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ADAPTING TO CLIMATE RISK WITH GUARANTEED CREDIT: EVIDENCE FROM BANGLADESH

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Climate change is increasing the frequency of extreme weather events, with low-income countries being disproportionately impacted. However, these countries often face market frictions that hinder their ability to adopt effective adaptation strategies. In this paper, I explore the role of credit market failures in limiting adaptation. To achieve this, I collaborate with a large microfinance institution and offer a randomly selected group of farmers access to guaranteed credit through an "Emergency Loan" following a negative climate shock. I document three key results. First, farmers who have access to the emergency loan make less costly adaptation choices and are less severely affected when a flood occurs. Second, I find no evidence of adverse spillover effects on households that did not receive the Emergency Loan. Finally, I demonstrate that providing the Emergency Loan is profitable for the microfinance institution, making it a viable tool for the private sector to employ in similar circumstances.

KEYWORDS: Climate, risk, agriculture, credit.

1. INTRODUCTION

CLIMATE CHANGE is increasing the frequency of extreme weather events. The number of disasters such as droughts, floods, storms, and extreme temperatures quadrupled in the 2010s. Low-income countries are disproportionately affected: they have been hit by nearly eight times as many natural disasters relative to the 1980s (International Development Association (2021), Burgess, Deschenes, Donaldson, and Greenstone (2017)). The agricultural sector, which 80% of the world's poor depends on for survival, is particularly vulnerable to these shocks, and bears 26% of damages from these events (FAO (2021)). In response, countries can implement adaptation measures to reduce these costs of climate change. Yet, adaptation appears to be constrained in many parts of the world, especially in low-income countries (Carleton et al. (2022)). It is unclear whether poor countries adapt less because of competing demands for limited resources, or whether market frictions prevent them from adapting further. If these adaptation gaps are driven by lower incomes, improving adaptation implies improving the cost-effectiveness of adaptation technologies Carleton and Hsiang (2016). However, if other constraints prevent optimal adaptation, then correcting these market frictions should allow improvements with existing resources.

To isolate whether market frictions drive these adaptation gaps, it is necessary to observe whether the negative consequences of climate shocks are reduced when these frictions are eliminated. This can be difficult to achieve, and may explain why the literature on this topic is scarce. In this paper, I focus on the relationship between credit market failures and adaptation. I engineer an exogenous change in credit access after a negative

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weather shock, and identify whether this change diminishes the impact of floods for poor households.

Specifically, I offer households living in flood-prone areas a guaranteed 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 a large MFI in Bangladesh. We randomize the availability of the credit line (the "Emergency Loan") across 200 bank branches located in flood-prone areas. We contacted over 150,000 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 benefit households even if no additional credit was disbursed. Treatment households could choose to take the loan provided a validated flood occurred in their area. Control branches continued their normal microfinance operations.

A simple model shows how guaranteed credit can enhance investment in productive activities and stabilize household consumption. This model is based on previous theoretical research by Deaton (1991, 1992), Karlan, Osei, Osei-Akoto, and Udry (2014), which acknowledges that credit can act as a buffer against income fluctuations. The model highlights that farmers who are risk-averse may reduce their profitable investments if they are concerned about being adversely affected by a shock. Households may be unwilling to take any risks because the consequences of not being able to meet their basic needs if their investments fail are too costly. In the aftermath of a shock, when most credit providers are hesitant to offer loans, extending guaranteed credit offers households an opportunity to maintain their current consumption levels even if they suffer damages from a shock. Therefore, the credit guarantee encourages households to increase their productive investments by weakening the relationship between a future negative shock and consumption levels.

The Emergency Loan is a particularly effective tool in this context because it 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, Winter, Benson, Kellogg, and Skees (2016), Labie, Laureti, and Szafarz (2017)). Similarly, the demand for insurance products remains low because farmers do 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, Giné, and Jacoby (2023), Emerick, de Janvry, Sadoulet, and Dar (2016), Dar, Emerick, Sadoulet, de Janvry, and Wiseman (forthcoming)). 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 Di Tommaso (2020)). This means that it may take longer for farmers to learn about the benefits of these technologies, and some may decide to dis-adopt if they do not see any returns in the first year (Dar, de Janvry, Emerick, Kelley, and Sadoulet (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 MFIs, without necessarily compromising the provider's bottom line, and it is a financial product that is well understood by households in low-income countries.

I describe my results in three steps. First, I find that the Emergency Loan can be an effective adaptation tool. Indeed, farmers with access to the Emergency Loan make less costly adaptation choices: instead of limiting the amount of land they cultivate to avoid risk, treated farmers expand the amount of land they rent. Specifically, I find that treated households increase the amount of land dedicated to agricultural cultivation by 18%. This land investment subsequently leads to a 19% increase in crop production on average. These production effects are concentrated in areas that are not affected by a flood, which experience a 35% increase in crop output, confirming that farmers respond to BRAC's guarantee by finding new investment opportunities that yield substantial returns, even though no additional credit was made available. These results suggest that farmers reap benefits they would have otherwise had to forgo because of their reluctance to cultivate more land in the presence of weather risk. Next, I find that households who are hit by a flood are less severely affected, an indication that the Emergency Loan helps households adapt to climate change by weakening the link between climate and adverse outcomes (Carleton and Hsiang (2016)). 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.

Second, I investigate if the Emergency Loan, which is only available to eligible borrowers, has any negative effects on those who are ineligible for the loan. This may occur if eligible borrowers' decision to rent more land means ineligible households have less land to rent, or have to pay higher prices because demand for this land has increased. I compare ineligible households in treatment branches to ineligible households in control branches, and find no evidence of negative spillovers. Rather, I find evidence that ineligible households in treated branches experience higher consumption levels. While many channels could explain this indirect benefit, I provide suggestive evidence that an increase in agricultural labor demand leads to more working days for ineligible households.

Finally, my data offer a unique opportunity to experimentally estimate the impact of the Emergency Loan on MFI outcomes. I show the Emergency Loan is profitable for the MFI, and hence a viable tool for the private sector to provide. Borrowers with access to the Emergency Loan exhibit higher repayment rates after a flood shock, and higher repayment rates overall. Branch profits increase, with the largest increases in profits coming from "marginal" clients who just qualified for the Emergency Loan. 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. This result is also encouraging for policymakers as it demonstrates the role for private sector involvement in tackling climate change. Key to the intervention's success is that the Emergency Loan leverages an existing relationship between an established private bank and its customer base, and reduces the overall riskiness of the provider's portfolio by limiting the defaults that normally occur when households experience a flood. Whether other private sector initiatives can replicate these results may depend on their ability to provide a profitable product their customer base finds attractive.

This paper makes two primary contributions. First, I show that financial products like the Emergency Loan can be an effective adaptation tool by overcoming existing market frictions. In doing so, I provide some of the first evidence that low levels of adaptation at least partly reflect constrained suboptimal 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) showed that large adaptation gaps remain, and poor countries remain disproportionately exposed to climate shocks. They highlighted 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—credit frictions—that is preventing optimal adaptation. My paper shows that the Emergency Loan effectively addresses a financial market failure which in turn encourages households to make profitable investments while maintaining higher consumption levels after a shock. 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.

Relatedly, I contribute to a small literature that examines how new technologies contribute to adaptation by breaking the relationship between climate shocks and adverse outcomes. For example, Barreca, Clay, Deschenes, Greenstone, and Shapiro (2016) and Chirakijja, Jayachandran, and Ong (2021) showed the important role that air conditioning (heat systems) plays in mitigating the number of hot (cold) temperature-related fatalities, while Burgess et al. (2017) demonstrated that bank branch openings in India dampen the temperature-mortality relationship. Work by Premand and Stoeffler (2022) shows that households can also use cash transfers to protect their earnings in agriculture and off-farm businesses when shocks occur. While not framed through the lens of climate adaptation, there also exist a set of papers that test the effectiveness of interventions that can boost households' resilience in the face of climate change. Brooks and Donovan (2020) showed 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) documented 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 in low-income countries, and overcomes some of 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)). Similarly 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 to make pay-outs (Cole, Giné, Tobacman, Topalova, Townsend, and Vickery (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 their overall impact on household welfare (Karlan and Zinman (2011), Karlan et al. (2014), Crépon, Devoto, Duflo, and Parienté (2015), Angelucci, Dean, and Zinman (2015), Banerjee, Duflo, Glennerster, and Kinnan (2015), Banerjee, Dean, 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, Pande, Papp, and Rigol (2013), and Beaman, Karlan, Thuysbaert, and Udry (2023) showed that delaying the start of repayment installments, reducing payment frequency, and allowing lump-sum repayments post-harvest reduces borrower transaction costs, and boosts investments and profits. More recently, Battaglia, Gulesci, and Madestam (2023) and Barboni and Agarwal (2022) showed that allowing borrowers to delay repayments improves business outcomes without harming repayment rates; while Aragón, Karaivanov, and Krishnaswamy (2020) showed 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. Policymakers should be encouraged by this result because it demonstrates the role of the private sector in tackling climate change. In related work, more papers are trying to document the profitability of financial products as they recognize that only financial tools that boost MFI profits are sustainable long term. Field et al. (2013) developed a structural model to show that longer grace periods are not sustainable for MFIs, while Barboni (2017) used 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. See Lane (2023) for the Appendix which includes additional tables and figures.

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 is 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, Islam, Sikder, and Islam (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, Groeneveld, Frank, and Müller (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 lower average returns. These include 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, Akter, Brander, and Haque (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 prior to this study, no MFIs 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) showed 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). 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 the private sector 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 similar along most dimensions (see Table A.1), although eligible borrowers are a few years older, less educated, have slightly less annual income, are slightly less likely to have taken a BRAC loan in the past year, and own more livestock.

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 up-front 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 up-front payments for uncertain returns—a common constraint that insurance products have faced.

[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.

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 5000 taka ($63) should a flood occur regardless of her existing loan balance at the time of disbursal. Clients were eligible for the Emergency Loan regardless of whether or not they currently had an active loan.[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 predetermined 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] It should also be noted that there are alternative methods available for verifying floods with greater accuracy and precision (Guiteras, Jina, and Mobarak (2015)), such as satellite imagery. While these methods were not utilized with BRAC due to operational constraints, they offer a potential solution to implement products like the Emergency Loan in areas where flood gauges are not actively maintained.

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 (VOs).[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 MFIs 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-

[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 its 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 if 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 positives—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, Bellemare, Carter, and Guirkinger (2013) estimated 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.

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 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 confirm 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 the agricultural season; or they could preserve their credit access as a buffer against future flood risk.

3.2. *Theoretical Framework*

This section presents a straightforward model to analyze the impact of guaranteed credit. It builds on Karlan et al. (2014), where MFI clients make decisions about investments in a risky environment. I briefly describe the model's setup and its predictions on how the Emergency Loan could affect households' investment decisions. To focus the predictions on investment choices, the model does not consider households' future concerns about the cost of loan repayment or default. A more complex model which also discusses the effect of the Emergency Loan on the MFI, presented in Appendix B, incorporates these dynamics.

Households derive utility from consumption $u(c)$, and can choose between a risky and a risk-less investment $x \in \{L, H\}$.[7] The risk-less investment pays the household L in all states of the world, while the risky investment pays $H > L$ when there is no shock, such as a flood, and zero when a shock occurs, which happens with probability p.[8] Consumption is limited by starting wealth (W_i), the investment payoff, and the amount the household is able to borrow (b_i).

[6] Thirty-seven percent of my sample were eligible for a Good Loan during the planting season.

[7] I assume that $u' > 0$, $u'' < 0$, and $\lim_{c\to 0} u(c) = -\infty$.

[8] Assume that $(1 - p)H > L$, such that the risky investment is on average more profitable.

The household problem is to maximize expected utility:

$$\max_{x\in\{L,H\}} (1-p)u(c_{NF}) + pu(c_F),$$
$$c_{NF} = H\mathbb{1}\{x=H\} + L\mathbb{1}\{x=L\} + b_i + W_i,$$
$$c_F = 0\mathbb{1}\{x=H\} + L\mathbb{1}\{x=L\} + b_i + W_i,$$

where c_{NF} is consumption when no flood occurs and c_F is consumption after a flood. The household decision problem then simply comes down to a comparison of expected utility under $x = H$ to $x = L$. The household chooses investment L or H that yields the highest expected utility.

To illustrate the impact of risk on this decision, I calculate the probability (p^*) at which the household is indifferent between the two investment choices:

$$p^* = \frac{u(L+b_i+W_i) - u(H+b_i+W_i)}{u(b_i+W_i) - u(H+b_i+W_i)}.$$

If the actual (or perceived) shock probability p is above this point, the household chooses the low-risk investment L. If actual p is below p^*, then the household chooses H. For poor households that have little access to credit (low b_i and W_i), p^* approaches zero. In other words, for households with few resources to fall back on, even very low-probability events are enough to deter risky (but profitable) investment.

In this framework, the Emergency Loan provides some guaranteed additional credit amount G in the event of a shock. This lowers the downside of a shock, and therefore causes a rise in households' shock probability indifference point $p^*_{EL} > p^*$. Specifically, p^* with the Emergency Loan becomes

$$p^*_{EL} = \frac{u(L+b_i+W_i) - u(H+b_i+W_i)}{u(G+b_i+W_i) - u(H+b_i+W_i) + u(L+b_i+W_i) - u(L+b_i+W_i+G)}.$$

To see how this compares to the status quo, note that only the denominator has changed. Therefore, it is enough to compare $u(b_i + W_i)$ to $u(G + b_i + W_i) + u(L + b_i + W_i) - u(L + b_i + W_i + G)$. Starting with the fact that $u'' < 0$ and $L > 0$, and thus $u(b_i + W_i) - u(G + b_i + W_i) < u(L + b_i + W_i) - u(L + b_i + W_i + G)$, it follows that $u(b_i + W_i) < u(G+b_i+W_i) + u(L+b_i+W_i) - u(L+b_i+W_i+G)$. In other words, the introduction of the Emergency Loan induces some households to choose to invest in the risky investment for a given shock probability.

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 selected from a larger group that satisfied two criteria. First, I only included branches located in flood-prone areas based on historical flooding outcomes from the past 15 years. 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 (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.[9]

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

Over the course of the 2016 Aman season, 91 branches were activated: 40 control and 51 treatment.[11] 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.[12] New credit scores were created for all branches, which meant that some previously eligible households lost their eligibility.[13] 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.

[9]Appendix Table A.3 shows balance for the Good Loan eligible subsample.

[10]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. 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.6 to A.8.).

[11]The difference is not statistically significant.

[12]Fourteen branches (7 treatment, 7 control) were removed from the experiment from 2016 to 2017 due to changes in the local topography (new dams and roads) that dramatically reduced the probability of local flooding in these regions. These 14 branches were replaced with back-up branches that had been pre-selected in the initial selection process described above.

[13]Appendix Tables A.9 to A.15 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.

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.[14] This data set contains borrowers' decisions to take loans, and all loan repayment activities. Detailed repayment data are available from April 2016 until January 2018. We observe approximately 300,000 unique individuals and 1.3 million unique loans within this data set.

Second, I use survey data collected from 4000 BRAC clients across the 200 experimental branches. BRAC sampled three village organizations at random from each branch and 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 network.[15]

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.[16] 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 time frame. Furthermore, 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. Finally, I create an investment index that takes into account all investment measures for which I have data, including land cultivation, fertilizer use, pesticide use, labor, seed, and non-agricultural business investment. This index is calculated using inverse-covariance weighting.

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 measured in two ways: by the total value of the current business stock, and by business profits accrued in the past month. Finally, I also create a welfare index, which includes all the measures that relate to wealth for which I have data, including consumption, income, crop production, business profits and assets, and livestock. This index is calculated using inverse-covariance weighting.

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

[14]Data were last accessed in April 30, 2018 (BRAC Data Center (2018)).

[15]Table A.5 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.

[16]Inputs include fertilizer, pesticide, seeds, and hired labor.

for the Emergency Loan had they been in a treatment branch. The baseline specification for household outcomes is therefore

$$Y_{ibdt} = \text{treatment}_{ibd}\beta + \alpha_d + \phi_t + \varepsilon_{ibdt},$$

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, a district fixed effect (the stratification level), 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 branch level. 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 whether a flood occurred during the growing season, and its interaction with treatment:

$$Y_{ibdt} = \text{treatment}_{ibd}\beta + \text{treatment}_{ibd} \times \text{flood}_{bdt}\gamma + \alpha_d + \phi_t + \varepsilon_{ibdt},$$

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:[17]

$$Y_{bdmt} = \text{treatment}_{ibd}\beta + \alpha_d + \phi_t + \rho_m + \varepsilon_{bdmt}.$$

5.1. *Credit as an Adaptation Tool*

First, I show that the Emergency Loan can be an effective adaptation tool that is valued by borrowers.

Ex ante Investment

The Emergency Loan can be an effective adaptation tool because it encourages farmers to make less costly adaptation choices. Namely, it encourages farmers to make investments they may have otherwise avoided because of their reluctance to cultivate more land in the presence of weather risk. I focus primarily on changes to agricultural investments (land, agriculture inputs) 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. Nevertheless, I also collect data on non-agricultural business investments, and I create an agricultural investment index which I present below.

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

TABLE I
LAND FARMED.

	(1) Own Land	(2) Rented Land	(3) Sharecrop Land	(4) Total Land	(5) Any Cult.
Treatment	0.006	0.062	−0.004	0.063	0.044
	(0.014)	(0.016)	(0.004)	(0.026)	(0.024)
Rand. Inf. *p*-val	0.696	0.001	0.272	0.018	0.098
Mean Dep. Var	0.13	0.20	0.02	0.35	0.46
Observations	4759	4755	4758	4754	4760

Note: 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 branch level. Land measured in acres. Total land is the sum of own land, rented land, and sharecropped land. Any Cult. is an indicator for whether or not a household planted any crops during the season.

Table I 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 31% (column 2), and the *total* land they cultivate by 18% (column 4). Neither owned nor sharecropped land show any change. Along the extensive margin, the number of households planting crops also increases by approximately 4.4 percentage points (column 5). This represents an 9% 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 sharecropped 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.[18] Columns 1 and 2 in Table II show insignificant positive point estimates on the amount of fertilizer and pesticides applied per acre of 6.3 USD (se 5.4) and 0.3 USD (se 0.2), respectively. Similarly, column 3 shows that the total amount of money spent on all inputs does not detectably increase.[19] Nevertheless, these results confirm that treatment households are maintaining normal levels of input usage per acre despite the overall expansion of cultivated land (Appendix Table A.18 reports treatment effects on total input levels). Moving outside of agriculture, column 4 of Table II shows that non-agricultural business investments increase by 31% ($12 USD) over the control group. Finally, column 5 summarizes the different dimensions of investment into an inverse-covariance weighted index, where we see that the Emergency Loan induced

[18]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. Second, 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. Finally, as discussed in the calibration exercise below, if land market frictions are small, then we would expect farmers to maintain a constant "optimal" ratio of inputs to land area.

[19]Total input cost includes the cost of fertilizer, pesticide, seeds, and hired labor.

TABLE II

EX ANTE INVESTMENTS.

	(1) Fert. Applied	(2) Pest. Applied	(3) Input Cost	(4) Non-Ag Invest	(5) Invest Index
Treatment	6.266	0.271	2.059	12.149	0.035
	(5.391)	(0.173)	(2.171)	(6.589)	(0.012)
Rand. Inf. *p*-val	0.247	0.116	0.362	0.074	0.004
Mean Dep. Var	140.71	1.58	65.87	38.65	−0.09
Observations	2186	2143	2019	4760	4760

Note: Sample includes only eligible BRAC members from both treatment and control groups. Data are pooled from both the 2016 and 2017 Aman season. Standard errors clustered at the branch level. Fertilizer and pesticide measured in kg/L per acre. Input cost is the sum of the cost of fertilizer, pesticide, seeds, and labor (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. Invest Index is an inverse-covariance weighted index of land cultivated, fertilizer, pesticide, seed, labor, and non-agriculture business investment.

households to increase investment by an average of 0.035 standard deviations across all measures.[20]

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.16 illustrates how flooding in the first year affects different investment categories. I can rule out that flooded households revert to baseline levels of investment if they were flooded in the first year relative to treated households that were not flooded; if anything, households who experienced flooding the previous year are weakly more responsive to treatment. This suggests that households that experienced a flood in 2016 still perceive the Emergency Loan as offering viable protection against flood risk.

Finally, it is useful to determine whether similar outcomes can be anticipated in other environments. In an effort to achieve this, I attempt to rationalize the observed treatment effects by calibrating a model of risky investment. The exercise uses the full model presented in Appendix Section B.[21] The exercise allows the model to generate predicted farmer choices for land and input investment both with and without access to an Emergency Loan, across a range of risk-aversion parameters. The quantitative results are presented in Section B.2, Appendix Figure B.1, where the predicted treatment effect is calculated by comparing the model-generated optimal choices with and without the Emergency Loan. The results show that investment falls as risk aversion rises under both treatment and control conditions. However, investment always remains higher when the household

[20]The simple model predicts that investment response should be heterogeneous with respect to household characteristics such as risk aversion, starting wealth, and pre-existing credit access. In general, I find weak evidence for any heterogeneity along these margins.

[21]I assume a Cobb–Douglas production function for agriculture production and a HARA utility function for households. The model is parameterized using values estimated from the data and contextual factors which are summarized in Appendix Table B.1.

has access to the Emergency Loan. Additionally, the predicted treatment effect for both input levels and land steadily increases with risk aversion. At the average level of risk aversion observed in the sample, the model predicts a treatment effect on land cultivation of 14%, which is nearly identical to the 15% increase observed in the experiment. However, the model predicts that input use per acre will not increase at all, a consequence of the assumption of perfect land markets and divisibility of land. This means that households will always keep a fixed optimal ratio of inputs to land size, as determined by the production function.[22] Last, in Figure B.2, I use the model to predict treatment effects in a scenario with a low shock probability of 5% (from 24%). Baseline investment levels and predicted treatment effects are similar in magnitude under both scenarios, which highlights the fact that even rare shocks can significantly impede investment. Thus, the Emergency Loan can still have a significant impact, even if it is infrequently utilized. While this analysis is somewhat constrained by the availability of reliable parameter data, it is encouraging that the model calibration largely accounts for the treatment effects observed in the experiment because it implies that the results can be explained by a straightforward risk model, without relying on specific factors unique to this particular context.

Ex Post Outcomes

The Emergency Loan is also an effective adaptation tool by weakening the link between climate and adverse outcomes. I examine the effect of treatment on four household outcomes: log weekly food consumption per capita, crop production from the Aman season, income during the previous months, the value of their current stock and profits from their business, and an inverse-covariance weighted welfare index of all welfare outcomes collected at endline.

Panel A of Table III shows that pre-approval leads to positive results. Per capita consumption increases by 8% on average in treatment households, while crop production increases by 50 kilograms, a 19% increase. While I find no clear effect of the treatment on overall household income, or any clear change in business outcomes, the welfare index shows that the Emergency Loan had on average a 0.022 standard deviation positive effect on all outcomes.

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 experience 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 35% increase in crop production among treated households, which suggests that pre-period investments are paying off (Table III, Panel B). However, we do not see

[22]In reality, there may be frictions in the land rental market, which may cause farmers to respond to reduced risk exposure by increasing the intensity of input use.

TABLE III

EX POST OUTCOMES.

	(1) Log Cons PerCap	(2) Crop Prod. (Kg)	(3) Income	(4) Bus. Stock Value	(5) Business Profit	(6) Welfare Index
Panel A: Ex Post Outcomes by Treatment						
Treatment	0.080	53.149	10.497	23.844	3.249	0.022
	(0.032)	(28.417)	(22.828)	(17.444)	(4.199)	(0.011)
Rand. Inf. p-val	0.020	0.071	0.651	0.205	0.453	0.063
Mean Dep. Var	5.93	275.30	769.12	128.77	37.13	0.12
Observations	4758	4760	4760	4760	4760	4760
Panel B: Ex Post Outcomes by Treatment and Flood Realization						
Treatment	0.046	96.466	−1.361	22.278	0.571	0.015
	(0.047)	(41.390)	(32.922)	(25.829)	(6.944)	(0.017)
Flood X Treatment	0.061	−78.516	21.485	2.838	4.857	0.014
	(0.065)	(51.473)	(47.516)	(35.252)	(9.305)	(0.024)
Flood	−0.066	5.140	5.753	−0.302	-3.162	0.004
	(0.058)	(37.285)	(42.542)	(27.816)	(8.393)	(0.019)
Rand. Inf. p-val Treat	0.355	0.032	0.973	0.381	0.933	0.427
Rand. Inf. p-val Inter.	0.366	0.138	0.679	0.946	0.608	0.574
Treat + Flood X Trt	0.016	0.610	0.541	0.293	0.337	0.069
Mean Dep. Var	5.93	275.30	769.12	128.77	37.13	0.12
Observations	4758	4760	4760	4760	4760	4760

Note: Sample includes only eligible BRAC members from both treatment and control groups. Data are pooled from both the 2016 and 2017 Aman season. Standard errors clustered at the branch 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. Income is 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 in the past month in dollars. Welfare index is an inverse-covariance weighted index of consumption, income, crop production, business profits and assets, and livestock. Flood is an indicator that equals 1 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.

significant differences in consumption between treatment and control households. This suggests that households reap the production 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 change in income or business outcomes, while the welfare index estimate shows an average 0.015 (se 0.017) standard deviation effect size on all outcomes when there is no flood.

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 82% of the crop production gains they experience when a flood does not occur (column 2). These losses suggest that treatment households expand cultivation on land that is particularly susceptible to floods. Nevertheless, treated households experience a large 10% increase in consumption compared to control households that also experienced a flood. Finally, the estimate on the welfare index shows an average 0.03 standard deviation effect size on all outcomes for those experiencing a flood. This suggests that the availability of the Emergency Loan allows households to improve their situation after an income shock.[23]

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.[24] Table IV 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 (also 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 rationale 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 to boost their consumption. Nevertheless, the

[23]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.17 examines this hypothesis. I expand the regression specification from Table III 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 on the welfare index 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.

[24]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.

TABLE IV

EMERGENCY LOAN UPTAKE.

	(1) Took Emergency Loan	(2) Took Emergency Loan
Baseline HH Income	−0.003	
	(0.003)	
Risk Aversion	0.006	
	(0.013)	
Baseline Time Preference	−0.003	
	(0.002)	
Number of Past Floods	−0.007	
	(0.005)	
Ex post Investment Opportunity		0.024
		(0.016)
Preparation for flood (1 = low, 5 = high)		−0.026
		(0.013)
Distress from flood (1 = low, 5 = high)		0.052
		(0.013)
Controls	No	No
District FE	Yes	Yes
Mean Dep. Var	0.03	0.05
Observations	1179	533

Note: 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 branch level. Column 1 shows results predicting Emergency Loan take-up using data collected at baseline. Yearly household income is measured in thousands of dollars. Risk aversion 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.

low take-up rates we observe overall suggest that the pre-period investments households made 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, migration rates, and cash transfers (see Appendix Tables A.19 and A.20). I find suggestive evidence that treatment households are able to maintain the amount of livestock they own after a flood, which could be because they are less likely to sell livestock. Additionally, using BRAC's administrative data, I find that savings deposits in treatment households are higher in the aftermath of flooding. I find no change in the number of migrants that leave the household 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.

Value for Borrowers

I can also show that borrowers recognize these ex ante and ex post benefits. I document this using 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.[25] 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. Forward-looking households may 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 V shows the results from comparing Good Loan eligible borrowers across treatment and control branches. 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. Columns 2 and 3 examine the extent to which this effect varies based on branch clients' need for liquidity, and their perceived risk of local flooding.[26] 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.[27] This is what we would expect if 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 to 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%.[28]

To further understand which borrowers are most likely to preserve their credit access, I estimate a local average treatment effect across bins of the Emergency Loan credit score (pooling all treatment and control branches together, respectively). Figure 1(a) 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 VI 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.

[25] Appendix Table A.3 reports balance between treatment and control among this subgroup. There are no large differences between the two treatment arms.

[26] 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.

[27] Perceived flood risk is measured at the branch level as reported by the branch manager.

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

TABLE V

UPTAKE OF GOOD LOAN BY EMERGENCY LOAN AVAILABILITY.

	Took Good Loan		
Treatment	−0.020	−0.022	−0.020
	(0.008)	(0.009)	(0.008)
Farming x Treatment		0.006	
		(0.016)	
Farming Main Activity		−0.007	
		(0.010)	
Flood Risk x Treatment			−0.015
			(0.006)
Flood Risk			0.011
			(0.004)
Rand Inf. p-val Treatment	0.03	0.04	0.01
Rand Inf. p-val Interaction	–	0.71	0.00
Year F.E.	Yes	Yes	Yes
Mean of Dependent Var	0.130	0.130	0.129
Unique Borrowers	66,232	66,232	63,744
Observations	75,818	75,818	73,282

Note: Sample is composed of Good Loan eligible clients who were offered a Good Loan in the pre-flood period. Observations at the month-person level. Data are 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 a 1–5 scale where 1 = least risk and 5 = high risk.

5.2. *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.[29] Table VII Panel A shows that consumption for ineligible households in treatment branches increases by 7% 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 11% in non-flooded areas (Panel B). While the point estimate on consumption in flooded branches remains positive (5%), it is imprecise. Table VII shows no other 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 VIII 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

[29]Baseline balance for the ineligible sample is reported in Appendix Table A.4.

TABLE VI

EFFECT MFI OUTCOMES BY CREDIT SCORE.

	Good Loan Uptake (1)	Dabi Uptake (2)	Missed Payment (3)	Per Person Profit (4)	NPV (5)
Treatment	−0.020	0.008	−0.044	106.4	33,500,846
	(0.011)	(0.002)	(0.014)	(78.3)	(14,520,366)
Credit Score x Treatment	−0.003	0.000	0.006	−25.9	−390,553
	(0.002)	(0.000)	(0.002)	(15.2)	(176,825)
Credit Score	0.004	−0.000	−0.011	11.9	3,072,508
	(0.001)	(0.000)	(0.002)	(5.8)	(131,194)
Rand Inf. p-value Treatment	0.06	0.00	0.00	0.17	0.03
Rand Inf. p-value Interaction	0.09	0.83	0.02	0.07	0.04
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	461,655	3706	3797

Note: In columns 1–3, the sample includes only Emergency Loan eligible clients. Columns 4–5 include all clients. Standard errors clustered at branch level. The outcome in column 1 is the probability of taking an offered Good Loan among Good Loan eligible 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 ($1 = 84 taka) per branch member assuming an annual cost of capital of 6% for the MFI. The outcome in column 5 is the branch NPV in taka as measured at the start of the experiment.

TABLE VII

SPILLOVERS: INELIGIBLE EX POST OUTCOMES.

	(1) Log Cons PerCap	(2) Income	(3) Crop Prod. (Kg)	(4) Bus. Stock Value	(5) Business Profit	(6) Welfare Index
Panel A: Ex Post Outcomes by Treatment						
Treatment branch	0.075	21.842	8.615	8.903	5.259	0.021
	(0.039)	(32.146)	(29.276)	(18.717)	(6.060)	(0.015)
Rand. Inf. p-val	0.067	0.523	0.789	0.651	0.401	0.191
Mean Dep. Var	6.01	809.51	224.51	89.04	31.23	0.14
Observations	1916	1917	1917	1917	1917	1917
Panel B: Ex Post Outcomes by Treatment and Flood Realization						
Treatment branch	0.109	37.942	2.489	4.464	14.309	0.021
	(0.054)	(52.891)	(43.344)	(24.918)	(9.598)	(0.022)
Flood X Treatment	−0.060	−30.153	10.439	8.069	−16.127	−0.001
	(0.076)	(72.765)	(51.648)	(34.868)	(12.171)	(0.031)
Flood	0.042	−31.571	−14.791	2.382	3.578	−0.010
	(0.061)	(59.861)	(41.181)	(26.265)	(8.236)	(0.026)
Rand. Inf. p-val Treat	0.068	0.463	0.946	0.860	0.149	0.355
Rand. Inf. p-val Inter.	0.471	0.637	0.844	0.827	0.196	0.986
Treat + Flood X Trt	0.367	0.861	0.714	0.629	0.811	0.362
Mean Dep. Var	6.01	809.51	224.51	89.04	31.23	0.14
Observations	1916	1917	1917	1917	1917	1917

Note: Sample includes only ineligible BRAC members from both treatment and control groups. Data are pooled from both the 2016 and 2017 Aman season. Standard errors clustered at the branch 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. Income is 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 in the past month in dollars. Welfare index is an inverse-covariance weighted index of consumption, income, crop production, business profits and assets, and livestock. Flood is an indicator that equals 1 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.

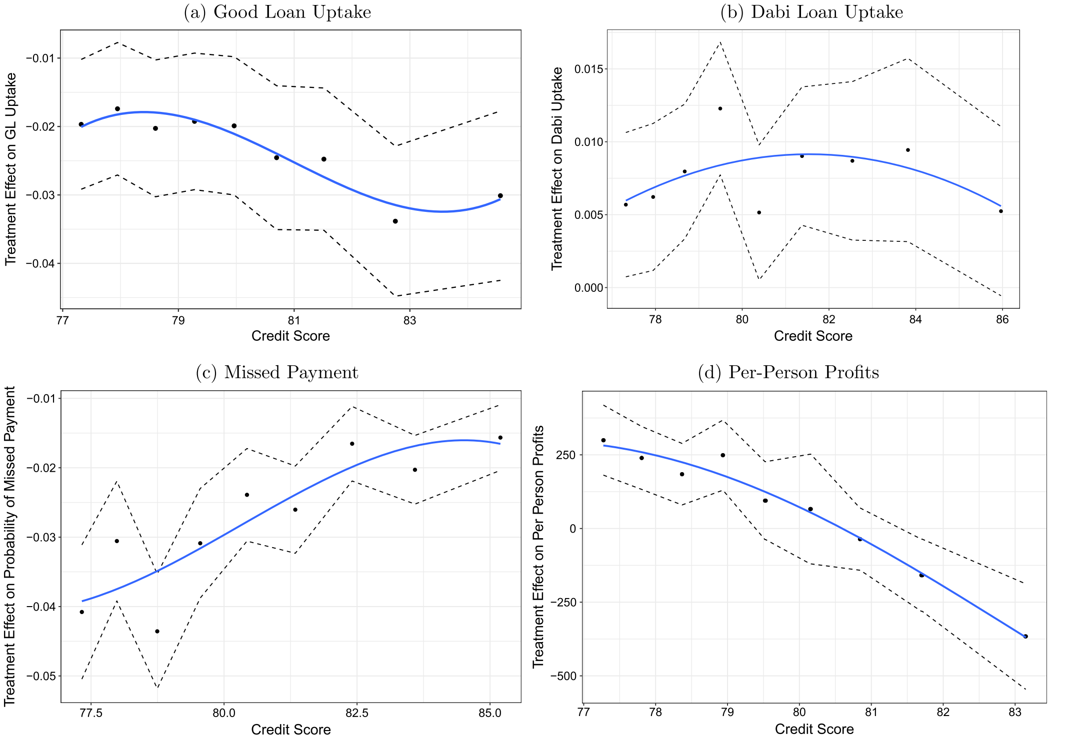

FIGURE 1.—Heterogeneity by credit score. *Notes*: Plots the treatment effect on the outcome in treatment branches by decile of borrower credit score. The sample is composed of Emergency Loan eligible borrowers. Data are pooled from both 2016 and 2017. For Good Loan Uptake, the sample is limited to those who were also eligible for a Good Loan in the pre-flood period. Standard errors are clustered at the branch level. Table VI tests whether the treatment effect heterogeneity is significant.

some evidence that in non-flooded branches, ineligible households work 2 more days as day laborers and earn 11 more dollars in wages (the latter is imprecise). This effect is 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.21 shows that ineligible households decrease the amount of land they rent-in by 0.019 acres (se 0.018), a 13% 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 (0.025 acres (se 0.023)—20% increase), a margin of adjustment that is feasible for most farmers who typically leave some of their land fallow every year.[30] 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

[30] I also investigate whether ineligible households use different amounts of inputs, which could arise if ineligible households farm lower quality land. I find no evidence of this (see Appendix Table A.22).

TABLE VIII

SPILLOVERS: LABOR AND TRANSFERS.

	(1) Days Worked	(2) Day Labor Earnings	(3) Transfers
Treatment branch	2.008	11.367	1.774
	(0.851)	(14.691)	(4.295)
Flood X Treatment	−2.392	−3.853	−5.771
	(1.316)	(22.654)	(6.303)
Flood	1.462	−4.755	10.750
	(1.067)	(19.176)	(4.700)
Rand. Inf. p-val Treat	0.020	0.470	0.703
Rand. Inf. p-val Inter.	0.072	0.858	0.370
Treat + Flood X Trt	0.671	0.646	0.453
Mean Dep. Var	9.98	133.05	12.23
Observations	1917	1917	1917

Note: Sample includes only ineligible BRAC members from both treatment and control groups. Data are pooled from both the 2016 and 2017 Aman season. Standard errors clustered at the branch 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. Transfers is the amount of cash and in-kind assistance received by the household in dollars. Flood is an indicator that equals 1 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.

Loan could have induced treated households to be more generous with their transfers, or disrupted these informal relationships, Table VIII 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.23). While no other ex post outcomes change significantly, the point estimate on crop production of 37.9 Kg (se 24.6) represents an economically meaningful 14% average 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 have seen above, consumption impacts on eligible households are largest in flooded areas while ineligible households benefit most in non-flooded areas. Finally, total crop production increases by 64 Kg (25%) in non-flooded areas with no change in flooded regions.

I conclude this section by investigating how ex ante investment outcomes change overall. I find that the effect on total land cultivated remains positive (0.042 acres, se 0.024), and represents a 13% increase in cultivated land (see Table A.24). This provides suggestive evidence that the introduction of the Emergency Loan brings new land into cultivation rather than reallocating land across households. However, given that I only observe villagers who are BRAC members, it is still possible that land is transferred from nonmembers to members. Finally, I examine total average effects on per-acre input use and the overall investment index. While I do not detect any change on per-acre agriculture inputs, the investment index indicates an average increase in investment of 0.02 standard deviations (Table A.25).

5.3. *The Emergency Loan Is Profitable for the Private Sector*

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.

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 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.[31] Table IX 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.[32] The first two results are not statistically significant, but do rule out large negative effects. 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 IX, 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). First, 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:

$$NPV_{bc} = \sum_{\text{members}} \sum_{t} (\text{revenue}_{bct} - \text{cost}_{bct})/\text{discount}^t,$$

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 1(d) plots the treatment effect on per-person profitability by credit score

[31]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.

[32]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.

TABLE IX

BRANCH PROFIT BY EMERGENCY LOAN AVAILABILITY.

	Profit (Taka)			
	Per Loan (1)	Monthly Branch (2)	Monthly Per Person (3)	NPV (4)
Treatment	161	76,312	96	2,129,951
	(233)	(95,405)	(46)	(974,008)
Rand Inf. p-value	0.46	0.41	0.04	0.06
Month F.E.	No	Yes	Yes	No
Mean of Dep. Var.	2823	1,745,794	2202	26,061,643
Observations	106,695	3706	3706	3797

Note: 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 branch level. The outcome for column 1 is the measured profit in Bangladeshi taka ($1 = 84 taka) for a given loan assuming an annual cost of capital of 6% for the MFI. The outcome for column 2 is overall branch profitability. The outcome in column 3 is overall branch profitability divided by the number of branch members. The outcome in column 4 is branch NPV in taka as measured at the start of the experiment.

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 VI shows 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.[33] 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.26). 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 1(c) 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

[33] 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.

3 of Table VI shows that this heterogeneity is statistically significant), and explains some of the heterogeneous effects on profits above.[34] The repayment heterogeneity likely stems from the fact that borrowers with high credit scores already repay at such high rates that further improvements are difficult to make.[35]

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. I find that treatment causes the probability of taking a Dabi loan to increase by 11% (0.7 percentage points) in the pre-period (see Appendix Table A.27)—and does not differ by borrower credit score (Figure 1(b) and Table VI 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 (United Nations (2020)). Under these circumstances, it is critical to find sustainable solutions that will help low-income households adapt to climate change. Yet recent literature suggests adaptation is constrained in many parts of the world, especially in low-income countries (Carleton et al. (2022)). I provide some of the first evidence that market failures in low-income countries constrain optimal adaptation. In particular, I show that by alleviating credit-market frictions, households are better able to adapt. This encompasses both proactive responses to anticipated climate risks and ex post outcomes when climate shocks occur.

To show this empirically, I run a large-scale RCT offering guaranteed credit in rural regions of Bangladesh where annual flood risk is high. To date, MFI's concerns about default risk has limited the supply of credit in the aftermath of a shock. Working with one of the largest MFIs in the world (BRAC), we design a product that assesses borrowers' eligibility before a flood shock occurs. In doing so, we overcome MFI's hesitancy to lend to households after a flood shock.

First, I show that the Emergency Loan is an effective adaptation tool by helping households invest in income-generating opportunities they may have otherwise avoided for fear of losing these investments in the event of a flood shock. In particular, I find that households increase investments in risky but profitable production by increasing the amount of land dedicated to agricultural cultivation by 18%. Moreover, I show that the Emergency Loan helps mitigate the impact of shocks when they do occur. Pre-approval for the Emergency Loan leads to a 19% increase in crop production and an 8% increase in per-capita consumption. I can show that borrowers recognize and value these benefits, and take the necessary steps to preserve their access to the Emergency Loan.

Second, I show that this product does not produce negative spillovers for households that are not eligible for the loan. In fact, consumption for ineligible households in increases by 7% in treatment branches relative to ineligible households in non-treatment

[34]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 V. This results in fewer loans going to borrowers who are most likely to repay, lowering overall profits among this cohort.

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

branches. I find suggestive evidence that this effect is driven by the fact 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.

Finally, I show that the extension of a guaranteed credit line confers benefits to lenders. I find that the introduction of the Emergency Loan has largely positive effects for MFI profits. Members take additional loans in the pre-period in response to the added security, repayment rates after a shock improve, and the NPV of the branch portfolio increases. This suggests that guaranteed credit can be offered by MFIs without third-party subsidies, provided that loan repayment rates remain similar in other settings. This is an important finding because MFIs are ubiquitous in low-income countries and can offer this type of product using their existing infrastructure. This finding is also promising for the policy community as a whole, as it indicates that the private sector has the potential to play a significant role in spearheading adaptation efforts.

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 to 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 necessarily 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 repayment 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 scalable and effective policy adaptation tool that organizations can use in low-income countries. As the frequency and severity of weather shocks increase 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 shock.

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