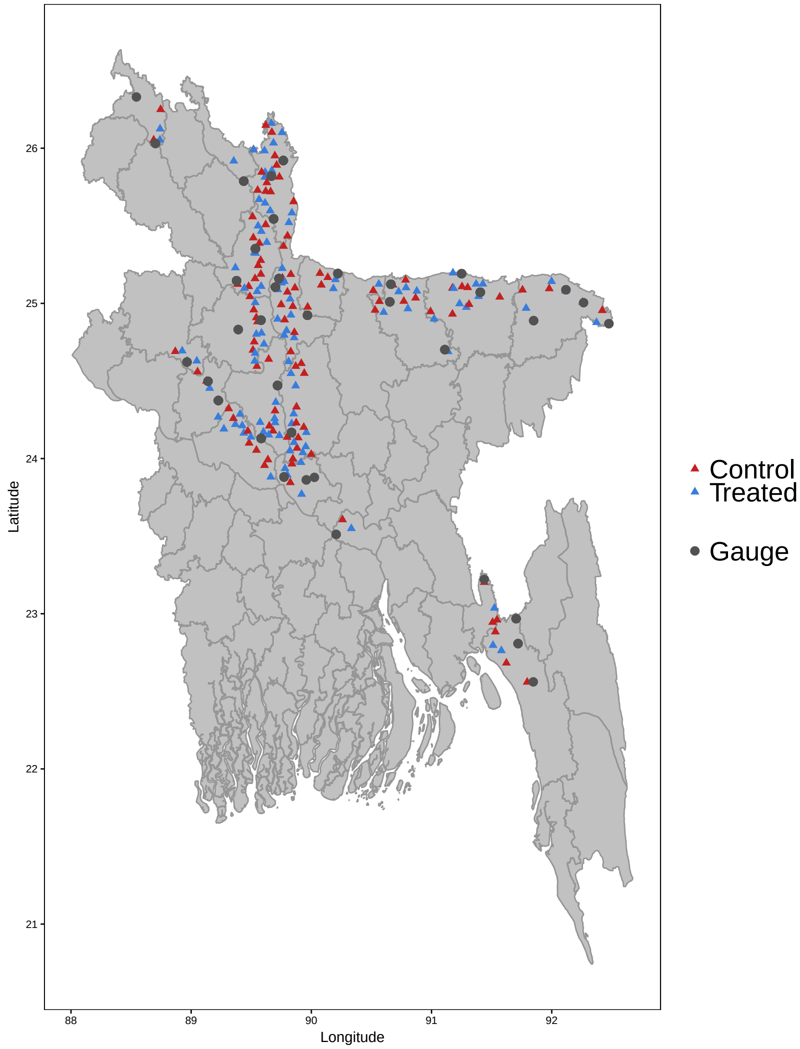
Notes: The Figure shows the referral slip (translated from Bangla) given to BRAC microfinance members eligible for the Emergency Loan. The slip records a client's name and BRAC identifiers, the maximum pre-approved loan size, as well as a brief description of the loan product. The bottom of the slip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

Figure A.2: Loan Choices for Eligible Members



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

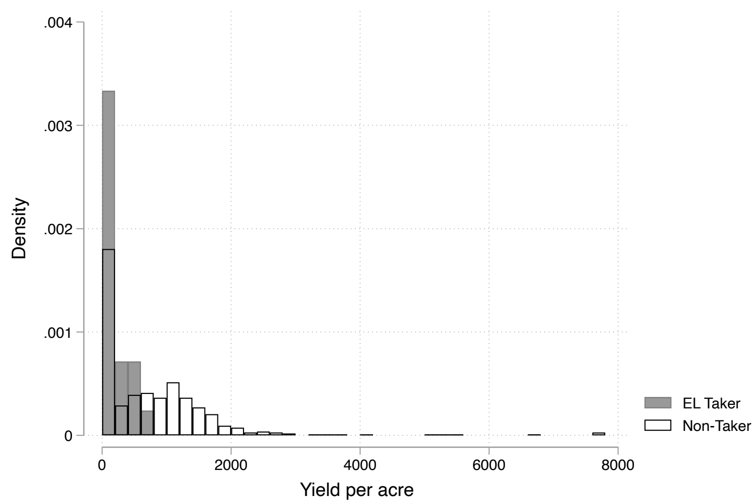
Figure A.3: Map of Sample Branches



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

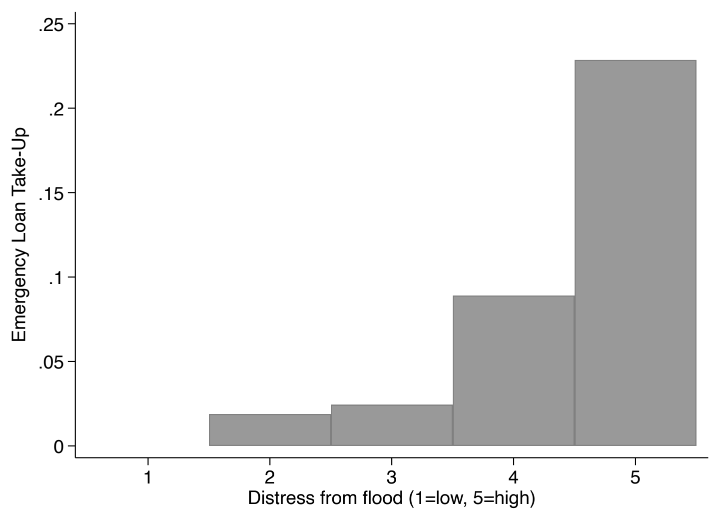
A.2.2 Emergency Loan Uptake

Figure A.4: Yield Per Acre by Emergency Loan Uptake



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

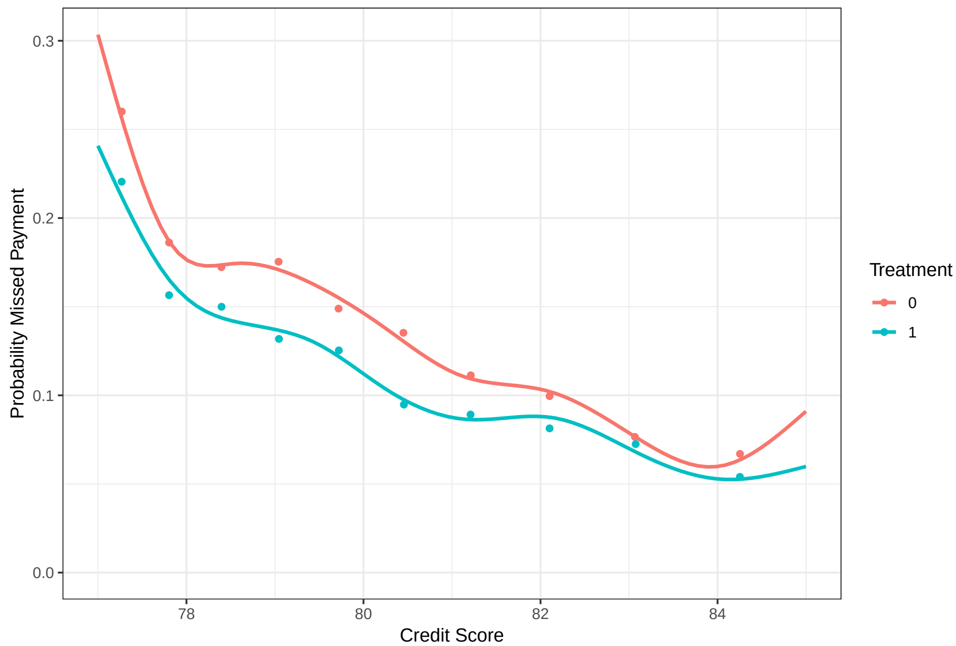
Figure A.5: Uptake of Emergency Loan by Flood Distress



Notes: Histogram of the take-up rate of Emergency Loan by level of self-reported flood distress. Sample pools data from both 2016 and 2017 and is limited to respondents who were Emergency Loan eligible and located in flooded branches.

A.2.3 Additional MFI Figures

Figure A.6: 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.

B Model Details

B.1 Model Predictions

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

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

In period 1, a household starts with exogenous cash on hand Y and has access to a risk free asset b^1 which it can buy (up to a limit) or sell on the market at interest rate R (positive values of b represent net borrowing, while negative values of b represent net saving). The household also has access to a concave production function $m_s f(x)$, which takes input x and provides output in the second period. The production function has a state dependent marginal product m_s which changes with the realized state s. In period two, the state of the world is resolved and the household decides whether to repay its initial loan (ND) with interest (Rb^1) or default (D) by paying zero. I also allow for borrowing in the bad state of the world b_B^2, with the Emergency Loan.[27] In period three, the household pays (or receives) return R on any period two loans, provided they have not already defaulted, and also receive exogenous risk free income (I). Finally, households that default are penalized K, which is the household-specific loss in utility from losing access to future dealings with the MFI. The basic household problem can be stated as:

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

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

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

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

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

No Default

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

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

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

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

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

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

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

Default

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

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

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

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

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

Repayment Decision

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

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

which is given by:

$$\begin{aligned} u(c_{ND}^1) + q\beta u\left(-Rb_{ND}^1\right) + (1-q)\beta u\left(m_G f(x_{ND}) - Rb_{ND}^1\right) + q\beta^2 u(I) + (1-q)\beta^2 u(I) \\ \geq \\ u(c_D^1) + q\beta u(0) + (1-q)\beta u\left(m_G f(x_D) - Rb_D^1\right) + q\beta^2 u(I) + (1-q)\beta^2 u(I) - qK \end{aligned} \tag{6}$$

To simplify the expressions, I define M as the difference in utility between those who default and those who repay – restricted to the differences that stem from first period investment and second period outcomes in the good state.[28] Rearranging, I can define K^*:

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

where K^* is the cost of lost access to microfinance that would make household indifferent

[28]
$$M = \underbrace{\left[u(c_d^1) - u(c_r^1)\right]}_{First\ Period} + \underbrace{\left[(1-q)\beta u\left(m_G f(x_d) - Rb_d^1\right) - (1-q)\beta u\left(m_G f(x_r) - Rb_r^1\right)\right]}_{Second\ Period\ Good\ State}$$

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 $M > 0$.

between repayment and default.[29] If a household's actual K is larger than K^*, they will repay; if it is lower, they will default. Therefore, assuming K is a random variable defined by the CDF F_K, the proportion of households that will default after a shock is given by $F_K(K^*)$.

Adding Liquidity in the Bad State (Emergency Loan)

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

No Default

With no default the household's problem is now:

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

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

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

Iintroducing credit after a second-period shock will increase consumption in this state (c^2_B). Thus, $u'(c^2_B)$ decreases as does the ratio $\frac{u'(c^2_B)}{u'(c^2_G)}$, and the entire RHS of equation (10). Thus, optimal first period input use will rise.[30] Turning to borrowing decisions, the optimal choice is defined by:

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

Again, the gap between $u'(c^2_B)$ and $u'(c^2_G)$ is reduced in equation 11 because of higher period 2 consumption, which causes the entire RHS of the equation to fall. This prospect of higher consumption in period 2 leads to an increase in period one consumption and borrowing.

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

$$u'(c^2_B)=\beta Ru'(c^3_B)+\lambda_2 \tag{11}$$

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

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

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

Therefore, the model yields four main predictions that result from extending a credit line in the bad state to households that do not default:

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

Default

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

Repayment Decision

It is possible that the introduction of the Emergency Loan will change whether a households plans to default after a shock. To understand how the introduction of second period borrowing in the bad state changes borrowers' loan repayment decisions, we can redefine K^*, which expands to include the option to borrow in the second period bad state, and to repay in the third period:

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

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

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

The first and second term above are negative – they capture improved good state outcomes and the reduced cost of repayment respectively when the Emergency Loan is available.

However, the last term is positive and captures the added benefit of defaulting when more credit is available. Therefore, the overall effect on repayment is ambiguous.

Comparative Statics for x and b

Given that ex-ante investments are the main outcome of the study, I now 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 8:

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

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:

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

Inverting the matrix

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

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

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

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

MFI Profits

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

I) is therefore given by:

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

We can use equation (14) to explore what happens to expected profits with the Emergency Loan, when the amount borrowed (b) is allowed to move from b^1 to $(b^1 + b^2_B)$.[31] The MFI will want to offer the Emergency Loan if $\Pi_E \geq \Pi_{NE}$, where E and NE stand for Emergency Loan and No Emergency Loan respectively. This is given by:

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

Where K^*_E, K^*_{NE} and b^1_E, b^1_{NE} represent the indifference points for repayment and optimal first period borrowing choice with and without the Emergency Loan respectively. Rearranging equation 15, we can write:

$$\begin{aligned} &\underbrace{q(R-1)\left[(1 - F(K^*_E)(b^1_E + b^2_B) - (1 - F(K^*_{NE})(b^1_{NE})\right]}_{A} + \\ &\underbrace{q\left[F(K^*_{NE})b^1_{NE} - F(K^*_E)(b^1_E + b^2_B)\right]}_{B} + \\ &\underbrace{(1-q)(R-1)(b^1_E - b^1_{NE})}_{C} \geq 0 \end{aligned} \tag{16}$$

Term A captures the change in profits from repayments. We know that b^1_E is at least as large as b^1_{NE}, such that $b^1_E + b^2_B \geq b^1_{NE}$.[32] However, as we saw in equation 15, the effect of the Emergency Loan on K^* is ambiguous. Thus, it is unclear whether $(1 - F(K^*_E))$ is greater or less than $(1 - F(K^*_{NE}))$. If the offer of the Emergency Loan improves repayment rates ($\frac{\partial K^*}{\partial b^2_B} < 0$) then A is positive. However, if the offer worsens repayment rates, then the sign of A is ambiguous.

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

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

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

[32] 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.

choose to preserve their access to the Emergency Loan. The size of these effects and the number of households that are in each situation will determine the overall sign of C. Therefore, taking all three terms into consideration, the overall change in MFI profits is ambiguous and will depend on i) the extent to which the Emergency Loan increases households' repayment rates and ii) how the number of loans the MFI extends (Dabi, Good, and Emergency) change.

B.2 Model Calibration

In this section I present results on a calibration exercise of the model outlined above. In this exercise I make three small changes to the model. First, I only consider the case where households always repay rather than incorporating the repayment decision into the calibration exercise to ensure tractability for estimation purposes. Second, I changed the production function so that it takes two arguments, inputs (e.g. fertilizer, pesticide) and land rather than a single combined input to better match the outcomes in the data. Third, I introduced an option for borrowers to take credit in the second period good state as per your suggestion above.

I use a combination of data from the experiment and contextual facts to assign values to the model parameters. Table A.26 summarizes these choices and discusses how each parameter value was chosen.

Using the model parameters, I simulate the farmer's three period problem, optimizing over the choice of five parameters: first period borrowing, inputs, land, second period bad state borrowing, and second period good state borrowing ($\{b^1, x, l, b_b^2, b_g^2\}$). I solve this optimization problem under two scenarios: i) the status quo, where farmers can borrow in the first period (up to $\bar{B}$) and the second period good state, but not in the bad state; and ii) the Emergency Loan scenario where farmers can borrow up to $0.5\bar{B}$ in the bad state as well. I calculate the optimal choice of all five parameters under each scenario over a range of risk-aversion parameters (0.2 to 0.99).[33]

Finally, by comparing the calculated optimal values for each scenario — status quo and Emergency Loan — I calculate the predicted percent increase of input choices (as well as inputs per unit of land) moving from control to treatment. Figure A.7 below shows the predicted choice values under these two scenarios (omitting good state borrowing because it is always zero) in panels a) and b) and then the predicted treatment effects in panel c). Panel c) also plots the actual observed treatment effect on land cultivated (horizontal dashed line) and well as the calibrated average risk aversion as measured at baseline (vertical dashed red line).

I use these optimal values under each scenario to calculate the predicted percent increase in input choices (as well as inputs per unit of land) if the farmer switched from the status quo to the Emergency Loan scenario. Figure A.7 below shows the predicted choice values under these two scenarios in Panels A and B. [34] In Panel C, I present the predicted treatment effect for cultivated land from the model at different levels of risk aversion, and I overlay the

[33]The optimization algorithm was erratic and would get stuck at corner solutions for risk aversion values below 0.2.

[34]The figure omits good state borrowing because it is always zero.

observed average treatment effect from the data (horizontal dashed line), and the observed average level of risk aversion in the data (vertical dashed red line).

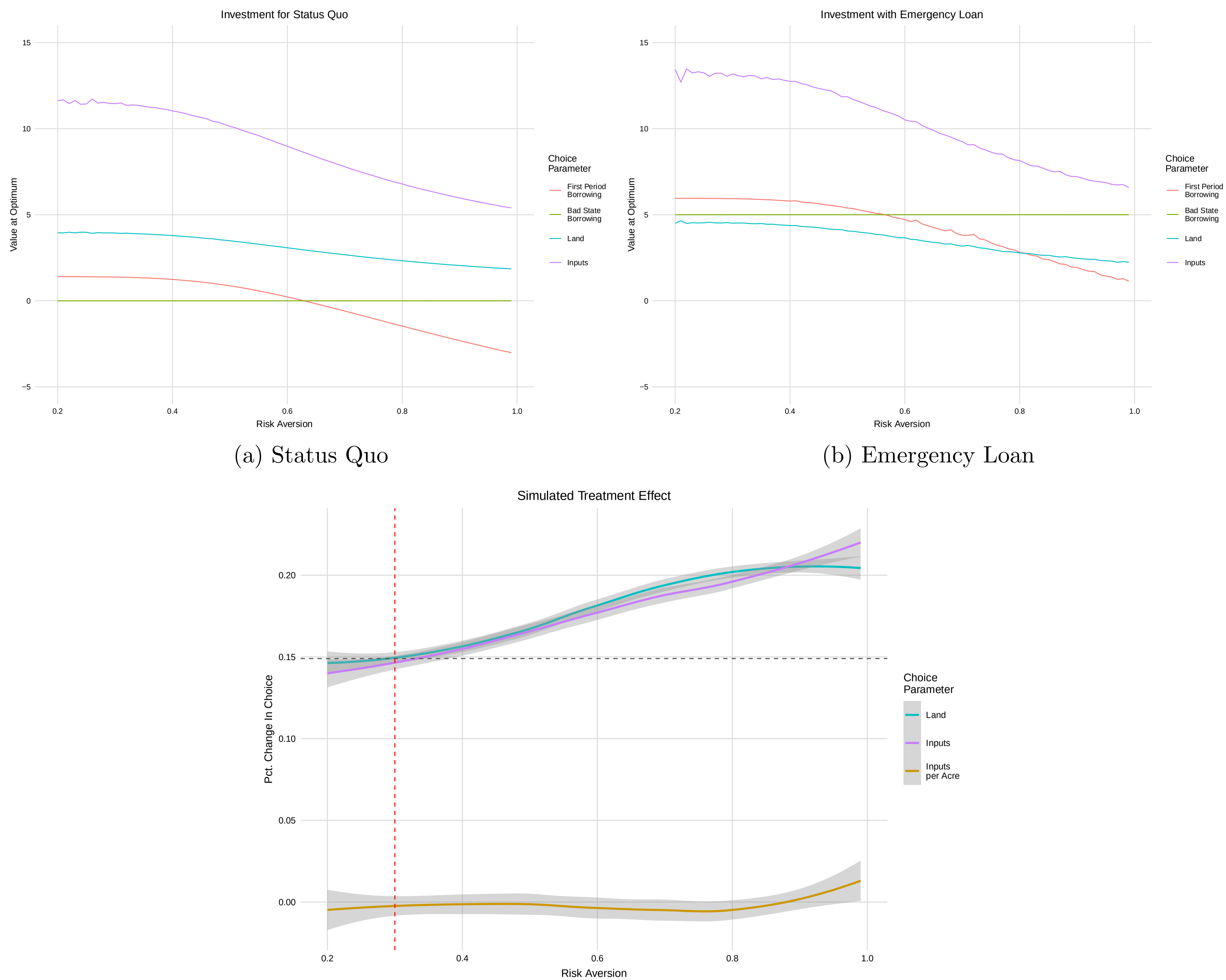
There are several take-aways from the simulation results. First, in the status quo, the level of investment in the first period declines with risk aversion, as we would expect. Second, at the average level of risk aversion observed in the sample, the model predicts that land size increases by 14%, which is nearly identical to the actual 15% increase in land cultivation we observe in the data.

Finally, the simulation shows that varying the probability that the Emergency Loan becomes available does not meaningfully change the magnitude of ex-ante investments for the treatment group. This is illustrated in Figure A.8 below, where I have re-estimated the model by lowering the shock probability to $q = 0.05$. With concave utility functions, households will want to avoid finding themselves with nothing to consume in the bad state of the world because of how damaging this will be. As a result, they will plan to have enough to consume in this bad state, even if the likelihood of falling into this state is low. This results also confirms that low-take up rates for the Emergency Loan do not limit the product's benefits. Even if the loan is useful in a small number of future states, the fact that it is guaranteed to be available should the bad state occur provides significant value to famers and unlocks substantial investments.

Table A.26: Model Assumptions

Input	Symbol	Value	Description
Utility Function	$u(c) = \frac{c^{(1-r)}-1}{(1-r)}$	$r = 0.3$	Iso-elastic utility to incorporate risk aversion parameter r, use model to predict outcomes over different values of r. Risk aversion parameter estimated using risk game.
Crop Production Function	$f(x, l) = m_G x^{\alpha} l^{\beta}$	$m_G = 1.52$, $\alpha = 0.66$, $\beta = 1.13$	Cobb-Douglas production with inputs and land. Parameter values estimated via regression using data on (log) crop production, inputs, and land amounts.
Interest rate	R	1.25	BRAC interest rate charged on loans
Probability of Shock	π_B, q	0.24	Estimated using the probability of crop failure from empirical data. Also test at lower value ($\pi_B = 0.05$).
Price of inputs	p_x	1	Normalized to 1 (numeraire good)
Price of land	p_l	5	Estimated ratio of cost of one acre of land compared to cost of inputs for one acre.[35]
Shock Production Penalty / Marginal Product After Shock	m_B	0.01	Assume nearly all production is lost after shock. Note, a small amount of production was left because setting to zero cause errors in the optimization algorithm.
Starting Cash	Y	30	Estimated using average total savings and estimated rental value of owned land reported by households at baseline.
Credit Availability	$\bar{B}$	10	Estimated by using BRAC's average loan size relative to calculated value of starting cash on hand. Estimated to be approximately 1/3 of cash on hand (including rental value of land).
Third Period Income	I	30	Set equal to starting cash on hand
Discount Factor	δ	0.90	Estimation from time-preference game at baseline

Figure A.7: Model Predictions

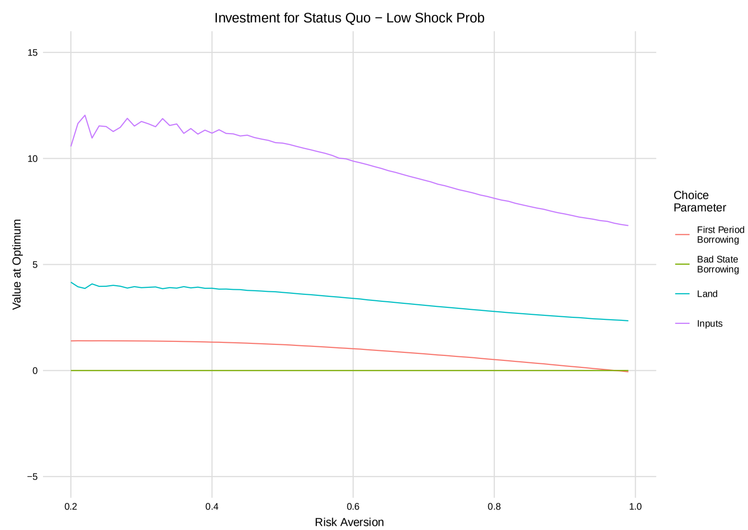


(a) Status Quo

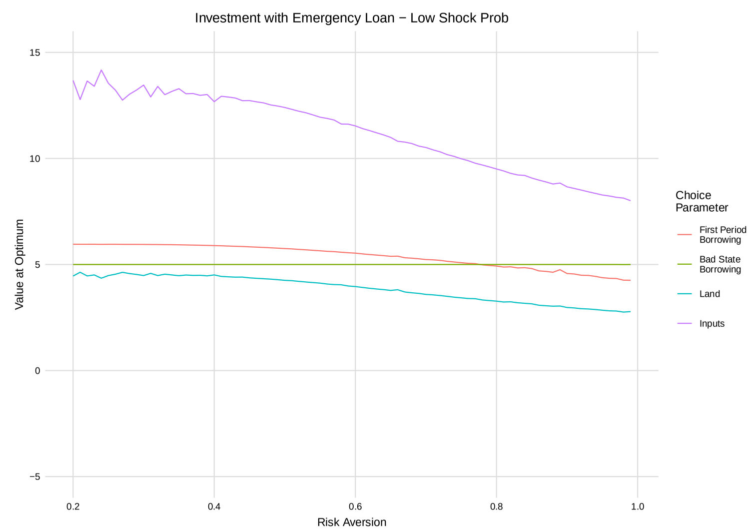
(b) Emergency Loan

(c) Treatment Effects

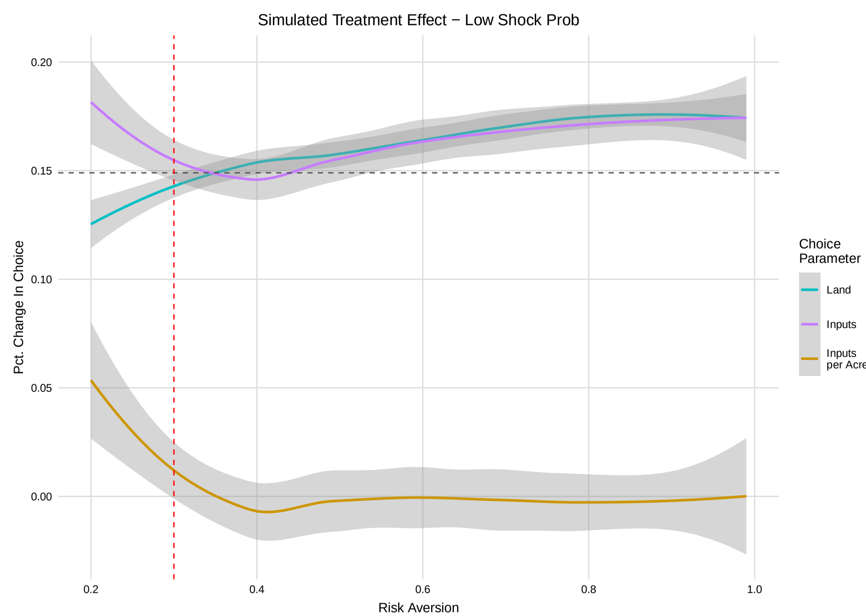
Figure A.8: Model Predictions - Low Shock Probability



(a) Status Quo



(b) Emergency Loan



(c) Treatment Effects