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By *Pejman Abedifar, Seyed Javad Kashizadeh, Steven Ongena*

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Using a rare flood in April 2019 in Iran as a natural experiment, we study the role of local banks in mitigating the financial consequence of natural disasters to smallholder farmers. We find that local branches immediately react to the disaster by increasing their lending for two months following the flood. Analyzing proprietary information on more than 70,000 farmers, we find that farmers with a stronger relationship with their bank - in particular when they are young and female - have a higher chance of access to new credit. Our findings underscore the importance of the presence of local banks in agricultural areas which are exposed to climate risk.

***Keywords:*** Local banks, Relationship lending, Climate Change, Farmers

***JEL Classifications:*** G21, G28, O13, Q14, Q54

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In recent years, climate change has escalated flood risk and exposed the farmers who live on riverbanks to flood-related hazards.[1] Farmers of the flood-hit areas need to have immediate access to credit to defray the cost of cleanup and damages. A key question is whether local banks accommodate farmers in the aftermath of catastrophes, given that their credit quality is deteriorated due to damages to their collateral and disruption of their farming operations. This question is pivotal in developing countries, where the majority of agricultural lands are cultivated by smallholder farmers, who do not generally purchase farm insurance or other financial instruments to protect themselves against climate risks. This paper seeks to answer this question by studying the response of a local bank in the aftermath of an unexpected deluge. The extant literature mainly examines banks' response to natural disasters in the mortgage market (Cortés and Strahan (2017), Cortés (2014), and Chavaz (2016)) and corporations (Koetter et al. (2020), Rehbein and Ongena (2022)). Our study extends this literature by focusing on the agricultural sector, where farmers are typically in the frontline of climate risk (Gutierrez and LePrevost (2016)).

We study Iran's biggest flood of the century induced by an extremely rare atmospheric river (AR) named Dena AR that struck the Middle-East in April 2019.[2] Unlike seasonal floods or hurricanes, Dena AR unexpectedly hit the region (Dezfuli (2020)). The flood occurred in the southwest of Iran, where many families rely on farming for living. It damaged 262,000 hectares of land and 56,000 residential properties (Specialized Working Group (2019)). The heterogeneous damage of the flood enables us to identify control and treatment units at the county level, apply the Difference in Differences (DiD) approach, and causally interpret local bank's response to the catastrophe.

[1] See Field et al. (2012), Milly et al. (2002) and Hirabayashi et al. (2013) for more information

[2] Atmospheric rivers are long, flowing corridors of the atmosphere that transport water vapor from the tropics to cooler regions.

In collaboration with one of the Iranian commercial banks, we compile a panel dataset of 126 branches in the southwestern region of Iran from September 2018 to September 2020 and restrict our analysis to lending to individual farmers. We find that branches operating in the flooded counties (henceforth: affected counties) react immediately to the disaster by increasing their lending within two months after the flood. This finding is similar to, for example, Cortés (2014) and Cortés and Strahan (2017) who find that depending on the severity of the disasters, credit expansion peaks up to six months after the disaster and then it dissipates.

Given this benchmarking with the literature, we next investigate the role of prior relationship in access to credit by scrutinizing proprietary information of more than 70,000 farmers living in the region hit by the flood. Using a linear probability model, we identify that clients with prior relationships are more likely to receive new loans during the bank's response. The effect dwindles a quarter after the flood. Our finding is in line with previous literature on the role of soft information in lending to small businesses during catastrophes (Chavaz (2016), Nguyen and Wilson (2020)). Berg and Schrader (2012) for example, also find that prior loan history alleviates lending restrictions for small businesses. We also examine whether farmers' age and gender affect access to finance during catastrophes. Our results show that young and female farmers are less likely to receive a new loan after the flood. However, prior relationships help them have more access to credit than old and male farmers. Hence, while initial access to bank credit may be more challenging for young and female farmers, once established, their relationships are more valuable.

We contribute to the literature on bank response to disasters by examining the agricultural sector in developing countries where smallholder farmers heavily rely on bank financing. Furthermore, to the extent that we are aware of, this manuscript is the first study on the importance of relationship banking in the agricultural sector where due to weather outcomes, the intertemporal insurance embedded in the relationship may play an important role. Our analysis also relates to the emerging literature that tries to further open up the black box of the relationship in retail banking. While current studies have investigated the disciplinary behavior of the relationship borrowers (Puri et al. (2017), Agarwal et al. (2018)), we examine the role of prior relationship in access to credit for smallholder farmers during a catastrophic event.

The remainder of the paper is organized as follows. The following section reviews existing literature and elaborates on the contribution of this study. Section II explains the flood and the exogeneity of the event. Section III and section IV describe the data and methodology, respectively. Section V discusses the result. Section VI presents robustness checks, and section VII concludes.

# I. Related Literature

Global warming has become a pivotal debate topic in the last decades after discovering the heat-trapping effect of the carbon dioxide produced by human activities (Callendar (1938)). The rising temperature trend has led to extreme precipitation in both amount and frequency (Stocker (2014)). Min et al. (2011) claim that about two-thirds of the observed torrential rains in the Northern Hemisphere are attributed to greenhouse gas emissions. It is predicted that flood frequency will increase around the world, especially in Southeast Asia, Peninsular India, Eastern Africa, and the northern half of the Andes (Seneviratne et al. (2012), Hirabayashi et al. (2013)).

While unexpected floods are going to affect different aspects of human life, their devastating consequences for farmers working on 570 million pieces of land around the world should be subject of particular attention. The issue becomes even more severe knowing that 87% of the lands are family farms, and 83% of them are smaller than 2 hectares (Lowder et al. (2014)).[3] This implies that flood damage to crops and livestock can affect many farmer families by cutting their main income channel. These circumstances strikingly demonstrate the vulnerability of farmer families in developing countries to the flood-related hazards. Surprisingly, such farmers rarely purchase insurance to protect themselves against these catastrophic events.[4]

Lack of insurance support and insufficient inclusion of microcredits[5] force farmers to rely the most on banking system to confront any liquidity shock. Banks' willingness to grant loans to disaster-ridden clients, however, depends on their ability to overcome the heightened adverse selection and moral hazard problems. A hike in information asymmetry in the aftermath of the disasters is derived from damage to clients' collateral (direct damage) or interruption in the production process (indirect damage) (Bradshaw (2003)). Sawada and Shimizutani (2008) show that collateral damage worsened credit constraint for households with lower collateralizable assets following the Kobe earthquake in Japan. The devastating consequence of natural disasters on credit rationing can be more severe in developing countries with poor credit history systems and weak law enforcement. In this regard, Berg and Schrader (2012) claim that microfinance institutions restrict credit provision to small

[3] There is a wide global heterogeneity in the share of the labor force working in the agricultural sector from 50% to 90% in the south and east of Asia and Sub-Saharan Africa to less than 5% in North America and West-Europe (ILO (2019)).

[4] Farms located in Asia and Sub-Saharan Africa, contribute to only 6% of global agricultural insurance premium (Lowder et al. (2016), Roberts (2005).

[5] Regional investigations show that agriculture sector is not the main subject of microfinance institutions, especially for long-term loans, due to the high covariant risks of drought, flood, and pest disease (Lesaffre (2000)) .

businesses in the wake of the volcanic eruption in Ecuador. Similarly, Nguyen and Wilson (2020) exploit the Indian Ocean tsunami as a quasi-natural experiment and show that overall lending in the affected regions decreases proportional to the intensity of the tsunami damage.

The soft information collected by local lenders over time, nonetheless, can play an important role in credit provision after natural disasters, when collateral of borrowers are damaged and retrospective credit scoring systems fail to adequately assess the creditworthiness of clients (Chavaz (2016)). Extant studies underscore that local banks privilege soft information to respond to elevated credit demand after disasters. Hence, the more local banks establish close tie with their clienteles, the better they can bolster disaster shocks. Studying the U.S. mortgage market Chavaz (2016) shows that local banks utilize private information and increase their lending to satisfy heightened demand on mortgage loans by reallocating credit to the affected areas. Cortés and Strahan (2017) investigate all U.S. natural disasters between 2001 and 2010 and find that banks reallocate resources to the affected regions where the presence of their branches enables them to exploit private information in lending. Their finding is consistent with the previous studies on the role of physical proximity in collecting soft information (Agarwal and Hauswald (2010), Brevoort and Hannan (2006)). Similarly, Koetter et al. (2020) study banks' response to the Elbe flood disaster in Germany and document that in the wake of the disaster, the local banking system mitigates adverse shocks through recovery lending.

In this paper, we attempt to open up the black box of local banks' response to the natural disaster in the agricultural sector. This is because while extant studies have explored the response of the banking system to natural disasters across different markets such as mortgage markets, there is no study, to the best of our knowledge, on the lending behavior of local banks in financing smallholder farmers following catastrophes.

To shed light on whether and how much prior relationships can ease access to credit for smallholder farmers during natural disasters, we connect the extant literature on the role of prior relationship in retail banking to the previous studies about the role of soft information during catastrophes. Existing literature on retail banking relationship points out that banks can use private information to mitigate adverse selection at the time of credit allocation and also to monitor borrowers during loan repayment period. Puri et al. (2017) show that individual borrowers with prior relationship behave with more discipline in loan repayment. The same effect is observed in the context of the credit card market, where accounts with stronger relationships exhibit lower default probability (Agarwal et al. (2018)). Our paper adds to this literature by exploring the value of retail banking relationship in agricultural sector during natural disasters.

# II. About the Flood

During 24 to 25 March and 2 April 2019, the southwestern region of Iran was hit by two unexpected flash floods caused by an extremely rare atmospheric river named Dena (Dena AR), which stemmed from an Atlantic Ocean's tropical moisture. The unpredictable rainfall pattern of Dena AR can be considered an example of the shift through climate change in the Middle-East (Dezfuli (2020)). The floods engulfed 262,000 hectares of land and destroyed 56,000 residential properties.[6] The estimated damage to the agricultural sector exceeded 580 million dollars (Specialized Working Group (2019)).[7]

The major losses after the catastrophe is attributed to the western counties of the region.

[6] The total area of agricultural lands in the region is about 2 million hectares.

[7] Total amount of activated agricultural insurance in the affected regions was about 4.3 million dollar that covers only 0.7% of the total damages (Specialized Working Group (2019)).

Figure I exhibits the spatial distribution of the affected and unaffected counties. Appendix A further discusses the flood in the three major rivers in the region: The Karkhe, Dez and Karoon.

[Insert figure I here]

# III. Sample and Descriptive Analysis

We obtain proprietary monthly data from an Iranian commercial bank on its 126 branches located in 35 counties. The branches provide financial services to individual farmers in the southwest of Iran that were hit by the flood. We collect the data for September 2018 to September 2020 timespan. The study period includes eighteen months before and twelve months after the flood. There are 80 branches operating in 16 counties that were hit by the flood. To investigate the role of prior relationship during catastrophe, we use proprietary data on over 70,000 farmers. Information about farmers' loans and account balances are collected from branches' monthly reports. Lower than 1% of farmers have accounts with more than one branch. Removing this minority helps us map each client to one branch. The sample includes monthly data on the number of loans granted to farmers, deposit balance of farmers' accounts, personal characteristics, and riskiness measures of the farmers. Table I describes sample variables. Part A of the table defines the branch level variables and part B describes the variables used to explain borrowers' characteristics.

[Insert table I here]

## A. Summary Statistics and Overlap Measures for Branch Level Data

Panel A of the table II provides descriptive statistics on the characteristics of branches. The sample consists of 880 and 506 branch-month observations for the affected and unaffected branches. The number of loans to farmers (*Loan*) in the affected and unaffected branches is about 18 and 30 loans per month. The average amount of accounts' balances (*Average Balance*) is 97.4 and 111.9 dollars for the affected and unaffected groups. Branch size represented by the number of clients with at least one active account (*Size*) is on average, 16,569 and 18,168 in the affected and unaffected areas, respectively. *Credit Risk* is a continuous index that is constructed from the default status of the branches' loan portfolio. The mean of the *Credit Risk* index is 22.16 for the affected branches and 21.19 for the unaffected ones.

[Insert table II here]

Beside continuous covariates, there are also some categorical characteristics. *Branch Score* is a categorical index constructed on branches' performance in credit allocation, attracting new clients, electronic services, opening letter of credit and etc. The overall score is annually calculated and categorized to five classes such that branch with class one score has the best performance. *Rural Branch* is a dummy variable that takes the value of one for the branches located in rural areas and zero otherwise. Figure III shows the histogram plot of these variables across two samples.

[Insert figure III here]

Besides the unconfoundedness assumption, one of the most critical requirements for causal inference is the covariate balance between treatment and control groups. Following Imbens and Rubin (2015), we use three measures for assessing the overlap of covariates' distribution: 1) *Normalized Difference*, defined as the two groups' mean difference, divided by the square root of the average of the two samples' variances ($\Delta_{\mathrm{ct}} = \frac{\mu_{\mathrm{t}} - \mu_{\mathrm{c}}}{\sqrt{\left(\sigma_{\mathrm{t}}^2 + \sigma_{\mathrm{c}}^2\right)/2}}$ where $\mu$, $\sigma$, $t$, and $c$ denotes mean, standard deviation, treatment, and control, respectively ). 2) *Dispersion Difference* that is the logarithm of the ratio of standard deviations of treatment group to control group ( $\Gamma_{\mathrm{ct}} = \ln\left(\sigma_{\mathrm{t}}/\sigma_{\mathrm{c}}\right)$ ). 3) *Coverage Frequency* that measures the degree of overlap between treated and control groups. It shows the proportion of the control (treated) units that have a covariate with values in the tails of the distribution of that covariate in the treated (control) group ($\pi_{\mathrm{t}}^{\alpha} = \left(1 - F_{\mathrm{t}}\left(F_{\mathrm{c}}^{-1}(1-\alpha/2)\right)\right) + F_{\mathrm{t}}\left(F_{\mathrm{c}}^{-1}(\alpha/2)\right)$ where for the specific value of $\alpha$, $\pi_{\mathrm{t}}^{\alpha}$ denotes probability mass of the covariate's distribution in the treated group that is located outside of the quantile $1-\alpha/2$ and $\alpha/2$ of that covariate in the control ). To look at the overall balance between two samples, we also estimate the propensity score (*Pscore*) and log odd ratio of propensity score (*Linearized propensity score*) by running logistic regression of treatment dummy (*Flood*) on both continuous and categorical covariates. Computing mentioned overlap measures (*Normalized Difference, Dispersion Difference* and *Coverage Frequency*) for the estimated propensity score enables us to look at the overall balance between the two groups.

As shown in Panel A of table II, branch level variables have quite similar distributions for the two samples. The *Normalized Difference* and *Dispersion Difference* statistics for *Credit Risk* are 0.0737 and 0.0982, respectively. *Coverage Frequency* at the 95% level ($\alpha = 5\%$) is also close to zero for *Credit Risk*. *Average Balance* and *Size* of the affected and unaffected branches are also similar in overlap measures. The *Normalized Difference*, *Dispersion Differ-*

*ence* and *Coverage Frequency* of control (treatment) group for *Pscore* are 0.577, 0.043 and 0.057 (0.183), respectively. The similar statistics for *Linearized Pscore* is also 0.413, 0.063 and 0.057 (0.183). The balance in the distribution of both single covariates and estimated propensity score (and log odd ratio of propensity score) ensures that our inference does not rely on extrapolation due to lack of corresponding control units in some regions of treatment values.

## B. Summary Statistics and Overlap Measures for Individual Level Data

Panel B of table II exhibits descriptive statistics and overlap measures for covariates of individual farmers in the affected and unaffected groups. The average amount of balance in checking, saving, and short-term accounts (henceforth: *Checking*, *Saving*, and *Short-term*) in the affected branches are 5.5, 67 and 53 dollars, respectively. These balances are about respectively 11, 47, and 64 dollars in the unaffected branches. On average, farmers are 48 and 49 years old in the affected and unaffected branches, respectively.

Overlap measures of all covariates are close to zero, showing that the distributions' balance across treatment and control groups is well suited.[8] The other control variables are *Education*, *Gender*, *Check Repayment Score* and *Social Reputation Score*. Education is a categorical variable that indicates farmers' education level from 1 to 3, where 1 is the lowest level of education. *Gender* is a dummy that takes the value of 1 for female farmers and 0 otherwise. *Check Repayment Score* is a categorical variable that takes the value of 1 to 4 and shows the history of check repayment of farmers where 4 is the best score. *Social Reputation*

[8] We use natural logarithm transformation to mitigate accounts' balance skewness. None of overlap measures for logarithmic transformation of accounts' balance exceed 0.05.

*Score* categorizes how well a farmer is known in the local society. The score ranges between 1 and 4, where 4 is the best category. We use histogram plot to depict covariate balance for these categorical covariates. Figure III shows that all covariates are distributed identically between the two samples. The similar distribution of continuous and categorical variables besides the unconfoundedness assumption enables us to casually interpret bank lending model estimations.

[Insert figure III here]

# IV. Methodology and Econometric Specifications

## A. Flood and Deposit Withdrawals

Despite financial crises, when we observe a re-intermediation (Saidenberg and Strahan (1999)), banks may face liquidity demand on both sides of their balance sheet in a catastrophic event. The affected clients may withdraw their deposits and even demand credit to cover the damages to their businesses. Hence, we examine whether deposits of the branches located in the affected area have been declined in the aftermath of the flood using the following difference-in-differences model:

$$\log(Balance_{bt}) = \beta_0 + \beta_1 T_t + \beta_2 Flood_b + \beta_3 Flood_b \times T_t + \sum_j \beta_j Branch_{bjt} + \epsilon_{bt} \qquad \text{(I)}$$

Where $b$, $t$ and $j$ denote branch, month, and branch's characteristics, respectively. $\log(Balance_{bt})$ denotes the natural logarithm of the average monthly balance across all accounts of customers at branch $b$ in month $t$. $T_t$ denotes month dummies, including six months before and five months after April 2019, the month during which the flood happened.[9] $Flood_b$ is a dummy variable indicating whether the branch $b$ is in the affected counties. Since the flood is exogenous, we can claim that the coefficient of $Flood_b \times T_t$ indicates whether and how long the flood induces deposit withdrawal in the affected area. $Branch_{bjt}$ presents characteristic $j$ of the branch $b$ in month $t$. To capture heterogeneity in branch activity, we include *Branch Score* to our model. The *Size*, and *Rural Branch* dummy are also controlled. Standard errors are clustered at the branch level to capture between-branch correlation.[10]

## B. Branch Lending After the Flood

To investigate whether branches increase lending in response to the flood, we use the following difference-in-differences regression model:

$$Loan_{bt} = \beta_0 + \beta_1 T_t + \beta_2 Flood_b + \beta_3 Flood_b \times T_t + \sum_j \beta_j Branch_{bjt} + \epsilon_{bt} \tag{II}$$

Where $b$, $t$ and $j$ denote branch, month, and branch characteristics, respectively. $Loan_{bt}$ measures the total number of loans that branch $b$ grants to the farmers in month $t$. The rest of the model is the same as equation I, except that we also control for *Average Balance* to capture the differences in branch resources for lending. The coefficient of $Flood_b \times T_t$ shows that whether the flood has changed the lending of branches in the affected region.

[9] We exclude April 2019 from the sample because branches do not grant new loans during the New Year holiday. Nonetheless, Cortés and Strahan (2017) show that banks' response to the loan applications starts from two months after the catastrophe.

[10] Since we have merely 35 counties, clustering at the county level will underestimate between-class correlation (Angrist and Pischke (2008), Chapter 8, Section 8.2.3) .

## C. Relationship Banking and Access to Finance after the Flood

Next, we study whether clients with prior relationships are more likely to receive new credit after the flood. To achieve our objective, we estimate the following triple difference regression:

$$\begin{aligned} \mathrm{P}(NewLoan)_{ft} &= \beta_0 + \beta_1 T_t + \beta_2 Relationship_{ft} + \beta_3 Flood_f + \beta_4 Flood_f \times T_t \\ &+ \beta_5 Flood_f \times Relationship_{ft} + \beta_6 T_t \times Relationship_{ft} \\ &+ \beta_7 Flood_f \times T_t \times Relationship_{ft} + \sum_j \beta_j \times Char_{fjt} + \epsilon_{ft} \end{aligned} \tag{III}$$

Where $f$, $t$ and $j$ denote farmer $f$, month $t$ and farmer's $j$'th characteristics, respectively. $\mathrm{P}(NewLoan)_{ft}$ is the probability of receiving a new loan in month $t$ by farmer $f$. $T_t$ denotes month dummies. $Relationship_{ft}$ represents the depth of relationship for farmer $f$ in month $t$. We follow Berg and Schrader (2012) and use the number of previous loans to measure $Relationship_{ft}$. The coefficient of the triple interaction term, that is, $Flood_f \times T_t \times Relationship_{ft}$, captures the impact of the strength of prior relationship on the probability of obtaining a new loan in the affected area after the flood. A positive coefficient shows that farmers with stronger previous relationships have a higher chance of being granted a new loan in the affected counties after the catastrophe.

$Char_{fjt}$ measures $j$'th characteristic of farmer $f$ in month $t$, including the monthly balance of farmer's accounts in the branch. The impact of deposit balance on access to new credit can be interpreted through three different channels. First, granting a new loan can directly depend on the amount of money deposited into the account. Second, holding an account and balance can help the branch collect soft information about clients. Finally, accounts' balance can be considered as a proxy for the wealth of the farmers (Puri et al. (2017)). We control for the balance in *Checking*, *Saving* and *Short-term* accounts of farmers.[11] We also include *Age*, *Gender*, *Education*, and two measures of riskiness - *Check Repayment Score* and *Social Reputation Score* - of the farmers in our model.

# V. Results

## A. Deposit Withdrawals after the Flood

To examine whether the deposit balance of the branches operating in the affected area is changed in the aftermath of the flood, we estimate equation I using OLS regression. Table III reports the results. As one of the most critical assumptions of the difference in differences model, we first check whether the pre-treatment parallel trend assumption holds. As we can see in both columns, estimation of the coefficient $Flood_b \times T_t$ for six months before the flood is insignificant. Column (1) shows the estimation of equation I without controlling for branch's characteristics and branch dummy. It reports that the affected branches experienced 15.5%, 10.2% and 8.9% decrease in their deposit balances in April, May and June 2019. In column (2), we include branch-level control variables, that is, *Branch Score*, *Rural Branch* and *Size*. The coefficient of *Rural Branch* is statistically insignificant which shows rural and urban branches hold more or less the same amount of deposit accounts' balances. The previous result remains unchanged, and the deposit balances of branches in the affected area decline

[11] Each type of accounts can affect chance of granting a new loan in a different way in Iran's banking system. For example, saving account's balance can be used as a collateral. Moreover, branches typically put different weight to the balance of the checking, saving and short-term accounts of farmers in making decision on the amount of loan. For instance, accepted loan applicants can receive credit up to six times of their average checking account's balance during last year. This factor is three times for saving and short-term accounts. It should be noted that the inclusion of these three types of accounts in the model does not create multicollinearity problem, because their pairwise correlations are less than 0.03.

after the catastrophe, which is similar to the findings of Brei et al. (2019) which shows that deposits are withdrawn after hurricanes in the North Atlantic Ocean basin.

[Insert table III here]

## B. Branch Lending after the Flood

Next, we explore whether lending is changed in the branches located in the affected regions. We estimate equation II using the OLS regression and report the results in table IV. We first check whether the pre-treatment parallel trend assumption holds. Estimation of the coefficient of $Flood_b \times T_t$ for six months before the flood is statistically insignificant which indicates that there is no significant difference in lending between the two groups prior to the event. Column (1) illustrates estimation of equation II without including branch's characteristics and branch dummy variables in the model. The coefficient of the interaction term between $Flood_b$ and $T_t$ is positive at the 5% and 10% significance levels for May and June 2019, respectively, showing that branches in the affected counties immediately reacted to the flood by credit expansion. The credit expansion is economically significant. Branches located in the affected counties lent on average 9 more loans during these two months, whereas the average number of lending in the affected areas six months before the disaster was about 18 loans per month.

In column (2), we add branch controls, including *Average Balance*, *Rural Branch*, *Size* and *Branch Score* to the model. The result for $Flood_b \times T_t$ is similar to our finding in column (1).[12] Our finding is in line with the recovery lending effect in the extant literature ( Koetter et al. (2020), Cortés and Strahan (2017), and Chavaz (2016)) and contrasts the studies that

[12] To capture heterogeneities in the agricultural products, we also control for the share of 18 types of different crops that are cultivated in the region of our study. The results on branches' response to the flood does not change qualitatively.

provide evidence in support of lending contraction (Berg and Schrader (2012), Brei and Schclarek (2015), Nguyen and Wilson (2020)).

[Insert table IV here]

## C. The Role of the Relationship Banking in Access to Finance after the Disaster

The results of the previous sub-sections indicate that branches immediately react to the flood by increasing their lending to the farmers within two months after the flood. In this sub-section, we study whether prior relationship eases access to credit after the catastrophe. We estimate equation III using linear probability model regression. Table V reports the results.

[Insert table V here]

Column (1) reports the result of estimating equation III without controlling for the farmers' characteristics. The insignificant coefficients of $Flood_f \times T_t \times Relationship_{ft}$ for six months before the flood ensures us that the pre-treatment parallel trend assumption holds. The estimated coefficients of this triple interaction term for May and June 2019 are significantly positive at the 5% level and they are economically meaningful. A one unit increase in the number of previous loans increases the likelihood of obtaining a new credit by 0.77% and 0.86% for May and June 2019, respectively, which is considerable given that on average, branches lent to only 3% of farmers six months before the flood. In the second column, we control for the monthly balance of *Checking*, *Saving*, and *Short-term* accounts of farmers. The estimation results show that the accounts' balance can positively affect access to credit. A 1% increase in the balance of *Checking*, *Saving*, and *Short-term* accounts is associated with respectively 1.4%, 0.02% and 0.09% higher chance of receiving a new loan.

In the third column, *Age* and *Gender* of farmers are included in the model. The coefficient of *Age* is insignificant. The result on the coefficient of *Gender* shows that, holding other observable factors constant, female farmers are less likely to receive credit than male farmers. The categorical variables for *Education*, *Check Repayment* and *Social Reputation Score* of the farmers are also controlled. The coefficient of the triple interaction term remains statistically significant for May and June 2019 in columns (2) and (3), showing that prior relationship facilitates access to credit in the aftermath of the disaster. Our finding aligns with Berg and Schrader (2012) which state that prior relationship can ease receiving loans after catastrophes.

### C.1. Relationship Banking and Age

Estimation results for equation III exhibit that prior relationship plays an important role in access to finance after the catastrophe. However, the importance of prior relationship can depend upon farmers' age. Young households have, on average, fewer historical records, are less risk averse (Morin and Suarez (1983)) and make more financial mistakes than older ones (Agarwal et al. (2009)), which expose them more to financial distress (Xiao and Yao (2014)). Therefore, exploiting private information generated from relationship banking is expected to be more essential for granting loans to young applicants. To explore whether the value of relationship banking in access to finance varies with farmers' age, we use the following regression model:

$$
\begin{aligned}
&\mathrm{P}(NewLoan)_{ft} = \beta_0 + \beta_1 Post_t + \beta_3 Flood_f + \beta_2 Relationship_{ft} + \beta_4 Age_f \\
&+ \beta_5 Post_t \times Flood_f + \beta_6 Post_t \times Age_f + \beta_7 Post_t \times Relationship_{ft} + \beta_8 Flood_f \times Age_f \\
&+ \beta_{10} Flood_f \times Relationship_{ft} + \beta_9 Relationship_{ft} \times Age_f \\
&+ \beta_{11} Post_t \times Relationship_{ft} \times Age_f + \beta_{12} Post_t \times Flood_f \times Relationship_{ft} \\
&+ \beta_{13} Flood_f \times Relationship_{ft} \times Age_f + \beta_{14} Post_t \times Flood_f \times Age_f \\
&+ \beta_{15} Post_t \times Flood_f \times Relationship_{ft} \times Age_f \\
&+ \sum_j \beta_j \times Char_{fjt} + \epsilon_{ft}
\end{aligned}
\tag{IV}
$$

Where $Post_t$ is a dummy variable that takes the value of one for the period after the flood and zero otherwise. The model is similar to equation III except that we include double, triple and quadruple interaction terms of $Age_f$ with $Post_t$, $Flood_f$, and $Relationship_{ft}$.[13] Table VI reports the results. The coefficient on $Post_t \times Flood_f \times Age_f$ is positive and significant at the 1% level. It indicates that the probability of receiving new loan increases by 0.046% for one year older farmers which is consistent with the extant literature on lower credit constraint of older borrowers (Duca and Rosenthal (1993)). The coefficient of $Post_t \times Flood_f \times Relationship_{ft} \times Age_f$ is, however, negative and significant at the 1% level. It shows that while older farmers are more likely to receive credit after the catastrophe, prior relationship

[13] To avoid having too many interaction terms between month dummies and other explanatory variables, we collapse time period around the flood to *Post* dummy that is one after the flood and zero otherwise. We find that there are adequate observations and variations in *Relationship* and *Age* across the four sub-samples constructed by *Flood* and *Post* dummies. Additionally, low correlations between *Relationship* and *Age* across the four sub-samples, which range between 0.14 and 0.18, ensure us that our results are not affected by multi-collinearity problem. The results are available upon request.

can help young farmers have more access to finance than older farmers. Controlling for deposit balance of farmers in column (2) and farmers' characteristics in column (3) does not change the results qualitatively.

### C.2. Relationship Banking and Gender

Extant studies illustrate that female borrowers are more likely to experience taste-based discrimination (Becker (2010)) in both credit availability (Bellucci et al. (2010)) and cost of financing (Alesina et al. (2013)), even though they do not experience higher delinquency (Beck et al. (2018)). In addition to taste-based discrimination in credit allocation, females' belief in rejection of their loan request discourages them from applying for credit (Ongena and Popov (2016)). Therefore, prior relationship can be more valuable for females as it can change their belief about their application's denial. Hence, we investigate whether prior relationship can affect access to finance across farmers' gender using the following regression model:

$$
\begin{aligned}
&\mathrm{P}(NewLoan)_{ft} = \beta_0 + \beta_1 Post_t + \beta_2 Flood_f + \beta_3 Relationship_{ft} + \beta_4 Gender_f \\
&+ \beta_5 Post_t \times Flood_f + \beta_6 Post_t \times Gender_f + \beta_7 Post_t \times Relationship_{ft} + \beta_8 Flood_f \times Gender_f \\
&+ \beta_{10} Flood_f \times Relationship_{ft} + \beta_9 Relationship_{ft} \times Gender_f \\
&+ \beta_{11} Post_t \times Relationship_{ft} \times Gender_f + \beta_{12} Post_t \times Flood_f \times Relationship_{ft} \\
&+ \beta_{13} Flood_f \times Relationship_{ft} \times Gender_f + \beta_{14} Post_t \times Flood_f \times Gender_f \\
&+ \beta_{15} Post_t \times Flood_f \times Relationship_{ft} \times Gender_f \\
&+ \sum_j \beta_j \times Char_{fjt} + \epsilon_{ft}
\end{aligned} \tag{V}
$$

Where $Gender_f$ is a dummy that takes the value of one for female farmers and zero otherwise.[14] Table VII shows the estimation results. The coefficient on $Post_t \times Flood_f \times Gender_f$ is negative and significant at the 5% level. Female farmers have 1.27% lower chance of receiving new loans after the flood, which is in line with the extant studies on females' credit constraints. The coefficient of $Post_t \times Flood_f \times Relationship_{ft} \times Gender_f$ is, however, positive at the 5% significance level which shows that while female farmers face tighter condition for access to credit, those with a prior relationship are 1.06% more likely to receive recovery loans than their male counterparts, holding other factors constant. The results are almost the same when we control for deposit balance and risk characteristics of farmers in column (2) and column (3), respectively. By demonstrating that prior relationship can help women have more access to credit during catastrophes, our result complements Beck et al. (2013) that show women are superior at establishing a trustful relationship.

## D. Further Analysis

### D.1. Branch Lending and Deposit Withdrawals

Estimation of equation I shows that branches experienced deposit withdrawals following the flood. This negative shock could adversely affect the lending capacity of the branches. Therefore, such branches may require new resources for lending to the affected family farmers. They can either reduce lending to non-agricultural sectors or borrowing in their intra-bank

[14] Similar to equation IV, we find that there are adequate observations and variations in *Relationship* across the eight sub-samples constructed by *Flood*, *Post*, and *Gender* dummies. Moreover, low correlations between *Relationship* and *Gender* across the four sub-samples constructed by *Flood* and *Post*, which range between -0.18 and -0.19, ensure us that our results are not affected by multi-collinearity problem. The results are available upon request.

branch network.[15] We estimate equation II using non-agricultural lending as the dependent variable to explore whether the branches use the former mechanism. However, we do not find significant evidence for it. Gilje et al. (2016) exploits oil and natural gas shale discovery and provides an empirical evidence for the latter mechanism. Unfortunately, we do not have data on inter-branch lending to examine whether branches fund themselves in their intra-bank branch network.

### D.2. Branch Lending and Credit Risk

We also analyze whether the recovery lending of the branches heightened the default rate of the loans. Unfortunately, we cannot identify the repayment of the loans granted after the disaster in our dataset. Instead, we use *Credit Risk* as an internal index for the overall status of the granted loans' delinquency. Controlling for branch level variables, we estimate equation II while *Credit Risk* is the dependent variable. We study delinquents up to two years after the flood. The results do not show that *Credit Risk* is significantly increased in the aftermath of the catastrophe. Our finding aligns with Cortés (2014), which study eighteen U.S. natural disasters and shows that there is not a significant hike in default rates of banks due to recovery lending.

[15] Cortés and Strahan (2017) identify that banks offer higher interest rates to depositors to fund local demand shock after the catastrophes. But this is not the case in the context of Iran's banking system, because government does not allow banks to change deposit or loan rates.

# VI. Robustness Checks

## A. Placebo Tests

Our analysis suggests that local branches immediately reacted to the flood by credit expansion two months after the flood. To validate whether the differential lending in the affected areas is driven by the unexpected flood and not a seasonal behavior of bank branches, we estimate equation II and equation III using data for exactly one year before the flood, April 2018.

Table VIII presents the placebo estimation of equation II using data from October 2017 to September 2018. Column (1) reports the placebo estimation of equation II without controlling for branches' characteristics. Unlike the recovery lending after the disaster, there is no significant difference in lending between the affected and unaffected branches in the year before the flood. In column (2), branch's characteristics, including *Average Balance*, *Rural Branch*, *Size* and *Branch Score* are controlled for. Similar to the previous results, the coefficients of the interaction terms between flood and months dummies remains statistically insignificant. We find no significant difference in lending between the two groups. Therefore, the increase in lending after the flood in April 2019 is not driven by unobserved factors or seasonality.

[Insert table VIII here]

We also run the placebo test for our results on the role of relationship banking in bolstering flood shock to farmers. We re-estimate equation II using data from October 2017 to September 2018. The estimation results are reported in table IX.

[Insert table IX here]

Column (1) reports the estimation of equation III without farmers' control variables. It does not show that farmers in the affected areas have exploited their relationship to receive credit. In column (2), we control for the monthly balance of *Checking*, *Saving*, and *Short-term* accounts of farmers. As in table V, accounts' balance positively affects the chance of receiving a new loan. In column (3), our specification includes farmers' *Gender*, *Age*, *Education*, *Check Repayment* and *Social Reputation Score*. As in column (1), the coefficient of the triple interaction $Flood_f \times T_t \times Relationship_{ft}$ in both columns (2) and (3) implies that our main finding is not driven by unobserved factors or seasonality.

We also conduct a placebo test for our results in sub-section C.1 where we show that the impact of relationship on access to credit depends on farmers' age. Estimation results are presented in table X.

[Insert table X here]

The coefficients of $Post_t \times Flood_f \times Age_f$ and $Post_t \times Flood_f \times Relationship_{ft} \times Age_f$ are insignificant that ensure us that the differential impact of relationship between young and old farmers is driven by the flood.

The same is true for equation V where the coefficients of both $Post_t \times Flood_f \times Gender_f$ and $Post_t \times Flood_f \times Relationship_{ft} \times Gender_f$ are insignificant.

[Insert table XI here]

## B. Alternative Measure of the Relationship

As a further robustness check, we change the measure of prior relationship with the branch from the number of previous loans to the monthly fees that branches receive from their clients for various financial services, ranging from the fee of using e-bank technology to the commission received for money transfer (henceforth: *Fee*). Therefore, a higher fee is directly related to more interactions between clients and their banks. We re-estimate equation III using *Fee* as a proxy for relationship. The results are presented in table XII.

Column (1) reports the estimation results without controlling for farmers' characteristics. As we can see, the coefficient of the $Flood_f \times T_t \times Fee_{ft}$ is significantly positive at the 5% level for three months following the flood. We control for the *Checking*, *Saving* and *Short-term* accounts in the second column. Similar to table V, the impact of accounts' balance on access to credit is positive and significant. A 1% increase in the balance of *Checking*, *Saving*, and *Short-term* accounts is associated with respectively 1.1%, 0.02% and 0.07% higher chance of receiving a new loan. In the third column, we add *Gender*, *Age*, *Education*, *Check Repayment Score* and *Social Reputation Score* of farmers to the model. The results on control variables are similar to our previous findings. The coefficient of *Age* is insignificant and male farmers are 0.45% more likely to receive a new loan. The coefficient of the triple interaction terms in columns (2) and (3) remains statistically significant at the 5% significance level for three months after the flood.

[Insert table XII here]

# VII. Concluding Remarks

The growing catastrophic events induced by climate change are going to expose smallholder farmers in low-income countries to flood-related hazards. This motivates us to explore two important questions. First, whether local banks increase their lending to the affected farmers after natural disasters. Second, whether prior relationship helps farmers have more access to credit after catastrophic events. Our results suggest that local branches immediately respond to the disaster by expanding their lending. We also uncover that following the catastrophe, local branches privilege farmers with prior relationship in access to new credit. Moreover, young and female farmers are more credit constrained following the flood, but prior relationship can help them have more access to finance.

Our findings imply that the presence of local banks in agricultural areas is essential, as they can provide immediate recovery credit to the affected farmers based on their prior relationship.

# Reference


Agarwal, Sumit, Souphala Chomsisengphet, Chunlin Liu, Changcheng Song, and Nicholas S Souleles, 2018, Benefits of relationship banking: Evidence from consumer credit markets, *Journal of Monetary Economics* 96, 16–32.

Agarwal, Sumit, John C Driscoll, Xavier Gabaix, and David Laibson, 2009, The age of reason: Financial decisions over the life cycle and implications for regulation, *Brookings Papers on Economic Activity* 2009, 51–117.

Agarwal, Sumit, and Robert Hauswald, 2010, Distance and private information in lending, *The Review of Financial Studies* 23, 2757–2788.

Alesina, Alberto F, Francesca Lotti, and Paolo Emilio Mistrulli, 2013, Do women pay more for credit? evidence from italy, *Journal of the European Economic Association* 11, 45–66.

Angrist, Joshua D, and Jörn-Steffen Pischke, 2008, *Mostly harmless econometrics* (Princeton University Press).

Beck, Thorsten, Patrick Behr, and Andre Guettler, 2013, Gender and banking: are women better loan officers?, *Review of Finance* 17, 1279–1321.

Beck, Thorsten, Patrick Behr, and Andreas Madestam, 2018, Sex and credit: Do gender interactions matter for credit market outcomes?, *Journal of Banking and Finance* 87, 380–396.

Becker, Gary S, 2010, *The economics of discrimination* (University of Chicago Press).

Bellucci, Andrea, Alexander Borisov, and Alberto Zazzaro, 2010, Does gender matter in bank–firm relationships? evidence from small business lending, *Journal of Banking and Finance* 34, 2968–2984.

Berg, Gunhild, and Jan Schrader, 2012, Access to credit, natural disasters, and relationship lending, *Journal of Financial Intermediation* 21, 549–568.

Bradshaw, Sarah, 2003, Handbook for estimating the socio-economic and environmental effects of disasters.

Brei, Michael, Preeya Mohan, and Eric Strobl, 2019, The impact of natural disasters on the banking sector: Evidence from hurricane strikes in the Caribbean, *The Quarterly Review of Economics and Finance* 72, 232–239.

Brei, Michael, and Alfredo Schclarek, 2015, A theoretical model of bank lending: Does ownership matter in times of crisis?, *Journal of Banking and Finance* 50, 298–307.

Brevoort, Kenneth P, and Timothy H Hannan, 2006, Commercial lending and distance: Evidence from community reinvestment act data, *Journal of Money, Credit and Banking* 38, 1991–2012.

Callendar, Guy Stewart, 1938, The artificial production of carbon dioxide and its influence on temperature, *Quarterly Journal of the Royal Meteorological Society* 64, 223–240.

Chavaz, Matthieu, 2016, Dis-integrating credit markets: diversification, securitization, and lending in a recovery, *Bank of England Working Paper* .

Cortés, Kristle Romero, 2014, Rebuilding after disaster strikes: How local lenders aid in the recovery, *Federal Reserve Bank of Cleveland Working Paper* .

Cortés, Kristle Romero, and Philip E Strahan, 2017, Tracing out capital flows: How financially integrated banks respond to natural disasters, *Journal of Financial Economics* 125, 182–199.

Dezfuli, Amin K, 2020, A strong atmospheric river responsible for the 2019 record floods in the middle east, in *AGU Fall Meeting Abstracts*, volume 2020, A179–0016.

Duca, John V, and Stuart S Rosenthal, 1993, Borrowing constraints, household debt, and racial discrimination in loan markets, *Journal of Financial intermediation* 3, 77–103.

Field, Christopher B, Vicente Barros, Thomas F Stocker, and Qin Dahe, 2012, *Managing the risks of extreme events and disasters to advance climate change adaptation: special report of the intergovernmental panel on climate change* (Cambridge University Press).

Gilje, Erik P, Elena Loutskina, and Philip E Strahan, 2016, Exporting liquidity: Branch banking and financial integration, *The Journal of Finance* 71, 1159–1184.

Gutierrez, Kristie S, and Catherine E LePrevost, 2016, Climate justice in rural southeastern united states: A review of climate change impacts and effects on human health, *International Journal of Environmental Research and Public Health* 13, 189.

Hirabayashi, Yukiko, Roobavannan Mahendran, Sujan Koirala, Lisako Konoshima, Dai Yamazaki, Satoshi Watanabe, Hyungjun Kim, and Shinjiro Kanae, 2013, Global flood risk under climate change, *Nature Climate Change* 3, 816–821.

ILO, 2019, *Share of the labor force employed in agriculture* (International Labor Organization).

Imbens, Guido W, and Donald B Rubin, 2015, *Causal inference in statistics, social, and biomedical sciences* (Cambridge University Press).

Koetter, Michael, Felix Noth, and Oliver Rehbein, 2020, Borrowers under water! Rare disasters, regional banks, and recovery lending, *Journal of Financial Intermediation* 43, 100811.

Lesaffre, Dominique, 2000, A propos de loffre et de la demande du financement du monde rural en afrique de louest, *Projet dutilisation des fonds suisses (PUF), Lomé* .

Lowder, Sarah K, Jakob Skoet, and Terri Raney, 2016, The number, size, and distribution of farms, smallholder farms, and family farms worldwide, *World Development* 87, 16–29.

Lowder, Sarah K, Jakob Skoet, and Saumya Singh, 2014, What do we really know about the number and distribution of farms and family farms worldwide?, *Background paper for The State of Food and Agriculture* .

Milly, P Christopher D, Richard T Wetherald, KA Dunne, and Thomas L Delworth, 2002, Increasing risk of great floods in a changing climate, *Nature* 415, 514–517.

Min, Seung-Ki, Xuebin Zhang, Francis W Zwiers, and Gabriele C Hegerl, 2011, Human contribution to more-intense precipitation extremes, *Nature* 470, 378–381.

Morin, Roger-A, and A Fernandez Suarez, 1983, Risk aversion revisited, *The journal of finance* 38, 1201–1216.

Nguyen, Linh, and John OS Wilson, 2020, How does credit supply react to a natural disaster? Evidence from the Indian Ocean tsunami, *The European Journal of Finance* 26, 802–819.

Ongena, Steven, and Alexander Popov, 2016, Gender bias and credit access, *Journal of Money, Credit and Banking* 48, 1691–1724.

Puri, Manju, Jörg Rocholl, and Sascha Steffen, 2017, What do a million observations have to say about loan defaults? Opening the black box of relationships, *Journal of Financial Intermediation* 31, 1–15.

Ralph, F Martin, Michael D Dettinger, Mary M Cairns, Thomas J Galarneau, and John Eylander, 2018, Defining atmospheric river: How the glossary of meteorology helped resolve a debate, *Bulletin of the American Meteorological Society* 99, 837–839.

Rehbein, Oliver, and Steven Ongena, 2022, Flooded through the back door: The role of bank capital in local shock spillovers, *Journal of Financial and Quantitative Analysis* 162.

Roberts, Richard AJ, 2005, *Insurance of crops in developing countries*, volume 159 (Food and Agriculture Org.).

Saidenberg, Marc R, and Philip E Strahan, 1999, Are banks still important for financing large businesses?, *Current Issues in Economics and Finance* 5.

Sawada, Yasuyuki, and Satoshi Shimizutani, 2008, How do people cope with natural disasters? Evidence from the great hanshin-awaji earthquake in 1995, *Journal of Money, Credit and Banking* 40, 463–488.

Seneviratne, Sonia, Neville Nicholls, David Easterling, Clare Goodess, Shinjiro Kanae, James Kossin, Yali Luo, Jose Marengo, Kathleen McInnes, Mohammad Rahimi, et al., 2012, Changes in climate extremes and their impacts on the natural physical environment, *A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change (IPCC)* .

Specialized Working Group, on Iran Floods, 2019, *Iran's 2019 Flood, Narration, Analysis, Lessons learned and Suggestions* (Tehran University).

Stocker, Thomas, 2014, *Climate change 2013: The physical science basis: Working Group I contribution to the Fifth assessment report of the Intergovernmental Panel on Climate Change* (Cambridge University Press).

Xiao, Jing Jian, and Rui Yao, 2014, Consumer debt delinquency by family lifecycle categories, *International Journal of Bank Marketing* 32, 43–59.

# VIII. Appendix

## A. Flood Information

### A.1. Extreme Precipitation of Dena Atmospheric River

Figure IIa shows the Vertically Integrated water Vapor Transport (IVT)[16] over the course of the Dena AR that raised to over 350 $kg\ m^{-1}\ s^{-1}$ before reaching Zagros Mountains.[17] Figure IIb demonstrates the extreme precipitation pattern of this 9,000 kilometers AR after hitting the Zagros Mountains. Figure IIc illustrates the rainfall anomalies in the affected region from 1980 to 2019. The 2019 rainy season has recorded the highest seasonal rainfall since 1980, such that the total amount of precipitation in October-March 2019 exceeds two standard deviations above the historical observation. Interestingly, the total rainfall for the same period in the previous year is two standard deviations lower than the historical average. This unpredictable transition can be considered an example of the shift through climate change in the Middle-East (Dezfuli (2020)).

### A.2. Flood in Karkhe River

Dena AR led to two waves of extreme precipitation on 24 to 25 March and 2 April 2019, which caused flash floods in three rivers in the southwest of Iran: The Karkhe, Dez, and Karoon rivers. These rivers originate in the Zagros Mountains, and then they join Tigris and the Euphrates to form the Arvand river, the biggest river in Mesopotamia.

Dena AR caused two heavy rainfalls in less than a week. Both of them led to flash floods upstream of the Karkhe dam, including the Karkhe river and its tributaries, where on average, 271 mm of rain fell. The river water flow exceed 3,350 $kg\ m^3\ s^{-1}$ during the first flood on 24 and 25 March and 6,000 $kg\ m^3\ s^{-1}$ in the following days due to the second flood. Damages were not limited to the lands located upstream of the dam. After the second massive inflow of water, the dam was brought to its maximum capacity, output water flow to downstream areas raised to over 2450 $kg\ m^3\ s^{-1}$, and extensive areas were drowned in water.

[16] IVT is a standard measure for how much water vapor is contained with an atmospheric river.

[17] According to Ralph et al. (2018) IVT greater than 250 $kg\ m^{-1}\ s^{-1}$ is defined as an atmospheric river.

### A.3. Flood in Dez and Karoon Rivers

Most of the damages in the Dez basin were related to the downstream of the Dez dam. From 3 to 7 April, water flow from the dam reached over 3226 $kg\ m^3\ s^{-1}$ such that the river completely overspilled its bank. The situation was the same for the Gotvand dam on the Karoon river, where water flow of 1500 $kg\ m^3\ s^{-1}$ damaged lands located after the dam. Moreover, the Dez flood joined with the Karoon flood that caused massive destruction in Ahvaz, the biggest city in the southwest of Iran.

### A.4. Unaffected Regions

While the Karkhe river and the downstream of the Dez and Karoon rivers' basins were hit by the flood, eastern counties of the region stayed immune. Four dams established on the Karoon river effectively saved their downstream lands from damage. Upstream of Dez river also did not experience a considerable overspill. In addition, the Maroon and Hendijan rivers located in the southeast of the region remained in their banks. Figure II shows the spatial distribution of the affected and unaffected areas by the AR Dena flood.

## B. Tables

## Table I: Variable Description

This table presents the definition of all variables. Panel A defines branch-level variables. Panel B defines individual-level variables.

| Panel A: Branch-Level Variables' Definition | |
|---|---|
| **Variable** | **Description** |
| **Credit Risk** | A continuous index which is constructed from the branch's monthly loan repayment performance. |
| **Branch Score** | The level of the branch activities that contains five categories, level 1 to level 5, where level 1 has the best performance. |
| **Rural Branch** | A dummy variable that is 1 for branches that are located in rural area and 0 otherwise. |
| **Average Balance** | The average amount of accounts' balance. |
| **Size** | Total number of clients that have at least one active account in the branch. |
| **Panel B: Individual-Level Variables' Definition** | |
| **Variable** | **Description** |
| **Relationship** | The number of prior loans which is granted to the farmer before each month. |
| **Fee** | The monthly fee that is paid to the branch for different services. |
| **Saving** | Average monthly balance in saving accounts. Saving account is defined as accounts that farmers cannot withdraw their deposit for at least one year but receive interest on the account balance. |
| **Checking** | Average monthly balance in checking accounts. The branch does not pay interest to checking accounts. |
| **Short-term** | Average monthly balance in short-term accounts. While the deposit-holder can withdraw from Short-term account, branch pays marginal interest to the average balance. |
| **Gender** | A dummy variable that is 1 for female and 0 for male farmers. |
| **Age** | Age of farmer. |
| **Education** | A categorical variable that indicates the farmer's education level, from level 1 to 3. Level 1 is the lowest level of education. |
| **Check Repayment Score** | A categorical variable that indicates the farmer's history in check repayment, from level 1 to 4. Level 1 is the worst repayment history. |
| **Social Reputation Score** | A categorical variable that indicates how much the farmer is known in his county, from level 1 to 4. Level 1 is the worst score. |

## Table II: Summary Statistics and Overlap Measures

This table presents summary statistics and overlap assessment of covariates. Panel A reports the branch-level variables. Definition of all variables are in table I. *Loan* indicates monthly number of granted loans to clients. The study period is from October 2018 to September 2019. The *Normalized Difference* is defined as the difference in means, scaled by the square root of the average of the two within-group standard deviations. *Dispersion Difference* is defined as the logarithm of the treatment and control standard deviations ratio. *Coverage Frequency* equals the fraction of the treated (control) units with covariate values in the tails of the distribution of that covariate for the control (treated) units. *Pscore* is the propensity score estimated by logistic regression of Flood on covariates used in equation II. Overlap measures for *Pscore* indicate overall balance in covariate distribution. *Linearized Pscore* is the logarithm of the odd ratio of *Pscore* (Imbens and Rubin (2015)). Panel B reports the descriptive statistics of farmers' account balances and Age. All balances are in U.S. dollars.

**Panel A: Summary statistics and covariate balance measures for branches**

| | Affected Branches | | Unaffected Branches | | Overlap Measures | | | |
|---|---|---|---|---|---|---|---|---|
| Branch Obs | 80 | | 46 | | Nor Diff | Dispersion Difference | Coverage | |
| Branch-Month Obs | 880 | | 506 | | | | Control | Treatment |
| Loan | Mean | Std. | Mean | Std. | | | | |
| Six months before the flood | 17.89 | 20.03 | 29.30 | 27.71 | | | | |
| Six months After the flood | 17.62 | 25.35 | 31.57 | 59.6 | | | | |
| Credit Risk | 22.16 | 13.93 | 21.19 | 12.79 | 0.0737 | 0.0982 | 0.0217 | 0.0625 |
| Average Balance | 97.46 | 45.94 | 111.95 | 58.47 | -0.273 | -0.245 | 0.087 | 0.1 |
| Size | 16569 | 12397 | 18168 | 12268 | -0.0696 | -0.006 | 0.1739 | 0.0125 |
| Multivariate Measures | | | | | | | | |
| Pscore | | | | | 0.577 | 0.043 | 0.057 | 0.183 |
| Linearized Pscore | | | | | 0.413 | 0.063 | 0.0571 | 0.183 |

**Panel B: Summary statistics and covariate balance measures for farmers**

| | Affected Farmers | | Unaffected Farmers | | Overlap Measures | | | |
|---|---|---|---|---|---|---|---|---|
| Individual Obs | 33598 | | 29324 | | Nor Diff | Dispersion Difference | Coverage | |
| | | | | | | | Control | Treatment |
| | Mean | Std. | Mean | Std. | | | | |
| Saving | 5.57 | 109.05 | 11.16 | 157.53 | -0.037 | -0.37 | 0.0257 | 0.0208 |
| Checking | 66.81 | 389.13 | 46.67 | 530.4 | 0.0270 | 0.072 | 0.02 | 0.0297 |
| Short-term | 53.04 | 560 | 63.84 | 622.82 | -0.0135 | -0.0957 | 0.0279 | 0.0222 |
| Age | 48.24 | 14.5 | 49.30 | 14.64 | 0.0034 | 0.0015 | 0.0279 | 0.0222 |
| Multivariate Measures | | | | | | | | |
| Pscore | | | | | -0.182 | 0.045 | 0.0634 | 0.045 |
| Linearized Pscore | | | | | -0.182 | 0.044 | 0.0634 | 0.045 |

## Table III: Deposit Withdrawals After the Disaster

This table reports the results of estimating equation I. The study period is from October 2018 to September 2019. The benchmark is 2018M10. The dependent variable is the natural logarithm of the average monthly balance of the branch. The reported coefficients are for $Flood_b \times T_t$ in equation I. Column (1) shows the estimation of equation I without controlling for branch's characteristics or branch fixed effects. In column (2), *Branch Score*, *Rural Branch* dummy and *Size* are controlled. Variables are defined in table I. Heteroskedasticity-robust standard errors clustered at the branch level and are reported in parentheses. *, ** and *** indicate significance at 10%, 5%, and 1%.

| | (1) Log(Balance) | (2) Log(Balance) |
|---|---|---|
| 2018M11×Flood | 0.00770 | 0.00770 |
| | (0.0203) | (0.0203) |
| 2018M12×Flood | 0.0115 | 0.0115 |
| | (0.0183) | (0.0183) |
| 2019M1×Flood | 0.0134 | 0.0134 |
| | (0.0170) | (0.0171) |
| 2019M2×Flood | 0.0164 | 0.0164 |
| | (0.0163) | (0.0163) |
| 2019M3×Flood | 0.0158 | 0.0158 |
| | (0.0155) | (0.0155) |
| 2019M4×Flood | -0.155*** | -0.155*** |
| | (0.0527) | (0.0528) |
| 2019M5×Flood | -0.102*** | -0.102*** |
| | (0.0387) | (0.0387) |
| 2019M6×Flood | -0.0898*** | -0.0898*** |
| | (0.0329) | (0.0330) |
| 2019M7×Flood | -0.0163 | -0.0163 |
| | (0.0253) | (0.0254) |
| 2019M8×Flood | -0.0175 | -0.0175 |
| | (0.0243) | (0.0244) |
| 2019M9×Flood | -0.0177 | -0.0177 |
| | (0.0229) | (0.0229) |
| Rural_Branch | | -0.115 |
| | | (0.0978) |
| Size | No | Yes |
| Branch_Score | No | Yes |
| Branch | No | No |
| N | 1488 | 1488 |
| F | 277.6 | 227.3 |
| r2 | 0.353 | 0.487 |

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

## Table IV: Branch Lending After the Flood

This table reports the results of estimating equation II. The study period is from October 2018 to September 2019. April 2019 is excluded from the sample because branches do not grant new loan during New Year holiday. The benchmark is 2018M10. The reported coefficients are for $Flood_b \times T_t$ in equation II. Column (1) shows the estimation of equation II without controlling for branch's characteristics or branch fixed effect. In column (2), *Average Balance*, *Branch Score*, *Rural Branch* dummy and *Size* are controlled. Variables are defined in table I. Heteroskedasticity-robust standard errors clustered at the branch level and are reported in parentheses. *, ** and *** indicate significance at 10%, 5%, and 1%.

| | (1)<br>Loan | (2)<br>Loan |
|---|---|---|
| 2018M11×Flood | -2.108 | -1.945 |
| | (3.277) | (3.354) |
| 2018M12×Flood | 4.205 | 4.497 |
| | (5.178) | (5.297) |
| 2019M1×Flood | 1.084 | 1.303 |
| | (4.940) | (5.055) |
| 2019M2×Flood | 3.414 | 3.435 |
| | (5.048) | (5.166) |
| 2019M3×Flood | 7.275 | 7.471 |
| | (7.578) | (7.749) |
| 2019M5×Flood | 8.562** | 7.843* |
| | (3.650) | (4.085) |
| 2019M6×Flood | 9.155* | 8.546* |
| | (4.682) | (4.704) |
| 2019M7×Flood | -13.80 | -14.70 |
| | (15.76) | (16.10) |
| 2019M8×Flood | -4.437 | -4.768 |
| | (4.523) | (4.594) |
| 2019M9×Flood | -0.305 | -0.595 |
| | (3.498) | (3.560) |
| Average_Balance | | -0.288** |
| | | (0.137) |
| Rural_Branch | | 7.059** |
| | | (2.942) |
| Size | No | Yes |
| Branch_Score | No | Yes |
| Branch | No | No |
| N | 1386 | 1364 |
| F | 11.92 | 10.48 |
| r2 | 0.101 | 0.222 |

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

### Table V: The Role of Relationship Banking in Access to Credit

This table presents the estimation result of equation III using linear probability model regression. The study period is from October 2018 to September 2019. April 2019 is excluded from the sample because branches do not grant new loan during New Year holiday. The benchmark is 2018M10. *Relationship* is defined as the number of granted loans. Column (1) shows the estimation of equation III without controlling for farmers' characteristics. Column (2) includes natural logarithm of the farmers' different accounts' balances. Column (3) controls for *Age*, *Gender*, *Education* and two measures of riskiness, *Check Repayment Score* and *Social Reputation Score*. For variable definition, please refer to table I . Heteroskedasticity-robust standard errors clustered at the branch level are reported in parentheses. *, ** and *** indicate significance at 10%, 5%, and 1%.

| | (1)<br>Pr(New Loan) | (2)<br>Pr(New Loan) | (3)<br>Pr(New Loan) |
|---|---|---|---|
| 2018M11×Flood×Relationship | 0.179 | 0.176 | 0.173 |
| | (0.290) | (0.288) | (0.287) |
| 2018M12×Flood×Relationship | 0.647* | 0.641* | 0.637* |
| | (0.337) | (0.334) | (0.333) |
| 2019M1×Flood×Relationship | 0.192 | 0.185 | 0.178 |
| | (0.280) | (0.278) | (0.278) |
| 2019M2×Flood×Relationship | -0.203 | -0.216 | -0.225 |
| | (0.336) | (0.337) | (0.338) |
| 2019M3×Flood×Relationship | -0.201 | -0.217 | -0.229 |
| | (0.356) | (0.353) | (0.353) |
| 2019M5×Flood×Relationship | 0.770** | 0.750** | 0.736** |
| | (0.365) | (0.357) | (0.355) |
| 2019M6×Flood×Relationship | 0.865** | 0.844** | 0.830** |
| | (0.428) | (0.420) | (0.418) |
| 2019M7×Flood×Relationship | 0.583 | 0.556 | 0.541 |
| | (0.552) | (0.545) | (0.544) |
| 2019M8×Flood×Relationship | 0.665 | 0.634 | 0.616 |
| | (0.487) | (0.476) | (0.473) |
| 2019M9×Flood×Relationship | 0.685 | 0.650 | 0.632 |
| | (0.436) | (0.426) | (0.423) |
| Log(Checking) | | 0.139*** | 0.121*** |
| | | (0.00665) | (0.00689) |
| Log(Saving) | | 0.0166*** | 0.0279*** |
| | | (0.00556) | (0.00616) |
| Log(Short_term) | | 0.0858*** | 0.0734*** |
| | | (0.00668) | (0.00633) |
| Age | | | 0.00216 |
| | | | (0.00206) |
| Gender | | | -0.390*** |
| | | | (0.0655) |
| Education | No | No | Yes |
| Check_Repayment_Score | No | No | Yes |
| Social_Reputation_Score | No | No | Yes |
| N | 679437 | 679437 | 679437 |
| F | 17.11 | 24.45 | 32.11 |

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

## Table VI: Relationship and Age

This table presents the estimation result of equation IV using linear probability model regression. The study period is from October 2018 to September 2019. April 2019 is excluded from the sample because branches do not grant new loan during New Year holiday. Column (1) shows the estimation of equation IV without controlling for farmers' characteristics. *Post* is a dummy variable that is equal to one after the flood. Column (2) includes the natural logarithm of the farmers' different accounts' balances. Column (3) controls for *Gender*, *Education* and two measures of riskiness, *Check Repayment Score* and *Social Reputation Score*. The estimation results for other variables are available upon request. For variable definition, please refer to table I. Heteroskedasticity-robust standard errors clustered at the branch level are reported in parentheses. *, ** and *** indicate significance at 10%, 5%, and 1%.

| | (1)<br>Pr(New Loan) | (2)<br>Pr(New Loan) | (3)<br>Pr(New Loan) |
|---|---|---|---|
| Post×Flood×Relationship | 2.843*** | 2.783*** | 2.769*** |
| | (0.757) | (0.738) | (0.737) |
| Post×Flood×Age | 0.0469*** | 0.0455*** | 0.0456*** |
| | (0.0155) | (0.0152) | (0.0152) |
| Post×Flood×Relationship×Age | -0.0425*** | -0.0417*** | -0.0416*** |
| | (0.0108) | (0.0106) | (0.0105) |
| Log(Checking) | No | Yes | Yes |
| Log(Saving) | No | Yes | Yes |
| Log(Short_term) | No | Yes | Yes |
| Gender | No | No | Yes |
| Education | No | No | Yes |
| Check_Repayment_Score | No | No | Yes |
| Social_Reputation_Score | No | No | Yes |
| N | 617670 | 617670 | 617670 |
| F | 43.05 | 44.46 | 38.80 |

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

## Table VII: Relationship and Gender

This table presents the estimation result of equation V using linear probability model regression. The study period is from October 2018 to September 2019. April 2019 is excluded from the sample because branches do not grant new loan during New Year holiday. Column (1) shows the estimation of equation V without controlling for farmers' characteristics. *Post* is a dummy variable that is equal to one after the flood. Column (2) includes the natural logarithm of the farmers' different accounts' balances. Column (3) controls for *Gender*, *Education* and two measures of riskiness, *Check Repayment Score* and *Social Reputation Score*. The estimation results for other variables are available upon request. For variable definition, please refer to table I. Heteroskedasticity-robust standard errors clustered at the branch level are reported in parentheses. *, ** and *** indicate significance at 10%, 5%, and 1%.

| | (1) | (2) | (3) |
|---|---|---|---|
| | Pr(New Loan) | Pr(New Loan) | Pr(New Loan) |
| Post×Flood×Relationship | 1.499*** | 1.466*** | 1.457*** |
| | (0.551) | (0.540) | (0.539) |
| Post×Flood×Gender | -1.280** | -1.262** | -1.269** |
| | (0.565) | (0.557) | (0.559) |
| Post×Flood×Relationship×Gender | 1.086** | 1.065** | 1.067** |
| | (0.438) | (0.432) | (0.433) |
| Log(Checking) | No | Yes | Yes |
| Log(Saving) | No | Yes | Yes |
| Log(Short_term) | No | Yes | Yes |
| Age | No | No | Yes |
| Education | No | No | Yes |
| Check_Repayment_Score | No | No | Yes |
| Social_Reputation_Score | No | No | Yes |
| N | 617670 | 617670 | 617670 |
| F | 46.14 | 51.45 | 43.24 |

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

## Table VIII: Placebo Test for Branch Lending

This table shows the result of the placebo estimation of equation II. The study period is from October 2017 to September 2018. April 2018 is excluded from the sample because branches do not grant new loan during New Year holiday. The benchmark is 2017M10. Column (1) shows the estimation of equation II without controlling for branch's characteristics or branch fixed effect. In column (2), *Average Balance*, *Branch Score*, *Rural Branch* dummy and *Size* are controlled. Variables are defined in table I. Heteroskedasticity-robust standard errors clustered at the branch level are reported in parentheses. *, ** and *** indicate significance at 10%, 5%, and 1%.

| | (1) Loan | (2) Loan |
|---|---|---|
| 2017M11×Flood | 1.627 | 1.643 |
| | (4.532) | (4.654) |
| 2017M12×Flood | -0.571 | -0.744 |
| | (6.715) | (6.895) |
| 2018M1×Flood | 6.797 | 6.950 |
| | (6.972) | (7.158) |
| 2018M2×Flood | 7.842 | 8.044 |
| | (5.769) | (5.920) |
| 2018M3×Flood | -1.217 | -1.066 |
| | (8.831) | (9.067) |
| 2018M5×Flood | 9.152 | 9.307 |
| | (6.010) | (6.313) |
| 2018M6×Flood | -2.039 | -2.448 |
| | (6.717) | (6.820) |
| 2018M7×Flood | -7.965 | -8.394 |
| | (8.424) | (8.558) |
| 2018M8×Flood | 5.810 | 5.729 |
| | (4.393) | (4.515) |
| 2018M9×Flood | 1.079 | 1.200 |
| | (4.696) | (4.826) |
| Average_Balance | | -0.105 |
| | | (0.0824) |
| Rural_Branch | | 6.087* |
| | | (3.140) |
| Size | No | Yes |
| Branch_Score | No | Yes |
| Branch | No | No |
| N | 1342 | 1320 |
| F | 8.873 | 7.970 |
| r2 | 0.0670 | 0.188 |

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

## Table IX: Placebo Test for Relationship Lending

This table presents the placebo test of equation III using probability linear regression estimation. The study period is from October 2017 to September 2018. April 2018 is excluded from the sample because branches do not grant new loan during New Year holiday. The benchmark is 2017M10. *Relationship* is defined as the number of granted loans. Column (1) shows the estimation of equation III without controlling for farmers' characteristics. Column (2) includes the natural logarithm of the farmers' different accounts' balances. Column (3) controls for *Age*, *Gender*, *Education* and two measures of riskiness, *Check Repayment Score* and *Social Reputation Score*. For variable definition, please refer to table I. Heteroskedasticity-robust standard errors clustered at the branch level are reported in parentheses. *, ** and *** indicate significance at 10%, 5%, and 1%.

| | (1)<br>Pr(New Loan) | (2)<br>Pr(New Loan) | (3)<br>Pr(New Loan) |
|---|---|---|---|
| 2017M11×Flood×Relationship | -0.769 | -0.603 | -0.606 |
| | (0.964) | (0.827) | (0.827) |
| 2017M12×Flood×Relationship | -0.497 | -0.396 | -0.398 |
| | (0.480) | (0.400) | (0.399) |
| 2018M1×Flood×Relationship | -0.146 | -0.103 | -0.107 |
| | (0.271) | (0.277) | (0.278) |
| 2018M2×Flood×Relationship | -0.131 | -0.0985 | -0.105 |
| | (0.283) | (0.288) | (0.290) |
| 2018M3×Flood×Relationship | -0.262 | -0.210 | -0.218 |
| | (0.332) | (0.339) | (0.341) |
| 2018M5×Flood×Relationship | 0.329 | 0.360 | 0.353 |
| | (0.279) | (0.283) | (0.284) |
| 2018M6×Flood×Relationship | -0.488 | -0.444 | -0.452 |
| | (0.480) | (0.479) | (0.481) |
| 2018M7×Flood×Relationship | -0.964** | -0.956** | -0.965** |
| | (0.408) | (0.407) | (0.410) |
| 2018M8×Flood×Relationship | -1.005** | -0.979** | -0.991** |
| | (0.385) | (0.386) | (0.390) |
| 2018M9×Flood×Relationship | -0.287 | -0.271 | -0.286 |
| | (0.279) | (0.278) | (0.281) |
| Log(Checking) | | 0.168*** | 0.154*** |
| | | (0.00796) | (0.00801) |
| Log(Saving) | | 0.0288*** | 0.0426*** |
| | | (0.00848) | (0.00816) |
| Log(Short_term) | | 0.116*** | 0.102*** |
| | | (0.00889) | (0.00796) |
| Age | | | 0.00988*** |
| | | | (0.00350) |
| Gender | | | -0.557*** |
| | | | (0.0770) |
| Education | No | No | Yes |
| Check_Repayment_Score | No | No | Yes |
| Social_Reputation_Score | No | No | Yes |
| N | 779363 | 754150 | 754150 |
| F | 12.64 | 25.03 | 35.06 |

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

### Table X: Placebo Test for Relationship and Age

This table presents the placebo estimation of equation IV using linear probability model regression. The study period is from October 2017 to September 2018. April 2018 is excluded from the sample because branches do not grant new loan during New Year holiday. Column (1) shows the estimation of equation IV without controlling for farmers' characteristics. *Post* is a dummy variable that is equal to one after the flood. Column (2) includes the natural logarithm of the farmers' different accounts' balances. Column (3) controls for *Gender*, *Education* and two measures of riskiness, *Check Repayment Score* and *Social Reputation Score*. The estimation results for other variables are available upon request. For variable definition, please refer to table I. Heteroskedasticity-robust standard errors clustered at the branch level are reported in parentheses. *, ** and *** indicate significance at 10%, 5%, and 1%.

| | (1)<br>Pr(New Loan) | (2)<br>Pr(New Loan) | (3)<br>Pr(New Loan) |
|---|---|---|---|
| Post×Flood×Relationship | -0.832 | -0.731 | -0.745 |
| | (0.817) | (0.786) | (0.788) |
| Post×Flood×Age | -0.0390 | -0.0333 | -0.0334 |
| | (0.0442) | (0.0408) | (0.0409) |
| Post×Flood×Relationship×Age | 0.0138 | 0.0108 | 0.0110 |
| | (0.0185) | (0.0171) | (0.0172) |
| Log(Checking) | No | Yes | Yes |
| Log(Saving) | No | Yes | Yes |
| Log(Short_term) | No | Yes | Yes |
| Gender | No | No | Yes |
| Education | No | No | Yes |
| Check_Repayment_Score | No | No | Yes |
| Social_Reputation_Score | No | No | Yes |
| N | 599510 | 578080 | 578080 |
| F | 11.95 | 36.53 | 44.30 |

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

## Table XI: Placebo Test for Relationship and Gender

This table presents the placebo estimation of equation V using linear probability model regression. The study period is from October 2017 to September 2018. April 2018 is excluded from the sample because branches do not grant new loan during New Year holiday. Column (1) shows the estimation of equation V without controlling for farmers' characteristics. *Post* is a dummy variable that is equal to one after the flood. Column (2) includes the natural logarithm of the farmers' different accounts' balances. Column (3) controls for *Gender*, *Education* and two measures of riskiness, *Check Repayment Score* and *Social Reputation Score*. The estimation results for other variables are available upon request. For variable definition, please refer to table I. Heteroskedasticity-robust standard errors clustered at the branch level are reported in parentheses. *, ** and *** indicate significance at 10%, 5%, and 1%.

| | (1) Pr(New Loan) | (2) Pr(New Loan) | (3) Pr(New Loan) |
|---|---|---|---|
| Post×Flood×Relationship | -0.243 | -0.245 | -0.254 |
| | (0.397) | (0.383) | (0.385) |
| Post×Flood×Gender | -0.0701 | -0.187 | -0.182 |
| | (0.832) | (0.754) | (0.756) |
| Post×Flood×Relationship×Gender | -0.0714 | -0.0151 | -0.0219 |
| | (0.416) | (0.386) | (0.387) |
| Log(Checking) | No | Yes | Yes |
| Log(Saving) | No | Yes | Yes |
| Log(Short_term) | No | Yes | Yes |
| Age | No | No | Yes |
| Education | No | No | Yes |
| Check_Repayment_Score | No | No | Yes |
| Social_Reputation_Score | No | No | Yes |
| N | 599510 | 578080 | 578080 |
| F | 10.52 | 43.26 | 52.88 |

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

## Table XII: Monthly Fee as a Measure of the Relationship

This table presents the estimation result of equation III using linear probability model regression. The study period is from October 2018 to September 2019. April 2019 is excluded from the sample because branches do not grant new loan during New Year holiday. The benchmark is 2018M10. *Fee* is defined as the logarithm of the monthly fee that branch receives from the farmer. Column (1) shows the estimation of equation III without controlling for farmers' characteristics. Column (2) includes the natural logarithm of the farmers' different accounts' balances. Column (3) controls for *Age*, *Gender*, *Education* and two measures of riskiness, *Check Repayment Score* and *Social Reputation Score*. For variable definition, please refer to table I. Heteroskedasticity-robust standard errors clustered at the branch level are reported in parentheses. *, ** and *** indicate significance at 10%, 5%, and 1%.

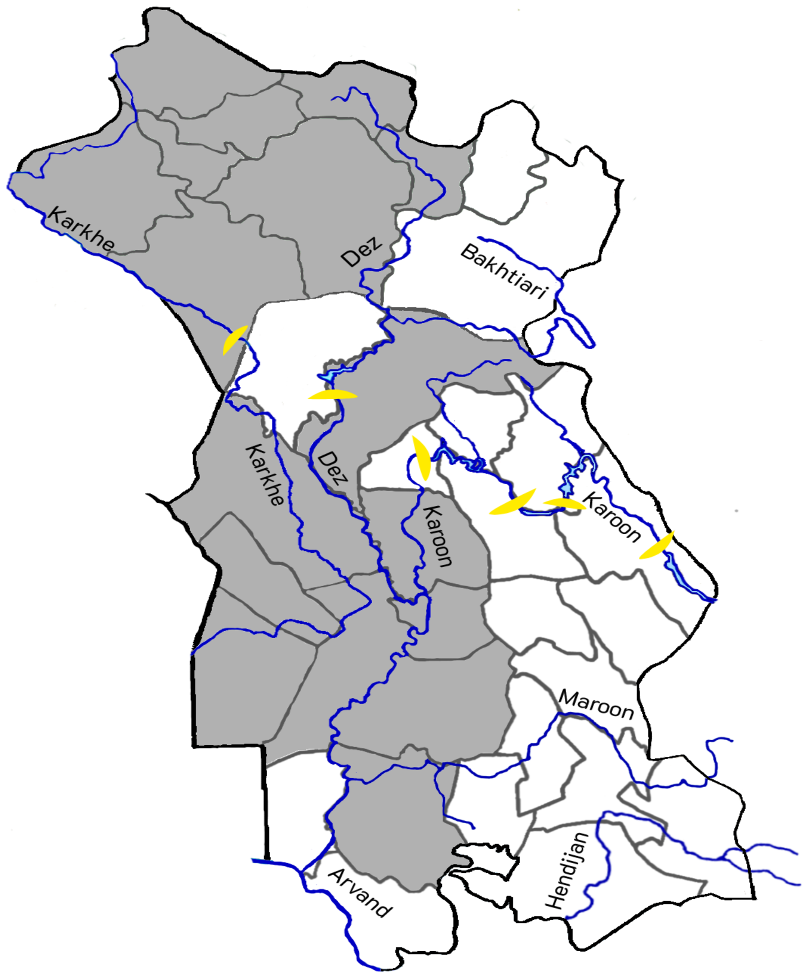
| | (1)<br>Pr(New Loan) | (2)<br>Pr(New Loan) | (3)<br>Pr(New Loan) |
|---|---|---|---|
| 2018M11×Flood×Fee | 0.00432 | -0.00102 | -0.000705 |
| | (0.0672) | (0.0681) | (0.0681) |
| 2018M12×Flood×Fee | 0.0998 | 0.103 | 0.103 |
| | (0.0729) | (0.0734) | (0.0734) |
| 2019M1×Flood×Fee | 0.0698 | 0.0695 | 0.0692 |
| | (0.0708) | (0.0710) | (0.0710) |
| 2019M2×Flood×Fee | 0.0879 | 0.0844 | 0.0845 |
| | (0.0708) | (0.0717) | (0.0718) |
| 2019M3×Flood×Fee | 0.0245 | 0.0271 | 0.0282 |
| | (0.0690) | (0.0694) | (0.0693) |
| 2019M5×Flood×Fee | 0.171** | 0.168** | 0.170** |
| | (0.0780) | (0.0777) | (0.0776) |
| 2019M6×Flood×Fee | 0.195** | 0.192** | 0.194** |
| | (0.0805) | (0.0803) | (0.0802) |
| 2019M7×Flood×Fee | 0.176** | 0.176** | 0.177** |
| | (0.0861) | (0.0858) | (0.0856) |
| 2019M8×Flood×Fee | 0.127* | 0.124 | 0.126* |
| | (0.0758) | (0.0753) | (0.0751) |
| 2019M9×Flood×Fee | 0.133* | 0.126* | 0.127* |
| | (0.0735) | (0.0732) | (0.0731) |
| Log(Checking) | | 0.112*** | 0.101*** |
| | | (0.00698) | (0.00672) |
| Log(Saving) | | 0.0175*** | 0.0270*** |
| | | (0.00658) | (0.00701) |
| Log(Short_term) | | 0.0693*** | 0.0617*** |
| | | (0.00647) | (0.00630) |
| Age | | | 0.00246 |
| | | | (0.00277) |
| Gender | | | -0.453*** |
| | | | (0.0822) |
| Education | No | No | Yes |
| Check_Repayment_Score | No | No | Yes |
| Social_Reputation_Score | No | No | Yes |
| N | 375983 | 370117 | 370117 |
| F | 15.62 | 19.40 | 25.04 |

Standard errors in parentheses
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

## C. Figures

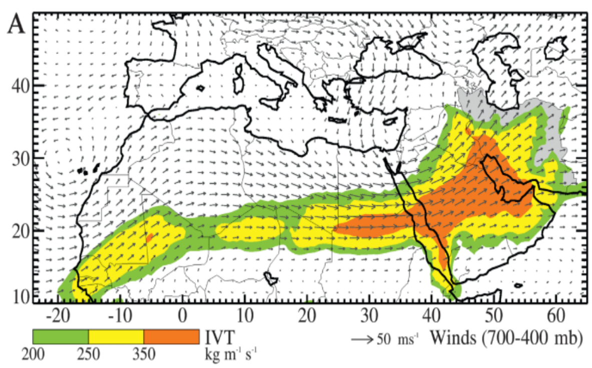
### Figure I: Spatial Distribution of the Flood

This figure plots counties and rivers downstream of the Dena mountains. The affected counties are shown with gray, and rivers are shown with blue color. Yellow crescents denote dams established on rivers.

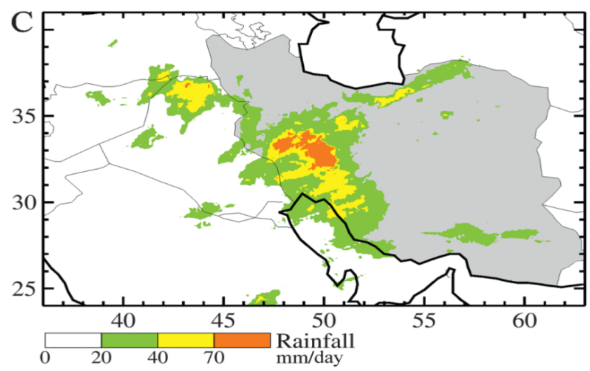


## Figure II: Dena Atmospheric River and Flood

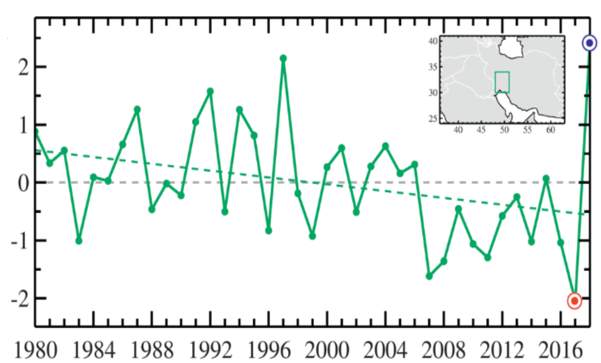
This figure presents the meteorological information of Dena AR and the following flood. Figure IIa exhibits Vertically Integrated water vapor Transport (IVT) for Dena AR. Figure IIb presents two-day mean rainfall rate over the Middle-East at the end of March 2019. Figure IIc presents the total amount of rainfall during the rainy season (October-March) in the southwest Iran since 1980. The total values have been standardized by removing the mean and dividing by the standard deviation. The driest (2017-2018) and wettest (2018-2019) years are marked with red and blue circles, respectively (Dezfuli (2020)).




**(a)**



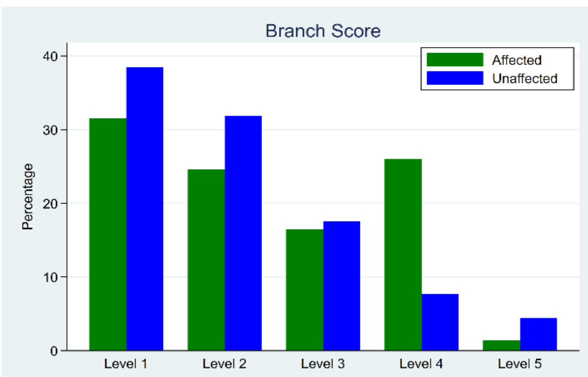

**(b)**



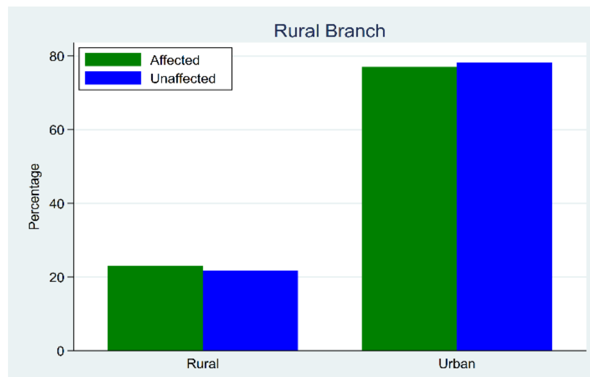

**(c)**

## Figure III: Balance of Branch-level Categorical Covariates Across the Affected and Unaffected Regions

This graph exhibits the balance of branch-level categorical covariates between the affected and unaffected regions. The green color is for the affected and the blue color is for the unaffected farmers. *Branch Score* is a categorical index constructed on branches' performance in credit allocation, attracting new clients, electronic services, opening letter of credit and etc. *Rural Branch* is a dummy variable that indicates whether branch is located in rural area.



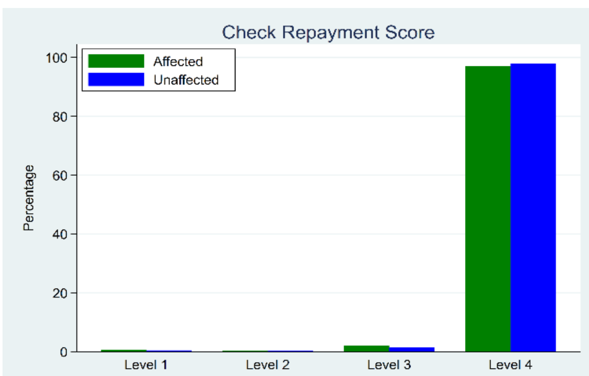

**(a)**



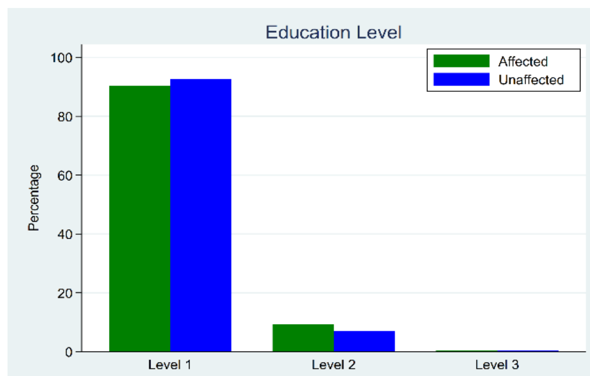

**(b)**

## Figure IV: Balance of Farmer-level Categorical Covariates Across the Affected and Unaffected Regions

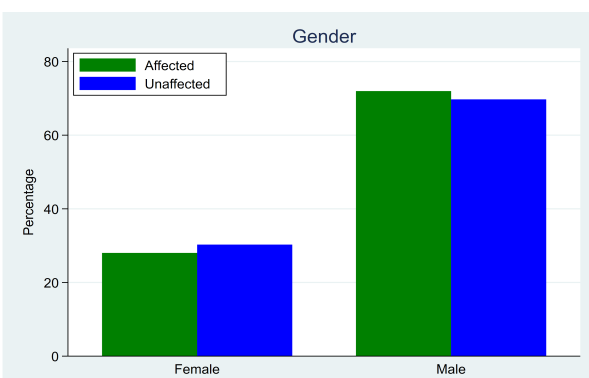
This graph exhibits the balance of farmer-level categorical covariates between the affected and unaffected regions The green color is for the affected and the blue color is for the unaffected farmers. *Gender* is a dummy variable that is 1 for females and 0 for male farmers. *Education* is a categorical variable that indicates the farmer's education level, from level 1 to 3. Level 1 is the lowest level of education. *Check Repayment Score* is a categorical variable that indicates the farmer's history in check repayment, from level 1 to 4. Level 1 is the worst repayment history. *Social Reputation Score* is a categorical variable that indicates how much the farmer is known in his county, from level 1 to 4. Level 1 is the worst score.



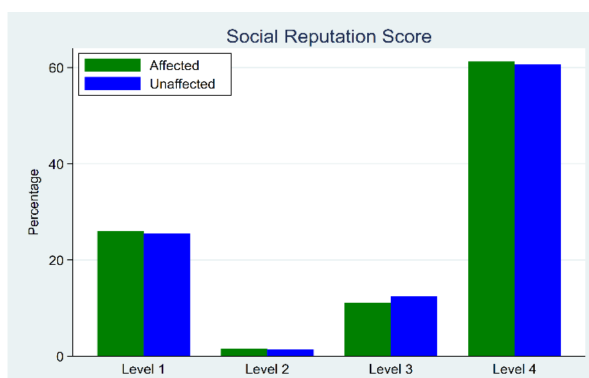

**(a)**




**(b)**




**(c)**




**(d)**

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