

FINANCE AND INEQUALITY: THE DISTRIBUTIONAL IMPACTS OF BANK CREDIT RATIONING.

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ABSTRACT. We analyze how, whom and why banks reduce credit using a natural experiment where massive flooding disproportionately impacted banks with differing exposures to certain geographic areas in Pakistan. Using a unique dataset that covers the universe of all consumer bank loans in Pakistan and this exogenous shock to bank funding, we find three key empirical results. First, banks reduce credit following an increase in their funding costs. Second, banks disproportionately reduce credit to new and less educated borrowers. Third, the reduction in credit is not compensated by more aggregate lending by the less affected banks. The empirical evidence suggests that adverse selection is the leading cause for why banks disproportionately reduce lending to new borrowers. Our results suggest that during periods of bank distress, the poorest individuals may become the most financially vulnerable.

KEYWORDS: Credit markets, capital, liquidity, financial stability, inequality, adverse selection, relationships

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1. INTRODUCTION

In this paper, we analyze how an adverse shock to banks' funding affects their ability to lend. Does it force banks' to reduce credit? If so, who is the marginal borrower? And why? First, we demonstrate that banks disproportionately reduce credit in a way that may exacerbate inequality (greatest reduction in credit to those individuals with little education or credit history). Second, we demonstrate the cause of this disproportionate reduction in credit is due to a market inefficiency, specifically, the increase in a bank's funding cost amplifies the problem of adverse selection in those submarkets.

Banks could raise external financing following a rise in non-performing loans or fall in deposits with no subsequent effect on lending. Yet, raising external financing is slow, costly, and difficult. Information and contracting frictions limit both the ability to rapidly raise external capital and the ability to sell loans (via securitization). If a bank cannot raise external financing – even if there is no change in a borrower's creditworthiness – the bank will have to reduce credit to some borrowers.

If a bank's funding costs rise, the bank may raise interest rates and reduce credit supply. However, the bank may *disproportionately* reduce credit to certain borrowers for both economically efficient or inefficient rationales.

To investigate why banks may disproportionately reduce credit we extend Stiglitz and Weiss [1981]'s model to give possible reasons and empirically investigate the validity of each reason. Finally, we consider the policy and welfare implications of banks' reductions in credit.

First, borrowers may have different interest rate elasticities of demand. In particular, some groups may be sensitive to small changes in interest rates. Similar to a profit maximizing multi-product monopolist whose marginal cost rises, the bank should equalize expected marginal revenues across products. Therefore, our model predicts that the bank credit will fall the most for those groups of borrowers who have the most elastic demand for credit.

Second, a bank's funding cost may depend on the bank's risk-weighted capital ratio. In particular, following a rise in non-performing loans, and subsequently a possible future negative effect on the bank's capital, banks may restrict lending for those loan products with the highest risk-weighted capital weightings to improve their risk-weighted capital ratio.

Third, long-term credit relationships can mitigate problems of adverse selection (Petersen and Rajan [1994], Berger and Udell [1995], Degryse and Van Cayseele [2000]) and subsequently reduce the costs of lending. Therefore we predict banks may disproportionately reduce credit to new borrowers as existing customers are less costly to finance.

Fourth, the increase in a bank's funding cost may lead to the complete unraveling of specific credit markets due to adverse selection or moral hazard (a la Stiglitz and Weiss [1981]). The rise in a bank's funding cost necessitates a rise in the bank's equilibrium interest rate. However, the interest rate rise may induce only the riskiest borrowers in some product categories to accept loans. In turn, this could lead to there being no interest rate that ensures expected average cost is lower than expected repayment in some product categories. Our model predicts that lending will decrease the most – and subsequently defaults will rise the most – in those sectors where the problem of adverse selection is worst.

In designing optimal policy, it is crucial to understand whether banks disproportionately reduce credit efficiently or due to an underlying market failure.

The model's first two predictions are an efficient response to a temporary or permanent rise in financial intermediation costs. Those borrowers who are least willing to accept the higher interest rate will not take loans – this may disproportionately be certain borrowers, such as low income households. This in itself does not suggest a role for policy makers. Similarly, following a deterioration in a bank's capital ratio, due to financial stability concerns banks may prefer to either reduce their risk-weighted capital ratio or increase their equity. Therefore, the reduction in credit to high-risk groups may be an efficient response to improve the bank's financial stability.

The model's third and fourth predictions are an outcome of market failure. Borrowers are unable to borrow due to a problem of adverse selection. The third prediction suggests that banks will in general give preference to their pre-existing borrowers and the fourth prediction suggests the increase in a bank's lending rate may amplify the problem of adverse selection potentially causing some markets to unravel (or face substantially higher interest rates).

To empirically investigate the model's predictions, we use an exogenous natural experiment which caused differential funding costs to banks¹ in Pakistan. In 2010, catastrophic floods hit Pakistan which affected more than twenty million people, destroyed 1.6 million homes and 'were the largest in modern history of Pakistan by several orders of magnitude' (Food and Agriculture Organization [2011], Dartmouth Flood Observatory (DFO) [2015], Fair et al. [2013]). We exploit variation in banks' exposures to the flooded area, which caused banks' deposits to fall (as depositors dissaved to rebuild homes and businesses) and banks' loan portfolios to deteriorate (as loans become more likely to default) to create a measure of the increase in a bank's funding cost.

¹For simplicity of terminology, we refer to any credit dispersing financial institution as a 'bank'. Hence our 'bank' definition includes banks, leasing companies, credit card companies, and non-bank financial institutions.

We use a unique dataset that comprises the universe of formal consumer lending in Pakistan to identify who and why banks reduce credit following a funding shock. The dataset is comprehensive with data on loan origination date, maturity date, product type, and demographic data such as a consumer's education level.

Using a difference-in-difference methodology, we compare loan amounts for individuals between different banks, who had different funding shocks, before and after the flood, in the *non-flooded area*. We focus our attention to lending in the non-flooded parts of Pakistan to overcome the direct effects of the flood shock on borrower demand for loans. Further, to overcome potential county-level demand changes in the non-flooded area, we include county-specific dummies interacted with time fixed effects in all of our specifications. For instance, suppose there are two banks, Bank X, whose exposure to the flooded area is thirty percent of its loan portfolio, and Bank Y whose exposure is sixty percent of its loan portfolio. We predict that Bank Y will reduce lending more. We then empirically compare how Bank X and Bank Y's loans change after the flood in the non-flooded area. We investigate *who* gets relatively less loans by bank Y and relate our results to the model's predictions.

We have three key empirical results: First, banks reduce credit following a funding shock: those banks which suffered a 1 percent funding shock were 0.7 percentage points less likely to lend to an individual one year after the flood in the non-flooded area. Second, banks disproportionately reduce credit to certain borrowers: consumers with little education and no credit history were reduced the most. Third, the reduction in credit was not compensated by more aggregate lending by the less affected banks.

Combining our empirical results with our theoretical predictions we find that adverse selection is the most likely cause for the disproportionate fall in lending to new borrowers and individuals with low education. Our model predicts adverse selection will cause those banks that reduce lending the most following the flood will also have the largest rise in defaults new loans. We have two empirical results which corroborate this prediction. First, loans originated immediately after the flood relative to loans originated immediately before the flood, in the non-flooded area, by the relatively more affected banks, were more likely to default than less affected banks. Second, relative loan defaults rose the most for the more affected banks in those sectors in which those banks reduced lending the most. This is the primary evidence that adverse selection is the key cause of the disproportionate reduction in credit to certain consumer groups.

Given the large reductions in credit to new borrowers (who are predominantly younger), this may have significant long-term implications for individuals' access to credit and for entrepreneurs' ability to develop their businesses.

Our paper contributes to two key questions: One, how spatially interconnected are credit markets? Two, what are the distributional impacts of bank expansions or contractions?

Our identification strategy relies on examining how a shock to banks in one locality (flooded Pakistan) affects bank lending in another locality (non-flooded Pakistan). The identification strategy is inspired by Peek and Rosengren [2000] seminal work which examined how falls in Japanese stock prices affected Japanese bank branches in the United States, and subsequently U.S. credit markets. This identification strategy has been exploited by a growing literature (Popov and Udell [2012], Cetorelli and Goldberg [2012], De Haas and Van Horen [2012], Schnabl [2012]) which quantifies how changes in bank funding affect bank lending using international shocks. Additionally, two recent papers, Chavaz [2014], Cortes and Strahan [2014] examine how domestic bank shocks affect domestic lending.

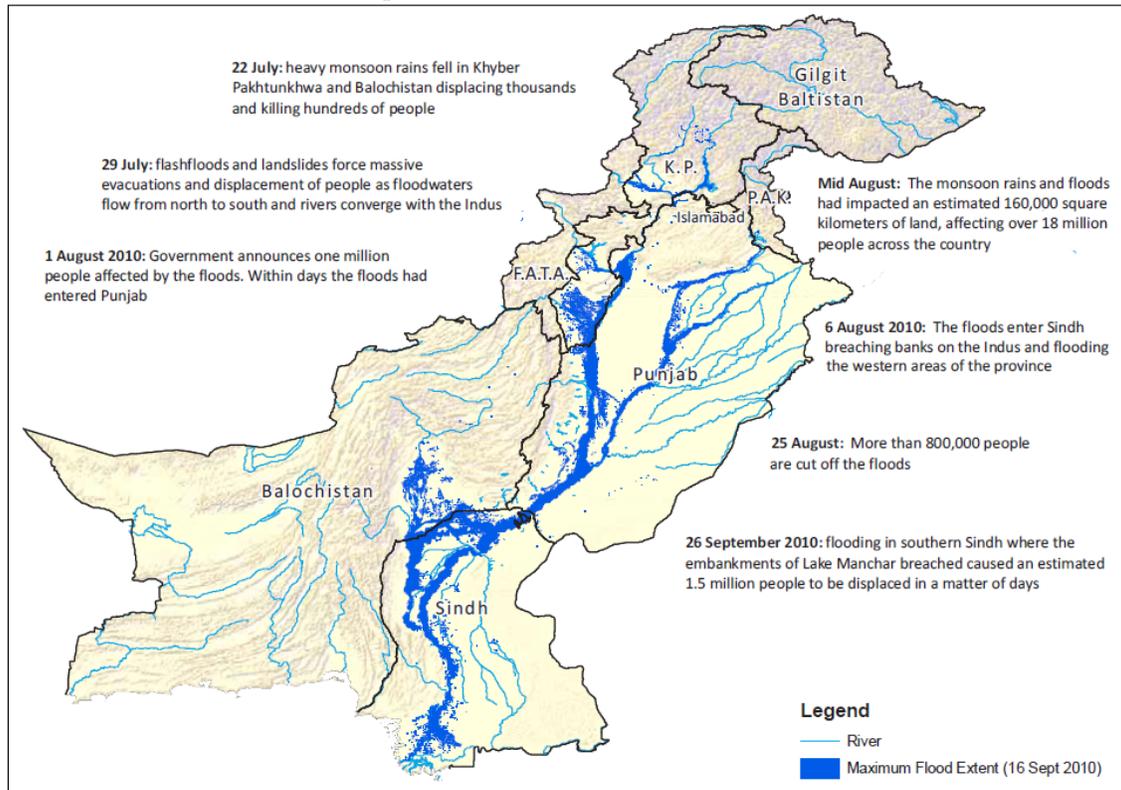
Our key contribution to this literature is through the deeper set of questions our unique dataset can address. We combine banks' exposure to the floods, bank's balance sheet data, individual loan-level data, and borrower characteristics to not only examine whether lending falls by those banks that suffered a funding shock – but to examine *which borrowers* were affected and *why* they were affected.

There is a growing discussion on inequality, especially with access to credit markets. Using panel data on U.S. credit card accounts and a regression discontinuity design, Agarwal et al. [2015] demonstrate that credit expansions do not have homogeneous credit increases for all consumers. In particular, those consumers with the lowest FICO score were offered the smallest rise in their credit limits. We have similar results, those individuals with the least credit history were most likely to be credit rationed. Moreover, our paper's most compelling evidence suggests adverse selection causes this disproportionate effect.

One of our paper's significant advantages is the ability to analyze *all* formal credit lending in a country at the loan level. Previous studies have been able to only examine either: the universe of firm credit, a certain consumer credit product, or a single bank. Therefore, our paper is able to examine how banks alter lending more broadly: do they change which credit products they offer, or the groups they lend to?

Section (2) details the flood and our dataset. Section (3) outlines a model which exhibits four features: (i) differing extent of adverse selection (ii) different demand elasticities (iii) different marginal costs across borrowers and (iv) differing bank funding costs. Section (4) explains how the model's predictions will be tested in the data. Section (5) details the econometric specifications. Section (6) tests the model's predictions and presents the results. Section (8) concludes.

FIGURE 1. Map and Timeline of the 2010 Pakistan Floods



Source:United Nations [2011].

2. EMPIRICAL SETTING

2.1. Pakistan's 2010 floods. “The 2010 floods in Pakistan were one of the most devastating natural disasters of our times” (Food and Agriculture Organization [2011]). The flood covered almost twenty percent of Pakistan's land mass, affected more than twenty million people (11.5 percent of Pakistan's population) displaced 10 million people, and destroyed 1.6 million homes (Food and Agriculture Organization [2011], Dartmouth Flood Observatory (DFO) [2015]). Figure (1) describes the timeline and maps the extent of the flood as of September 2010. Although flooding regularly occurs in Pakistan, “in terms of the number affected and the number displaced, the 2010 floods were the largest in the modern history of Pakistan by several orders of magnitude” Fair et al. [2013]. A total of 191 tehsils² were affected by the floods out of 591 tehsils in all of Pakistan.

²A tehsil is an administrative unit in Pakistan. The average size of a tehsil is 300,000 individuals, and are similar in size (and variance in size) to counties in the United States.

2.2. The effect of the flood on banks. The effect of the flood on banks came through two different channels: (i) a rise in non-performing loans [capital shock] and (ii) a deterioration in deposits [a liquidity shock].

First, banks' existing loan portfolios in the flooded area became riskier. The large devastation affected individuals' and firms' incomes causing existing loans to become more likely to default. Evidence from banks' annual reports makes this clear:

"The year 2010 saw a continuous rising trend in the industry non-performing loans (NPLs) in the domestic banking sector. The mid-year floods further devastated this situation as the exposure of agriculture and SME brought a sharp hit to lenders" MCB Limited [2010].

Similarly, "the bank disbursed an amount of Rs. 69,561 million during 2010 (calendar year) as against Rs. 77,680 million in 2009 showing a decline of 10.5 percent mainly as a result of unprecedented rains/floods due to which agricultural activities in the country were badly affected" Zarai Taraqati Bank Limited [2010].

The deterioration in bank's loan portfolio was also evidenced by the banks' credit ratings. On September 2nd 2010, Moody's changed the financial strength of Pakistan's five biggest banks from stable to negative, citing "the country's main banks face the threat of a wave of non-performing loans as the natural disaster undermines Pakistan's financial fundamentals." Financial Times [2010]

To provide empirical evidence for the deterioration in loan portfolios, in section (6.1) we show that loans in the flooded area were significantly more likely to default than loans in the non-flooded following the flood.

Second, similar to other emerging market economies, Pakistani banks are predominantly deposit financed (an aggregate loan-to-deposit ratio of 0.7 in 2009, IMF [2009]). Therefore, those banks which were primarily based in the flooded area had to contend with decreasing access to retail deposits as individuals and firms dissaved. To provide empirical evidence for the deterioration in bank liquidity, in section (6.1) we show that banks' deposits fell relatively more for those banks that were more exposed to the flooded area.

Overall, banks' funding costs increased following the flood. In particular, those banks which were more exposed to the flooded area, were more affected.

2.3. Data. We use two main sources for our empirical investigation: (i) the credit data comes from the State Bank of Pakistan (SBP) and (ii) the extent of the damage to each tehsil comes from the United Nations and Pakistan's Space and Upper Atmosphere Research Commission (SUPARCO).

The credit and individual data comes from the State Bank of Pakistan's electronic Credit Information Bureau (e-CIB), which legally requires all banks and lending institutions to

submit data on all borrowers. Some of this data has been used before by Khwaja and Mian [2005, 2008], Mian [2006], Khwaja et al. [2011], Choudhary and Jain [2015]. However, previous economists only had access to a partial list of corporate borrowers, whereas, we have access to *every* consumer loan by 72 different financial institutions.³ Our dataset includes every credit card, mortgage, car loan, personal loan, small and medium enterprise loans, and agricultural loan in Pakistan – averaging three million different borrowers and five million different loans in any one month.

The dataset stretches from August 2008 to November 2012. For data management purposes we randomly use 10 percent of the consumer borrowers (we randomize at the borrower-level, to ensure we retain a balanced panel).

Table (1) shows the loan, borrower and lender characteristics for loans in August 2008 (the start of our dataset). To examine how the borrowers differed across lenders that were less or more affected by the floods, we split our dataset by the median bank funding shock. Column 1 has the less affected banks and column 2 has the more affected banks. Those institutions that were most affected by the floods were relatively more likely to be public banks and non-bank financial institutions.

Since the floods affected rural areas more than urban areas, those banks that lent proportionally more in cities were less affected than those that lent more in rural areas. Therefore, since most foreign banks lent mainly in large cities, they were barely affected by the floods. Additionally, since rural populations are generally less educated, the banks that were more affected by the floods lent relatively more to less educated borrowers.

Some of the information collected by the SBP is passed back to the banks to facilitate lending as part of the SBP’s role as a credit registry. The information is provided through “credit worthiness reports.” The consumer’s creditworthiness report detailed various attributes of the loan: the type of loan, the size of the loan, the amount outstanding, and whether the loan was secured. Additionally, the credit report details the consumer’s credit history: how many times the account had been overdue in the last twelve months, and how many payments were late in the last twelve months.

Financial institutions use the credit reporting system as an initial appraisal and to monitor the ongoing creditworthiness of individuals. In an interview a former loan officer remarked: “The e-CIB is used to verify credit history and monitor exposure, both during and after approval [of the loan].” Additionally, the banks’ written notes on individual borrowers mention that credit reports were checked.

³These include public, private, and foreign commercial banks, Islamic banks, development finance institutions, leasing companies, modarbas, micro finance banks, non-bank finance companies and housing finance companies.

3. MODEL

We modify Stiglitz and Weiss [1981] to highlight three key features of how changes in a bank's funding cost can affect who a bank is willing to finance. First, different consumer groups may have different demand elasticities, second, different consumer groups may suffer from differing levels of adverse selection and the change in a bank's marginal cost may differ across different consumer groups.

3.1. Setup. There are multiple different consumer groups, each of measure one. Every consumer has a project that requires funding. The value of the project and the expected success of the project is private information to the consumer. However, the consumer's group is public information. There is a single bank who can finance these projects.

Consumers have limited liability, and will only repay the loan if their project is successful. This causes consumers to choose loans which are socially inefficient, that is, the expected repayment from the loan is lower than bank's funding costs.

We model consumer i in group g 's different project returns and probability of success by the parameter $\theta_{i,g}$, which is uniformly distributed between zero and one. $\theta_{i,g}$ is private information to the consumer, and is neither observable or verifiable by the bank.

A consumer of type i in group g , with a successful project will earn $(\theta_{i,g}/b_g)$. An unsuccessful project will earn zero. We normalize the utility of consumers who do not take a loan to be zero. Note that those consumers with a higher θ_i have a higher earnings if the project is successful.

A consumer of type i with interest rate R_g will have the following utility if the loan is successful (note since the consumer's group is public information, the bank can offer different interest rates to each group) :

$$U_{i,g}(\theta_{i,g}, R_g) = \frac{\theta_{i,g}}{b_g} - R_g$$

where, b_g is a parameter that measures the interest rate elasticity of demand, which varies across groups. A higher b_g ensures that the consumer's demand for a loan is more sensitive to rises in the interest rate.

To complete the idea of adverse selection, even though, agents with a higher $\theta_{i,g}$ have projects – which if successful – earn more, they are less likely to succeed. In particular, the likelihood a project will succeed, as a function of $\theta_{i,g}$, $p(\theta_{i,g})$, is:

$$\begin{aligned} \Pr(\text{Success}|\theta_i) &= p(\theta_{i,g}) = 2(1 - \theta_{i,g})s \\ p'(\theta_{i,g}) &= -2s < 0 \end{aligned}$$

where, s is a parameter that determines the extent of adverse selection in the market. Note, that as $\theta_{i,g}$ rises, the project's successful return rises, but the likelihood of success falls ($p'(\theta_{i,g}) < 0$).

The cost of a bank making a loan to a consumer in group g is $\kappa_g c$. Where κ_g may vary across consumer groups, for instance, the cost of servicing repeat consumers may be lower due to some form of relation-specific capital or the absence of a set-up/switching cost for the bank.

To ensure the problem is well set-up, we assume (i) b_g , $\kappa_g c$, and s are all greater than zero, (ii) s is strictly less than $1/2$ and (iii) $b_g \kappa_g c / s$ is strictly less than $1/3$.

3.2. Timing.

- (1) Nature draws a consumer's type ($\theta_{i,g}$)
- (2) The consumer decides whether to ask the bank for a loan.
- (3) The bank offers an interest rate R_g to the consumer.
- (4) The consumer decides whether to accept or reject the bank's offer.
- (5) If the consumer accepts the bank's offer, the project is undertaken. Otherwise, the game ends and payoffs are realized.
- (6) The project is successful or not, and payoffs are realized.

3.3. Equilibrium. We assume only those agents who could earn a positive rent take a loan.⁴ Therefore, the demand function for loans by consumers of type g is:

$$\begin{aligned}
 (1) \quad D_g(R_g) &= \int 1_{(U_{i,g}(\theta_{i,g}, R_g) > 0)} f(\theta) d\theta \\
 (2) &= \int 1_{(\theta_{i,g}/b_g - R_g > 0)} d\theta \\
 (3) &= 1 - b_g R_g
 \end{aligned}$$

Equation (1) follows from only those consumers who expect a positive utility if their loan succeeds will take a loan. Equations (2) and (3) follow from substituting the uniform distribution of θ into equation (1).

The bank's expected profit from offering loans at an interest rate R is equal to:

$$(4) \quad \pi_g(R_g) = D_g(R_g) \cdot R_g \cdot \tilde{p}_g(R_g) - \kappa_g c D_g(R_g)$$

⁴A simple extension to the model would require consumers to pay some tiny cost to apply for loans. Therefore, only those consumers than earn a positive rent if their project succeeds (those consumers where $\frac{\theta_{i,g}}{b_g} - R_g > 0$) would apply for a loan.

where $\kappa_g c$ is the bank's marginal (and average cost) for offering a loan to a consumer in group g , and $\tilde{p}_g(R_g)$ is the expected repayment if the bank charges an interest rate R_g , which equals:

$$\begin{aligned}
 \tilde{p}_g(R_g) &= \frac{1}{1 - F(\theta|\theta_{i,g}/b_g - R_g > 0)} \int p(\theta_{i,g})|\theta_{i,g}/b_g - R_g > 0 f(\theta) d\theta \\
 &= \frac{1}{1 - b_g R_g} \int_{bR}^1 2(1 - \theta_{i,g})s d\theta \\
 (5) \quad &= (1 - b_g R_g)s = D_g(R_g)s
 \end{aligned}$$

Substituting equation (5) into equation (4), the bank's optimal profit problem becomes:

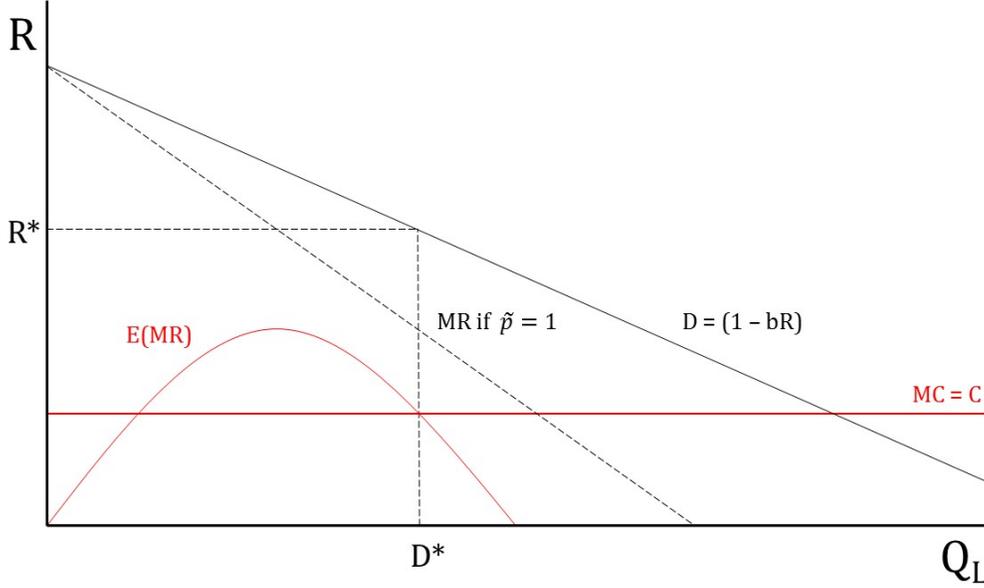
$$E[\pi_g(D_g)] = \max_{D \in [0,1]} D_g \left[\frac{s}{b_g} D_g(1 - D_g) - \kappa_g c \right]$$

The bank will maximize expected profits by adjusting the interest rate, and thereby demand. Assuming the bank's optimal lending is non-zero, the bank's optimal interest rate, will set the marginal revenue of lending equal to the marginal cost of lending.

$$\begin{aligned}
 \frac{\partial E[\pi_g(D_g)]}{\partial D_g} &= \frac{\partial C_g(D_g)}{\partial D_g} \\
 \frac{s}{b_g}(2D_g - 3D_g^2) &= \kappa_g c
 \end{aligned}$$

Figure (2) shows how the expected marginal revenue, demand functions and the equilibrium supply and interest rates are related.

FIGURE 2. How expected marginal revenue and demand are related.



This figure shows how the expected marginal revenue is affected by the adverse selection. As the bank initially lowers the interest rate, the bank's expected marginal revenue actually rises. As the bank lowers the interest rate the bank benefits from the converse of the adverse selection effect. Without adverse selection (if $\tilde{p}_g(D_g)$ was a constant), then the expected marginal revenue curve would be decreasing in the number of loans issued.

Solving the bank's optimal problem (assuming an interior solution) for the optimal provision of loans $D_g^*(b_g, \kappa_g c, s)$ and an interest rate $R_g^*(b_g, \kappa_g c, s)$:

$$D_g^*(b_g, \kappa_g c, s) = \frac{1}{3} \left[1 + \left(1 - 3 \frac{b_g \kappa_g c}{s} \right)^{0.5} \right]$$

$$R_g^*(b, \kappa_g c, s) = \frac{1}{3b_g} \left[2 - \left(1 - 3 \frac{b_g \kappa_g c}{s} \right)^{0.5} \right]$$

If the bank's funding cost increases, the bank will charge a higher interest rate and will reduce the number of loans issued.

3.4. Model's predictions. Using this simple model, we model how a change in a bank's funding cost (in this model proxied by the bank's marginal cost of lending) affects how and who the bank is willing to finance.

Theorem 1. *Assuming the bank continues to lend, the bank will reduce lending more to those consumer groups that have a more elastic demand for loans (higher b_g) following a rise in the bank's funding cost.*

This follows from the bank's expected marginal revenue curve is steeper the lower the elasticity of demand. Therefore, the change in the provision of loans following a rise in the bank's cost will be larger for those consumer groups which are more sensitive to changes in the interest rate. The proof of the theorem (and theorem (2) and (3)) is in subsection (A.1) in the Appendix.

Theorem 2. *Assuming the bank continues to lend, the bank will reduce lending more to those consumer groups where the problem of adverse selection is the largest.*

If a consumer group has a larger problem of adverse selection, as the bank raises the interest rate, it will cause a higher fraction of individuals to no longer be profitable borrowers. This causes the bank's expected marginal revenue to be flatter, thereby a small rise in a bank's cost will have a larger impact in those markets which have a larger problem of adverse selection.

Theorem 3. *Assuming the bank continues to lend, the bank will reduce lending more to those consumer groups for which the marginal cost of lending changes the most (κ_g).*

An increase in a bank's funding cost c will cause the costs to rise the most for those borrowers which have the highest cost of lending, κ_g , this will cause lending the most to fall in those consumer groups.

4. MAPPING THE MODEL TO THE DATA

As bank's funding costs rise, banks will ration credit. To differentiate between the model's four different predictions in section (3.4), we will identify the how, and why bank's ration credit by assessing the different theories' predictions for the credit market.

4.1. Prediction consistent with higher interest rates amplifying the problem of adverse selection causing greater reductions in lending. To explore if adverse selection is driving the disproportionate rationing of credit, we need to demonstrate that the composition of borrowers is different following the flood. Our model suggests that as banks reduce credit, banks choose a higher interest rate causing only riskier borrowers to accept the loans. Therefore, we would expect those banks that had the largest funding shock also had the largest rise in default rates, for those loans originated immediately after the flood relative to loans originated immediately before the floods.

4.2. Prediction consistent with bank costs are lower for existing customers.

If we assume that banks and consumers develop some form of relation-specific capital through a repeated relationship, then banks may be more willing to continue to finance existing customers at the detriment to new customers as their funding costs rise. Therefore banks would prefer to only lend to their own existing customers at their costs rise.

4.3. Prediction consistent with bank costs are higher for loans which have a higher Basel II risk weights.

If following the flood, the more exposed banks need to improve their risk-weighted capital ratio more, then the more affected banks may relatively reduce lending more for those loans which have a higher Basel II risk weight.

4.4. Prediction consistent with different demand elasticities causing banks to reduce credit the most for the most demand elastic customers.

If different demand elasticities cause banks to disproportionately reduce credit to certain borrower groups, we should see no change in overdue rates in those sectors were lending falls the most.

5. THE EFFECT OF THE FUNDING SHOCK ON BANK LOANS.

5.1. Econometric specification. The paper's main question is: What is the effect of a funding shock on a bank's ability to lend? We answer this question using a natural experiment that exogenously increased banks' non-performing loans (NPLs) and reduced banks' deposits in way that varied across banks. We argue this exogenous and unexpected surge in NPLs and reduction in deposits raised a bank's funding cost. We investigate did banks' compensate for this increase in costs by decreasing leverage and subsequently decreasing lending? If so, who did banks reduce lending to, and by how much?

The main source of identification in the paper will be to compare loan amounts for individuals between different banks who had different funding shocks, before and after the floods. To construct our measure of a bank's funding shock, we use a bank's exposure to the flooded area in Pakistan.

We estimate equations of the form:

$$Y_{bpit} = a_{bpi} + a_{ct} + \beta_1 \times \text{Time}_t \times \text{Funding Shock}_b + \beta_2 \times \text{Post Time}_t \times \text{Funding Shock}_b + \epsilon_{bpit}$$

The unit of observation is at the bank-product-individual-date level, so Y_{bpit} is the variable of interest at bank b , credit-product p for individual i in quarter t . For example, it could be the size of the credit card amount outstanding by individual i at bank b , in quarter t . Funding Shock $_b$ is a continuous variable between zero and one, and measures the bank's

exposure to the flooded area. ‘Time’ is the number of quarters since August 2008, and ‘Post Time’ is the number of quarters since the start of the flood (September 2010) and zero for all quarters before the flood.

All the main regressions contain a tehsil interacted with date fixed effect, α_{ct} . This fixed effect ensures that we are estimating the effect of the funding shock only using banks which were differentially affected by funding shocks while controlling for any differences in tehsils over time (tehsils are similar to counties in the United States). For instance, any aggregate demand shifts over time across tehsils would be accounted using these fixed effects. The inclusion of a bank dummy interacted with a product dummy interacted with an individual dummy fixed effect, a_{bpi} , ensures we are controlling for any individual-bank-product specificity (this also ensures we are including a fixed effect for each observation in the panel’s cross-section).

In contrast to a standard difference-in-difference specifications, we add a linear time trend for the funding shock ($\text{Time}_t \times \text{Funding Shock}_b$). We introduce this extra variable to ensure we do not conflate a pre-existing linear trend in bank lending with the effect of the funding shock on a bank’s lending. Further, you would expect the effect of a funding shock to appear in the data over time (as the rate of new loans issued and rate of existing loans renewed decreases). This suggests the optimal specification would be to estimate a trend break (β_2) in the volume of active loans (as opposed to a level change in the number of existing loans following the funding shock). The coefficient of interest, β_2 , should be interpreted as the causal effect of a 1 percent change in funding shock on a bank’s willingness to lend per quarter.

We create a measure for the ‘Funding Shock $_b$ ’ for bank b by multiplying the damage in each tehsil, c , by the fraction of bank b ’s loan portfolio in tehsil c and summing over all flooded tehsils.

Definition 1. The ‘Funding Shock $_b$ ’ for bank b is defined as the fraction of the bank’s loan portfolio that was exposed to the flooding⁵:

$$(6) \quad \text{Funding Shock}_b = \sum_c \frac{(\text{Bank } b\text{'s loans outstanding in tehsil } c) \times (\text{fraction of tehsil } c \text{ flooded})}{\text{Bank } b\text{'s total loans outstanding}}$$

For robustness, we use alternative measures for the banks’ funding shocks. We restrict the sample to those banks which report Tier 1 capital to the State Bank of Pakistan, and then replicate the main specifications by replacing the denominator in equation (6) with the bank’s total tier 1 capital. Section (7) details these robustness checks in more detail.

The standard errors ϵ_{bpit} are clustered at the bank level.

⁵All loan amounts are as of August 2008 – eighteen months before the start of the flood.

5.1.1. *Outcomes of interest.* There are two main outcomes of interest in the paper:

- Active loan $_{bpit}$
- Log loan size $_{bpit}$

“Active loan $_{bpit}$ ” is a dummy variable equal to one if individual i at bank b at date t has an outstanding loan in credit product p .

“Log loan size $_{bpit}$ ” is defined as the log of loan size outstanding in date t at bank b for product p by individual i . If there is no active loan, this is coded as missing. Given the endogeneity that a positive loan size is conditional on being granted a loan, our results mainly concentrate on the extensive margin—whether consumers get loans or not.

6. RESULTS

As a precursor to our main results we first demonstrate that immediately after the floods, loans in the flooded area were more likely to default (capital shock) and, for those banks that more exposed to the flooding area, their deposits relatively decreased (liquidity shock). These two effects suggests the floods caused a funding shock to banks. Second we show, immediately following the flood, those banks with larger funding shocks relatively decreased lending more in the non-flooded area. Third, using these initial results, we show that banks with larger funding shocks reduced credit more to consumers with little education or credit history. Fourth, we show that the evidence suggests banks disproportionately reduced credit across consumer groups due to differing degrees of adverse selection within consumer groups. Finally, we show that the reduction in credit is not compensated by more aggregate lending by the less affected banks suggesting both partial and general equilibrium effects.

6.1. Both a capital and liquidity shock for banks causing an increase in banks’ funding costs. In figure (6), we show that loans in the flooded area were more likely to default immediately after the floods (capital shock). To construct figure (6) we regress whether a loan defaults on a dummy variable for whether the loan was originated in a flooded area interacted with a set of quarter dummies and additional fixed effects⁶. The figure plots the resultant coefficients for each interacted flood and quarter dummy. The figure clearly shows that default rates in the flooded area rapidly climbed following the flood. This corroborates the information in banks’ annual reports and suggests those banks that were exposed to the flooded area suffered a capital shock.

⁶Following Hertzberg et al. [2011] we code a loan to be overdue in only the first quarter it is observed as overdue. To ensure we do not double count our overdue observations we code the loan as missing for all loan observations after this quarter.

In figure (7) we show a dramatic, sudden and sustained relative decrease in banks' liquidity for bank's with greater exposure to the floods (liquidity shock). To do this, we show that, following the flood, average deposits for more affected banks (defined as those banks with an above median funding shock) declined relatively to less affected banks. This evidence is consistent with individuals dissaving and reducing deposits at banks.

6.2. Those banks with a larger funding shock relatively reduced credit more than those banks with smaller funding shocks. Those banks which suffered a larger funding shock, immediately following the flood, reduced lending in the non-flooded area. Figure (8) shows the difference in lending, pre- and post- flood between banks with different funding shocks. We plot figure (8) by regressing whether a loan is active on the magnitude of the bank's funding shock interacted with a full set of time dummies—while controlling for (i) a bank dummy interacted with a borrower dummy interacted with a credit product dummy fixed effect (α_{bip}) and (ii) a tehsil dummy interacted with a time dummy fixed effect (α_{ct}). These fixed effects ensure that we control (i) for any bank-borrower specificity and (ii) for any aggregate credit changes within the tehsil over time.

In figure (8), we show prior to the flood, the banks which suffered the largest funding shock were expanding the most (as seen by an upwards sloping trend line prior to the floods). But immediately after the flood, these banks reduced lending and stopped expanding relative to the banks which had a smaller funding shock (as seen by an almost flat trend line following the flood). This is the primary evidence that the funding shock relatively reduced lending.

The estimates in table (2) demonstrate that a 1 percentage point increase in the funding shock led to a 0.7 percentage point decrease in the likelihood a bank will offer a loan to a given borrower a year after the flood. The median (weighted by bank size) funding shock to a bank was just under 1 percent, suggesting that the funding shock caused 14,000 fewer loans in the non-flooded area, one year after the flood.⁷

6.3. Who did banks reduce credit to? Those banks that suffered a larger funding shock, immediately following the flood, relatively reduced lending to borrowers with little credit history and little education in the non-flooded area..

In table (3) we do similar regressions to table (2), except we separate our results by the consumer's educational attainment. The more affected banks relatively reduce lending for those consumers with the lowest educational attainment. Yet, there is no statistically significant effect on those consumers with a graduate or post-graduate degree.

⁷There was a total of 2 million borrowers in the non-flooded area prior to the flood. Therefore multiplying 0.7 (casual effect of the flood shock) by 1 percent (median magnitude of the funding shock) by 2 million (number of borrowers) gives 14,000 fewer borrowers.

In table (4), column 1, we analyze only whether new borrowers (those that did not have a loan in August 2008) were less likely to get a loan at more affected banks following the flood. When we analyze only the new borrowers, we see that the more affected banks were statistically significantly relatively less likely to offer new loans to new borrowers following the flood. Whereas, in column 2, where we analyze only those borrowers who had an active loan in August 2008, banks were not statistically significantly less willing to offer these individuals new loans.

Overall, the largest effects of the banks' reduction in credit following their funding shock is on those consumers with little credit history and little education.

6.4. Why did banks reduce lending disproportionately to some consumers?

6.4.1. *Did adverse selection or moral hazard cause banks to reduce lending disproportionately to some groups?* Rises in banks' funding costs could be passed onto consumers through higher interest rates. However this may cause a different set of borrowers. For instance, the higher interest rates may cause a riskier pool of borrowers to take loans (adverse selection) or the same borrowers to take riskier actions (moral hazard). In turn, this may lead banks to charge even higher interest rates and cause even greater reductions in credit. Consistent with this mechanism, our model predicts that those banks with the largest funding shock would also have the largest rises in default rates following the flood.

We first test the model's adverse selection prediction. To do this, we test whether loans originated after the flood by the more affected banks were relatively more likely to default. As before, we examine only loans originated in the non-flooded area. Furthermore, to isolate the change in banks' lending practices, we examine only loans originated within a narrow window around the floods—120 days before, and 120 days after the flood. We follow each loan up to 600 days from origination (or until it ends, whichever is earlier).

Specifically, we run regressions of the form:

$$\text{Overdue Ever}_{bpi} = \beta_1 \times \text{Originated Post Flood}_{bpi} + \beta_2 \times \text{Originated Post Flood}_{bpi} \times \text{Funding Shock}_b \\ + \text{Controls} + \epsilon_{bpi},$$

where $\text{Overdue Ever}_{bpi}$ is a dummy variable equal to 1 if the loan for bank b , in product p , for borrower i , goes overdue within the first 600 days of being originated or before maturing, whichever is sooner, and 0 otherwise.⁸ $\text{Originated Post Flood}_{bpi}$ is a dummy variable equal to 1 if the loan was originated within the 120 days following the flood, and 0 if the loan was originated within the 120 days before the flood.

⁸In contrast to the regressions in the previous section, we collapse our data by date to exploit the loan origination dates.

The results in table (5) columns 1 and 2 show that default rates relatively rose for those loans originated after the flood by the more affected banks in the non-flooded area. This is the primary evidence that more affected banks' pool of borrowers became riskier following the flood.

To provide further causal evidence for banks changing who they lend to following their funding shock, we do a placebo test. In columns 3 and 4, we do the same specifications as in columns 1 and 2, except we use those loans originated just before and after *September 2009* – exactly one year before the flood. In the placebo test there is no difference in default rates between the more and less affected banks. This provides further evidence that it was the banks' funding shock (caused by the floods) which caused the more affected banks to take a riskier portfolio of borrowers.

Finally, if adverse selection is the key reason for the disproportionate reduction in lending, the model predicts that the larger the fall in demand, the larger the increase in default rates. To test this prediction, in table (6), we include dummies for an individual's education level interacted with when the loan was originated and the bank's funding shock. This triple difference-in-difference specification tests whether those loans originated to individuals with little education, following the flood, at those banks with the largest funding shock were more likely to default.

In figure (9) we show how the relative reduction in credit across education group and the relative rise in overdue rates are related for the more affected banks in the non-flooded area. Less educated individuals were less likely to receive a loan from more affected banks and were more likely to default on their loans following the flood. This is compelling evidence that adverse selection is driving the disproportionate large reduction in credit to certain consumers.

Is the evidence consistent with moral hazard causing disproportional reduction in lending? If banks' raise interest rates this will cause a borrower's return to fall, which in turn, may lead borrowers to take riskier actions causing higher default rates.

To explore this possibility we exploit the intertemporal differences in maturity dates. We showed that the more affected banks were less likely to offer loans following the flood. Subsequently borrowers' *dynamic repayment incentive*—the incentive to repay the current loan to ensure they get new loans—will also fall. If moral hazard was driving the reduction in credit to certain borrowers, due to the dynamic repayment incentive, we would expect the loans that matured just after the floods, at the more affected banks, would be relatively more likely to default.

Similar to our adverse selection tests, we test the model's moral hazard prediction by comparing loans that *matured* 120 days before and 120 days after the flood..

We present our results in table (7) and table (8). Table (7) shows that default rates did not relatively rise for those loans that matured just after the flood for the more affected banks in the non-flooded area. Table (8) shows relative default rates for the more affected banks did not rise systematically for those with low education. Furthermore, in figure (10) we show that default rates did not relatively rise in any pattern which is related to the groups that had the largest reductions in credit.

Overall, our results are suggestive that adverse selection—and not moral hazard—drove the disproportionate reduction in credit.

6.4.2. *Did banks' preference for pre-existing customers cause banks to reduce lending disproportionately to some groups?* If banks' costs for servicing new customers are larger than for servicing existing customers, we may expect a disproportionate reduction in credit to new consumers following a bank funding shock. For example, costs for new customers may be higher due to the lack of bank-customer-specific capital. Consistent with this mechanism, you would expect similar reductions in credit to *all* of a bank's new customers—not only those without a prior credit history.⁹ To test this conjecture, we separate a bank's new customers into two mutually exclusive groups: (i) those consumers that have a loan relationship with *some other bank* (as of August 2008)—therefore, there is hard credit information in the borrower's credit report—and (ii) those consumers that do not have a loan relationship with *any bank* (as of August 2008).

In table (4) columns 3 and 4, we examine how banks' lending patterns changed for new consumer lending relationships following the flood. The more affected banks were significantly less likely to lend to those consumers who did not have any credit history. In contrast, the more affected banks were willing to start new lending relationships with consumers who had a prior credit history at similar rates as the less affected banks.

Therefore, consumers with some credit history were able to make new lending relationships—even if the bank had suffered a large funding shock. Only those consumers with no credit history were unable to make a new lending relationship. These results suggests the disproportionate reduction in credit to new consumers is not being driven by the presence of a bank-customer-specific capital, or a repeated bank-customer relationship..

6.4.3. *Did bank capital regulation cause banks to reduce lending disproportionately to some groups?* Those banks that were more exposed to the floods may try to maximize their risk-weighted capital by reducing lending in the categories that have the largest Basel II risk weights, the most capital expensive loans.¹⁰ To explore this conjecture, we examine if

⁹Once a consumer has a loan, her biographic and credit information would be recorded within the e-CIB database which is accessible to other eligible financial institutions.

¹⁰In 2010, Pakistan followed the standardized approach when calculating loan's risk weights.

the more affected banks were more likely to increased mortgage lending, relative to less affected banks, since loans collateralized by residential property only have a risk weight of 35 percent, whereas all other retail loans have a risk weight of 75 percent (assuming the loans are not overdue).

In table (9) column 1, we use a triple difference-in-difference estimator to examine whether the more affected banks relatively *increased* mortgage lending relative to less affected banks following the floods. Our results, clearly show that our 'PostTime \times Mortgage \times Shock' variable is both negative and not statistically significantly different to zero.

Our results suggest that the disproportional reduction in credit to borrowers with little education or credit history is not being driven by differing risk-weights on bank loans. If the more exposed banks relatively preferred lending with lower risk weights, we should observe higher relative mortgage lending for these banks. Not only do we find a non-statistically significant effect, but we also find that the point estimate is negative.

6.4.4. *Did banks' preference for specialization or maintaining market share cause banks to reduce lending disproportionately to some groups?* The more affected banks may prefer to reallocate credit to those loan categories in which they are heavily specialized or to those sectors in which they have a large market share (De Jonghe et al, 2016). To explore this conjecture, we construct the following measures for a bank's product specialization, and a bank's product market share. As previously, we construct the measures using loan balances as of August 2008.

$$\text{Bank product specialization}_{bp} = \frac{\text{total lending in product } p \text{ by bank } b}{\text{total lending by bank } b}$$

$$\text{Bank product market share}_{bp} = \frac{\text{total lending in product } p \text{ by bank } b}{\text{total lending in product } p \text{ by all banks}}$$

We interact our measures of bank product specialization, and bank product market share, by our time variables and our funding shock variables to examine if specialization or product shares may be driving the disproportionate reduction in lending to some groups.

In table (10) column 1, we examine if the more affected banks reallocated credit toward those loan categories for which they were more specialized. The small, negative, and not statistically significant coefficient for 'PostTime*Bank Product Specialization*Shock', suggests that product specialization was not driving our disproportionate reduction in credit for some consumer groups.

In column 2, we examine if the more affected banks reallocated credit toward those loan categories for which they have a larger market share. Similar, to our results in column 1, we see a small, and not statistically significant coefficient for 'PostTime*Bank Product

Market Share*Shock'. This result suggests that more affected banks were not prioritizing those products for which they have a large market share.

Overall, the results suggest that the more affected banks did not prioritize credit towards those products for which they are either heavily specialized or have a large market share.

6.5. Did less affected banks compensate for the fall in lending by the more affected banks? To explore the general equilibrium effects to total lending from banks' funding shocks, we consider how lending changed in different tehsils depending on the original banking structure in that tehsil. In particular, we create a measure of the tehsil's shock by noticing that some banks lent more in some tehsils than others. Therefore, those tehsils that were dominated by the more affected banks should also be more affected—since these tehsils will have the largest reduction in credit.

If there was no aggregate credit shock to the non-flooded tehsils following the flood, this would require the less affected banks to lend relatively more in those tehsils that were more affected. To explore this possibility in more detail, we define a 'tehsil shock' in the following way:

Definition 2. The '*tehsil shock_c*' to tehsil c is defined as the fraction of the tehsil's lending (as of August 2008) which was exposed to the funding shock¹¹.

$$(7) \quad \text{Tehsil shock}_c = \sum_b \frac{(\text{Funding cost shock}_b) \times (\text{fraction of lending in tehsil } c \text{ by bank } b)}{\text{Tehsil } c\text{'s total loans outstanding}}$$

The tehsil shock corresponds to the mean bank funding shock (weighted by bank lending) in that tehsil. Figure (3) shows the distribution of tehsil shocks across all non-flooded tehsils.

Understanding the general equilibrium impacts are crucial for the welfare and policy implications. If a single bank is (or many banks are) unable to distribute credit, one important mechanism to mitigate the reduction in credit would be for other banks to increase their supply of credit—in such a way that total credit in the tehsil does not fall.

In table (11), we interact banks' funding shock with the tehsil's shock. The results suggest there was no substitution of credit from the more affected banks to the less affected banks in those tehsils that were affected the most. The coefficient on 'PostTime × Funding Shock × Tehsil Shock' is positive and not statistically significant. If the less affected banks lent more in the more affected tehsils, this coefficient would be negative.

¹¹All loan amounts are as of August 2008 – eighteen months before the start of the flood.

Our results show that following banks' funding shock there was no aggregate substitution of credit to the less affected banks. This suggests that shocks to individual banks can have large distributional impacts, which are not offset by greater lending by less affected banks.

7. ROBUSTNESS

In this section we examine alternative predictions for how the flood could affect lending in both the flooded and non-flooded area.

7.1. Alternative reasons why the most affected banks may have reduced credit the most in the non-flooded area.

7.1.1. *Is this a credit demand story?* Specifically, did credit fall in the non-flooded area by the most affected banks due to higher credit demand in the flooded area? The large destruction in the flooded region could spur large credit demand in the flooded region – consumers and firms, after all, need to rebuild homes, factories and inventory. We might expect that banks which had a larger initial exposure to the flooded area would also have a comparative advantage in lending more in the flooded area following the flood – better institutional and borrower knowledge, larger branch network (this would be consistent with Chavaz [2014]). Then the large relative decreases in the non-flooded area by the most affected banks could be a consequence of increased credit demand in the flooded area. However, the empirical results in table (12) in Appendix (B) refute this explanation.

The banks that were exposed more to the flood, relatively reduced lending more in the flooded area following the flood. A 1 percent increase in the funding shock was correlated with a bank being 0.6 percentage points less likely to lend to a borrower relative to other banks in the flooded area one year after the flood.

7.1.2. *Are the results distorted by non-bank financial institutions?* Our dataset has 72 financial institutions that lend to consumers. One potential concern is that only 31 of these institutions are banks—the rest are non-bank financial institutions, such as credit card companies and development agencies. These institutions are generally smaller and do not take deposits. Therefore, we may expect that these institutions will react differently to banks following the funding shock. To explore this possibility we restrict our dataset to only banks and replicate the regressions in table (2). Table (13) in Appendix (B) shows the results are very similar, whether we include or exclude the non-bank financial institutions. These results suggest that both the large formal banking sector and the smaller shadow banking sector were similarly affected by the funding shock.

8. CONCLUSION

Well functioning credit markets are crucial for the effective allocation of resources, and in turn, economic growth. However, shocks to financial intermediaries can hinder their effectiveness. These shocks may take many different forms such as: a surge in mortgage defaults (e.g. global financial crisis), large ‘hot-money’ outflows (e.g. Asian financial crisis), international sanctions (e.g. Pakistan’s nuclear testing), or U.S. monetary policy changes (e.g. ‘Taper Tantrum’ in emerging markets following the end of the U.S.’ Quantitative Easing program). Exploring how these shocks to banks and through their role as financial intermediaries to borrowers is often complicated by other contemporaneous changes in the economy. To overcome this problem, this paper uses a bank’s exposure to unprecedented large floods in Pakistan to explore how a change in a bank’s funding cost, affects how much it lends, and who it lends to, and why it’s lending decisions change.

We have three key empirical results: First, banks ration credit following a funding shock: those banks which suffered a 1 percent funding shock were 0.7 percentage points less likely to lend to an individual one year after the flood in the non-flooded area. Second, banks disproportionately reduce credit to certain borrowers: consumers with little education and no credit history were rationed the most. Third, the reduction in credit was not compensated by more aggregate lending by the less affected banks.

Combing our empirical results with our theoretical predictions we find that adverse selection is the most likely cause for the disproportionate fall in lending to new borrowers and individuals with low education. First, loans originated immediately after the flood, in the non-flooded area, by the relatively more affected banks were more likely to default than less affected banks. Second, relative loan defaults rose the most for the more affected banks in those sectors in which those banks reduced lending the most. This is the primary evidence that adverse selection is the key cause of the disproportionate reduction in credit to certain consumer groups.

Our paper demonstrates that individuals who have the least capacity to signal their credit-worthiness – either through a public credit history or through education, were most likely to be a bank’s marginal borrower. Further, these individuals are marginal due to financial frictions (adverse selection) as opposed to more elastic demand for loans. Therefore the rise in intermediation costs amplified pre-existing market failures.

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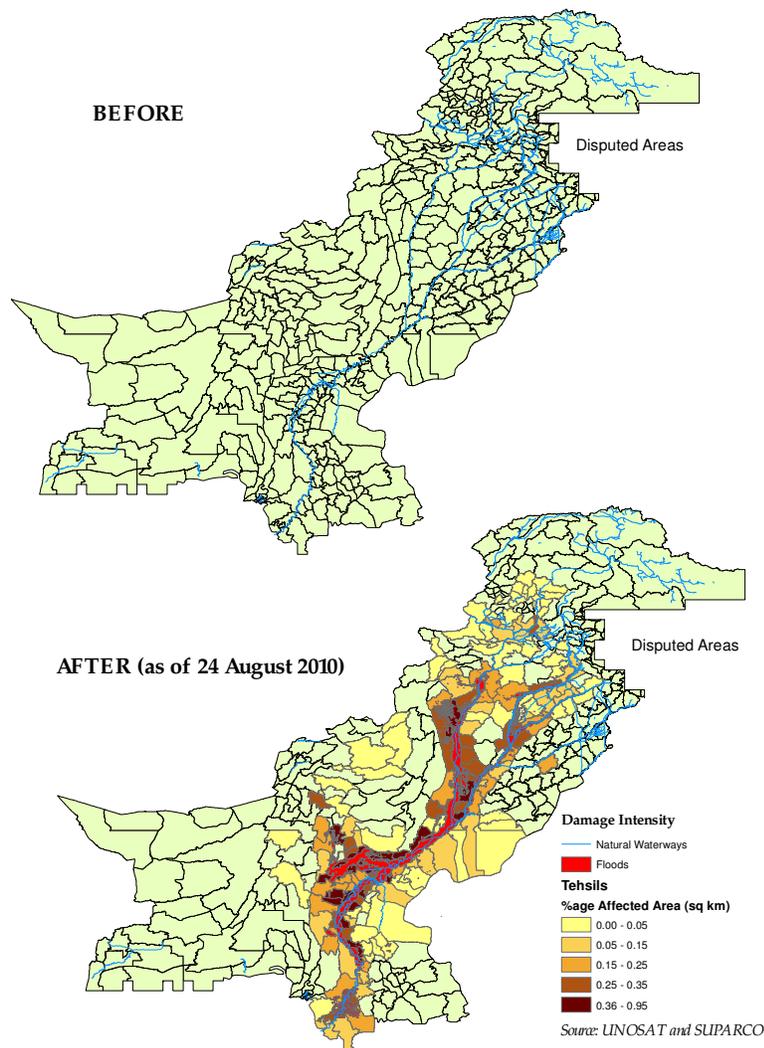
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9. FIGURES AND TABLES

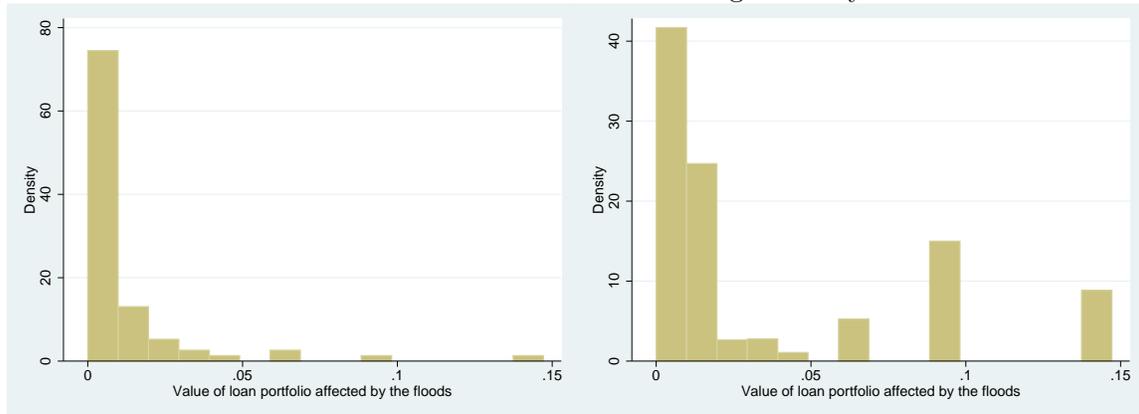
FIGURE 3. Effect of the floods by tehsil

Pakistan maps before and after the rains and floods 2010



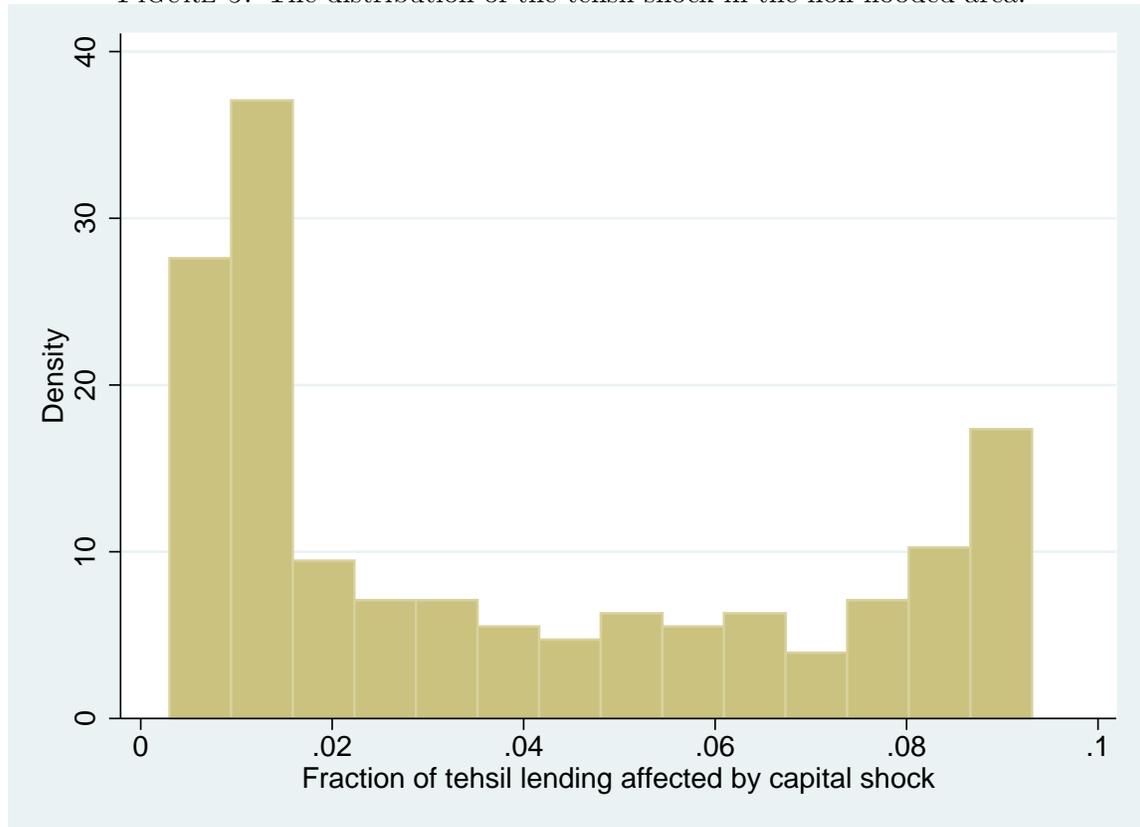
Source:United Nations [2011].

FIGURE 4. The distribution of the funding shock by bank.



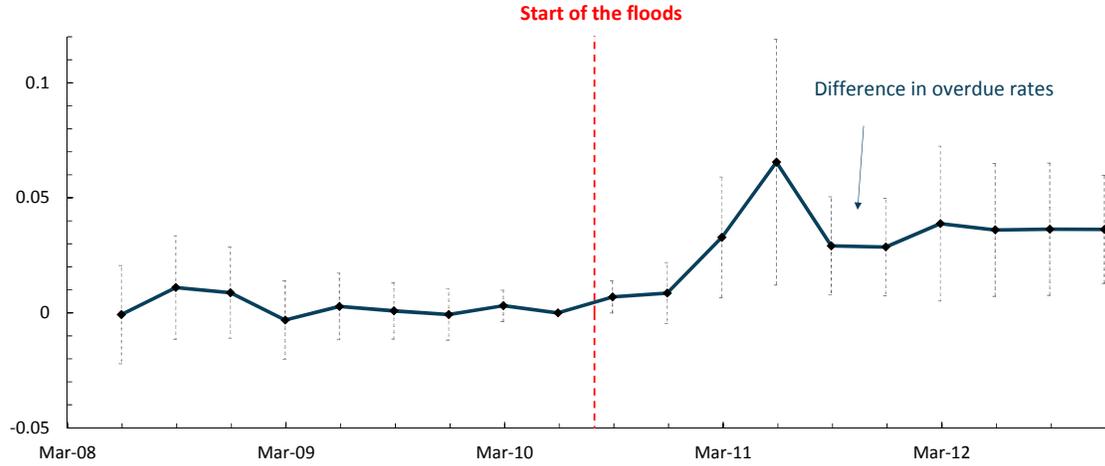
The left panel shows the distribution for the size of the flood shock for each bank. The right panel shows the distribution for the size of the flood shock for each bank, normalized by the number of loans each bank extends. The smallest financial institutions were least affected by the floods, some of these banks geographical focus is not within the flooded area. In our robustness results, we demonstrate that excluding the non-banking financial institutions (the smallest financial institutions) from our regressions do not affect our results (table (13) in Appendix B).

FIGURE 5. The distribution of the tehsil shock in the non-flooded area.



This graph shows the distribution of the ‘tehsil shock’ (see definition (2)) across tehsils in the non-flooded area. The ‘tehsil shock’ is the proportion of total lending in that tehsil affected by the funding shock.

FIGURE 6. The effect of the flood on overdue rates between flooded and non-flooded areas.



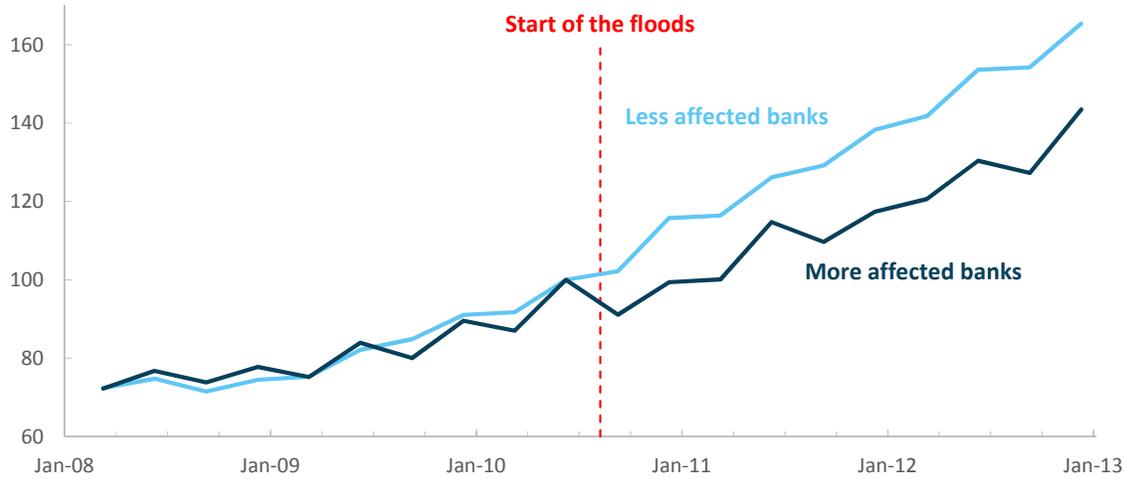
We regress whether a loan is overdue on the percentage of a tehsil that is flooded. The solid blue line is the quarterly coefficient for the increase in overdue rates for a one percent rise in the area of a tehsil that was flooded. The regression includes ‘bank×product × individual’ and ‘bank×time’ fixed effects and the standard errors are clustered at the tehsil level. The light blue dotted lines are point-wise 95% confidence intervals. The full regression is

$$y_{bict} = a_{bpi} + a_{bt} + \beta \times \mathbf{TimeDummies}_t \times \text{Fraction of tehsil flooded}_c + \epsilon_{bpit}$$

The graph shows a dramatic, sudden and sustained increase in the overdue rate for loans in the flooded area immediately following the floods. Following the flood a tehsil that was flooded by 1 percent, the loans in that tehsil were 0.15 - 0.25 percentage points more likely to be overdue every quarter following the flood. This increase in the percentage of non-performing loans (NPLs) in the flooded area is the primary evidence for a sustained increase in a bank’s funding costs following the floods in 2010.

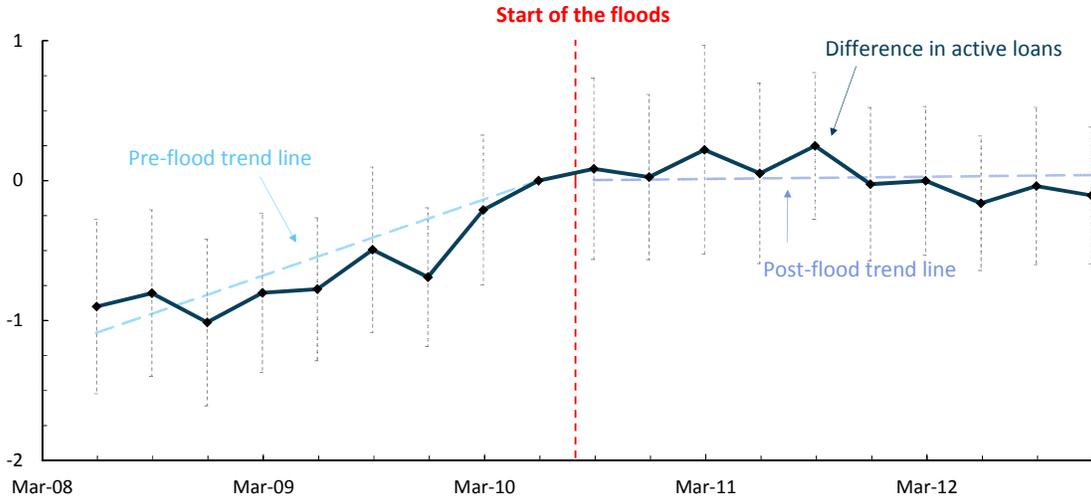
FIGURE 7. The effect of the flood on banks' deposit-to-asset ratio.

Average deposits. June 2010 = 100



We split banks that take deposits into two groups—those banks that had an above median exposure to the flood (more affected banks), and those banks that had a below median exposure to the flood (less affected banks). We normalize banks' average deposits in June 2010 to be 100, and show that deposits grew significantly slower for the more affected banks than the less affected banks following the flood.

FIGURE 8. The effect of the flood on a bank’s likelihood to lend in the non-flooded areas.

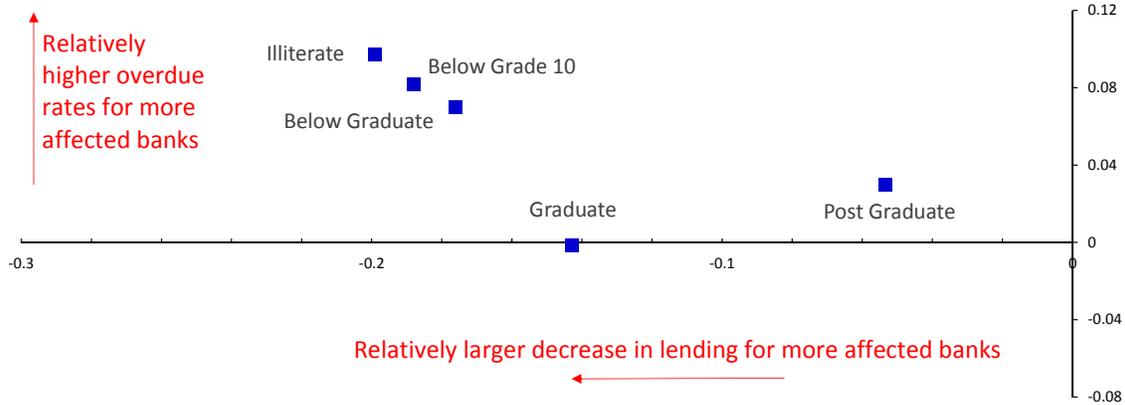


The blue squares are the quarterly coefficient for the effect of the *funding shock*_{*b*} on banks’ likelihood to lend in the non-flooded area over time. The funding shock is defined as the fraction of a bank’s loan portfolio that was in the flood affected region as of August 2008. The regression includes ‘bank×product × individual’ and ‘tehsil×time’ fixed effects. The black bars are point-wise 95% confidence intervals. The full regression is

$$y_{bict} = a_{bpi} + a_{bt} + \beta \times \mathbf{TimeDummies}_t \times \text{Funding shock}_b + \epsilon_{bpit}.$$

The graph shows a dramatic and sudden decrease in the trend of active loan growth by those banks that were most affected by the floods immediately following the floods in June 2010. This is the visual analogue of column 1 in table 2, where we are plotting the estimated coefficient and the standard errors from a regression of active loan on the funding shock interacted with a quarter dummies with various controls.

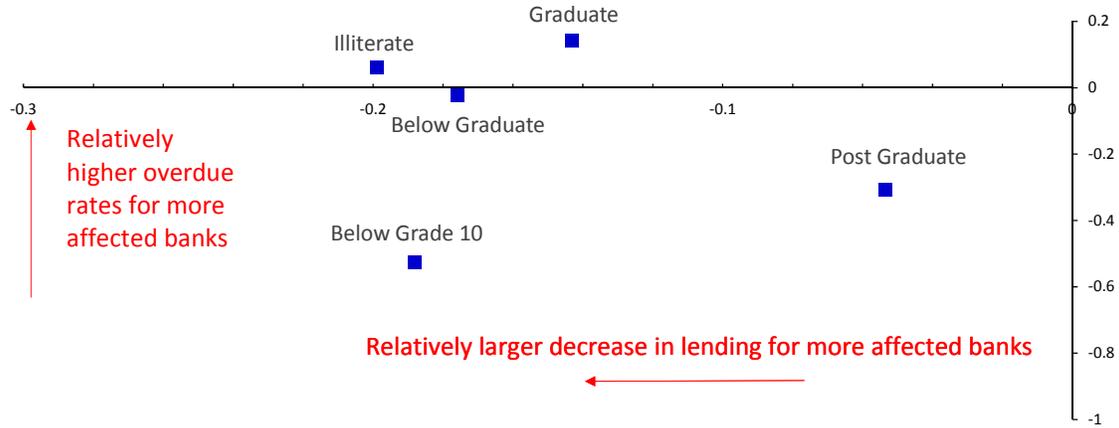
FIGURE 9. The most affected banks relatively reduced lending the most for those groups that also had the largest rise in relative overdue rates following the flood.



This figure shows the relationship between changes in lending and changes in overdue rates for the most affected banks for loans *originated* close to the flood date. On the x -axis we plot the relative change in lending following the flood for more affected banks (the coefficients are reported in the regressions in table 3). On the y -axis, we plot the rise in overdue rates for more affected banks for those loans originated just after the flood (within the first 120 days after the flood) relative to loans originated just before the flood (within the last 120 days before the floods). The coefficients are reported in the regressions in table 6.

This figure shows the more affected banks reduced lending more for the least educated borrowers *and* the more affected banks also had a greater relative rise in overdue rates for these borrowers.

FIGURE 10. The overdue rates for loans maturing just after the flood did not increase relatively more for those consumer groups that also had the largest reduction in lending by the more affected banks.



This figure shows the relationship between changes in lending and changes in overdue rates for the most affected banks for loans that *matured* close to the flood date. On the *x*-axis we plot the relative change in lending following the flood for more affected banks (the coefficients are reported in the regressions in table 3). On the *y*-axis, we plot the rise in overdue rates for more affected banks for those loans that *matured* just after the flood (within the first 120 days after the flood) relative to loans that *matured* just before the flood (within the last 120 days before the floods). The coefficients are reported in the regressions in table 8.

This figure shows that even though the more affected banks relatively reduced lending more for less educated groups, loans to these groups that matured just after the flood did not relatively rise. In fact, relative overdue rates *fell* for those consumers who did not finish school ('below grade 10').

TABLE 1. Loans, borrowers and lender characteristics.

Loans in the non-flooded tehsils		
	Less affected banks	More affected banks
Loan Characteristics		
Log Loan Size Outstanding	10.9	10.5
Overdue	19.4%	30.0%
Bank Characteristics		
Public Bank	13.7%	38.7%
Domestic Private Bank	65.9%	38.9%
Foreign Bank	18.0%	0%
Islamic Bank	0.99%	0%
Non-bank Financial Institution	1.4%	22.3%
Borrower Characteristics		
Illiterate	11.4%	9.7%
Below Grade 10	10.0%	41.8%
Below Graduate	31.2%	19.8%
Graduate	32.3%	19.6%
Post Graduate	15.1%	9.0%
Observations	194296	

This table shows the loan, borrower and lender characteristics for loans in August 2008 (the start of our dataset). To examine how the borrowers differed across lenders that were less or more affected by the floods, we split our dataset by the median bank funding shock. Column 1 has the less affected banks and column 2 has the more affected banks. Those banks that were most affected by the floods were relatively more likely to be public and non-bank financial institutions. Since the floods affected rural areas more than urban areas those banks that lent more in cities were less affected than those that lent more in rural areas. Therefore, foreign banks were barely affected by the floods. Additionally, since rural populations are generally less educated, the banks that were more affected by the floods lent relatively more to less educated borrowers.

TABLE 2. The effect of the funding shock on a bank's likelihood to lend in non-flooded areas.

	Active Loan	Log Loan Size
Time*Flood Shock	0.136*** (0.0268)	0.204 (0.133)
PostTime*Flood Shock	-0.133*** (0.0320)	-0.341** (0.148)
Constant	0.491*** (0.00888)	10.59*** (0.0475)
Observations	8080719	3463247
Tehsil*Date FE	Yes	Yes
Bank*Borrower*Product FE	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Each regression shows that banks which incurred a larger funding shock were significantly less likely to lend in the non-flooded area immediately following the flood. For a 1 percent increase in the funding shock, banks were 0.15 percentage points per quarter less likely to lend to particular a consumer.

The full regression is: $Y_{bpi} = a_{bpi} + a_{ct} + \beta_1 \times \text{Time}_t \times$

Funding Cost Shock $_b + \beta_2 \times \text{Post Time}_t \times \text{Funding Cost Shock}_b + \epsilon_{bpi}$.

All standard errors are clustered at the bank level.

TABLE 3. The effect of the funding shock on a bank's likelihood to lend to borrowers with different education levels in the non-flooded area.

	Active Loan
Time*Illiterate*Shock	0.195*** (0.0224)
Time*Below Grade 10*Shock	0.166*** (0.0524)
Time*Below Graduate*Shock	0.154*** (0.0253)
Time*Graduate*Shock	0.166 (0.135)
Time*Post Graduate*Shock	0.178 (0.166)
PostTime*Illiterate*Shock	-0.199*** (0.0238)
PostTime*Below Grade 10*Shock	-0.188*** (0.0637)
PostTime*Below Graduate*Shock	-0.176*** (0.0290)
PostTime*Graduate*Shock	-0.143 (0.137)
PostTime*Post Graduate*Shock	-0.0534 (0.153)
Constant	0.490*** (0.0170)
Observations	6977294
Tehsil*Date FE	Yes
Bank*Borrower*Product FE	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The banks' report information on each borrower's education level. In this table, we separate our effect by the education level of the borrower. Those individuals with the least education (illiterate, below high school, and high school graduates) were the least able to get loans from the most affected banks following the flood. The results for graduates is much noisier but the point estimates suggest they were more able to get loans from all banks. We omit all individuals for whom education information is not reported. Standard errors are clustered at the level of the bank.

TABLE 4. The effect of the funding shock on a bank's likelihood to lend to new and existing borrowers in the non-flooded area.

	Active Loan	Active Loan	Active Loan	Active Loan
New Borr*Time*Shock	0.0876** (0.0408)		0.211*** (0.0790)	
PostTime*New Borr*Shock	-0.0807* (0.0420)		-0.378*** (0.102)	
Time*Shock		0.0512 (0.0491)	-0.0843 (0.0882)	0.0575 (0.108)
PostTime*Shock		-0.0444 (0.0718)	0.232** (0.0940)	-0.0253 (0.0914)
Constant	0.412*** (0.0216)	0.587*** (0.0131)	0.425*** (0.0204)	0.468*** (0.0187)
Observations	2596977	4281650	3799069	1202092
New Borrowers	X		X	
Existing Borrowers		X	X	X
New Relationships	X		X	X
Existing Relationships		X		
Tehsil*Date FE	Yes	Yes	Yes	Yes
Bank*Borrower*Product FE	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table analyzes how lending changed to new and existing borrowers, at more and less affected banks, before and after the flood. In columns 1 and 2, we separately analyze whether new borrowers (those with no credit history) and existing borrower relationships respectively were less or more able to procure loans following the flood at more affected banks. Column 1 shows that new consumers were statistically significantly relatively less likely to be able to get loans at more affected banks following the flood. Whereas, column 2 shows that existing borrowers were not statistically significantly less able to get loans at more affected banks following the flood.

In columns 3 and 4, we analyze whether the more affected banks also rationed all new customers to that bank. To do this, we exclude the set of pre-existing lending relationships (as of August 2008) and separate consumers into two groups: (i) those consumers that have a loan relationship with some other bank (as of August 2008) and (ii) those consumers that did have a loan relationship with any bank (as of August 2008). Column 3 demonstrates that the new consumers – those with no credit history were significantly less likely to be able to get new loans at those banks that suffered the largest funding shock. Whereas, those consumers with some credit history were able to equally likely to get new loans at less or more affected banks following the flood.

All standard errors are clustered at the bank level.

TABLE 5. The effect of the funding shock on loan origination standards in the non-flooded area in the non-flooded area: Loans originated just before and after the flood.

	Overdue Rate	Overdue Rate	Overdue Rate	Overdue Rate
Originated Post Flood	-0.00674 (0.00539)		0.00245 (0.00375)	
Originated Post Flood*Shock	0.0544 (0.0369)	0.0787* (0.0435)	-0.00562 (0.0309)	0.0124 (0.0186)
Observations	28227	28227	33840	33840
Tehsil FE	Yes	N/A	Yes	N/A
Bank FE	Yes	N/A	Yes	N/A
Bank*Tehsil FE	No	Yes	No	Yes
Tehsil*Preloan FE	No	Yes	No	Yes
Placebo			X	X

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

To explore why banks disproportionately reduced credit across groups, we restrict our sample to loans *originated* just *before* the flood (120 days before), and just *after* the flood (120 days after) in the non-flooded area. We regress whether the loan defaulted within two years of being originated at more or less affected banks before and after the flood. We include bank and tehsil fixed effects in columns 1 and 3. We include bank interacted with tehsil fixed effects and tehsil interacted with origination period in columns 2 and 4. The full regression in column 1 is:

$$\text{Overdue Ever}_{bpi} = a_b + a_t + \beta_1 \times \text{Originated Post Flood}_{bpi} + \beta_2 \times \text{Originated Post Flood}_{bpi} \times \text{Funding Shock}_b + \epsilon_{bpi}.$$

The regression in column 2 is similar except we include more fixed effects.

Columns 1 and 2 provide compelling evidence that those banks that suffered the largest funding shock had the largest increase in default rates from the those loans originated *after* the flood. We estimate a 1 percent increase in a bank's exposure to the flooded area caused the bank to originate loans which were 0.08 percentage points more likely to default in the non-flooded area.

Columns 3 and 4 do the same experiment as columns 1 and 2, except we analyze loans originated just before, and after, September 2009 – exactly one year before the flood. These results show no difference in overdue rates between less and more exposed banks following this placebo flood date.

This table provides the most compelling evidence that adverse selection drove the large disproportionate reductions in credit following the flood.

All standard errors are clustered at the bank level.

TABLE 6. The effect of the funding shock on loan origination standards in the non-flooded area by education level.

	Overdue Rate	Overdue Rate
Or. Post Flood*Illiterate	0.00261 (0.0143)	0.0150 (0.0102)
Or. Post Flood*Below Grade 10	0.00870 (0.0128)	0.00203 (0.00468)
Or. Post Flood*Below Graduate	0.00877 (0.0139)	-0.00501 (0.00894)
Or. Post Flood*Graduate	0.00326 (0.0112)	-0.00215 (0.00827)
Or. Post Flood*Illiterate*Shock	0.0974** (0.0480)	-0.0651 (0.0574)
Or. Post Flood*Below Grade 10*Shock	0.0820 (0.0602)	-0.00770 (0.0214)
Or. Post Flood*Below Graduate*Shock	0.0702 (0.0473)	0.0545 (0.0403)
Or. Post Flood*Graduate*Shock	-0.00130 (0.143)	0.152 (0.120)
Or. Post Flood*Post Graduate*Shock	0.0374 (0.244)	0.0113 (0.0682)
Observations	22518	26293
Education*Tehsil FE	Yes	Yes
Bank*Tehsil FE	Yes	Yes
Tehsil*Preloan FE	Yes	Yes
Education*Bank FE	Yes	Yes
Placebo		X

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table repeats the exercise in table (5) but separates the data by a consumer's education level. This is a triple difference-in-difference specification which examines whether those individuals with the least education, were more likely to default on their loans at more exposed banks following the flood.

In column 1, we show that the point-estimates for relative overdue rates at more affected banks following the flood are significantly higher for those individuals with little education. Yet, the point-estimates are negligible (with large standard errors) for individuals who at least graduated from high-school. In column 2, we present placebo results where we analyze loans originated just before, and after September 2009 – exactly one year before the flood. These results show no difference in overdue rates between less and more exposed banks across education groups following this placebo flood date. All standard errors are clustered at the bank level.

TABLE 7. The effect of the funding shock on loan default in the non-flooded area: Loans which matured just before and after the flood.

	Overdue Rate	Overdue Rate	Overdue Rate	Overdue Rate
Matured Post Flood	0.000656 (0.00731)		-0.00913 (0.0176)	
Matured Post Flood*Shock	-0.200 (0.229)	-0.0568 (0.104)	-0.137 (0.248)	0.104 (0.127)
Observations	70886	70886	78909	78909
Tehsil FE	Yes	N/A	Yes	N/A
Bank FE	Yes	N/A	Yes	N/A
Bank*Tehsil FE	No	Yes	No	Yes
Tehsil*Preloan FE	No	Yes	No	Yes
Placebo			X	X

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

To explore if moral hazard may be driving the reduction in credit to individuals with little education, we exploit the maturity structure of different loans. We restrict our sample to loans that *matured just before* the flood (120 days before) and just *after* the flood (120 days after) in the non-flooded area. We then analyze whether those loans that matured after the floods by the more affected banks were relatively more likely to default.

We include bank and tehsil fixed effects in columns 1 and 3. We include bank interacted with tehsil fixed effects and tehsil interacted with origination period in columns 2 and 4. The full regression in column 1 is:

Overdue Ever $_{bpi}$ =

$$a_b + a_t + \beta_1 \times \text{Matured Post Flood}_{bpi} + \beta_2 \times \text{Matured Post Flood}_{bpi} \times \text{Funding Shock}_b + \epsilon_{bpi}.$$

The regression in column 2 is similar except we include more fixed effects.

Columns 1 and 2 provide compelling evidence that loans that matured just after the flood were not more likely to default at the more affected banks following the flood.

Columns 3 and 4 do the same experiment as columns 1 and 2, except we analyze loans that matured just before, and after, September 2009 – exactly one year before the flood. These placebo results show no difference in overdue rates between less and more affected banks after September 2009.

This table provides compelling evidence that moral hazard did not drive the disproportionate reductions in credit following the flood.

All standard errors are clustered at the bank level.

TABLE 8. The effect of the funding shock on loan default rates in the non-flooded area by education level.

	Overdue Rate	Overdue Rate
Mat. Post Flood*Illiterate	-0.00541 (0.0135)	-0.0411*** (0.0145)
Mat. Post Flood*Below Grade 10	-0.00184 (0.00750)	-0.0195 (0.0168)
Mat. Post Flood*Below Graduate	0.000363 (0.00839)	-0.0269*** (0.00725)
Mat. Post Flood*Graduate	-0.00305 (0.00584)	-0.00879 (0.00710)
Mat. Post Flood*Illiterate*Shock	0.0607 (0.0888)	0.264* (0.157)
Mat. Post Flood*Below Grade 10*Shock	-0.526*** (0.123)	-0.260 (0.273)
Mat. Post Flood*Below Graduate*Shock	-0.0218 (0.0691)	0.158 (0.108)
Mat. Post Flood*Graduate*Shock	0.141 (0.315)	-0.224 (0.578)
Mat. Post Flood*Post Graduate*Shock	-0.306 (0.265)	-0.468 (0.702)
Observations	60989	70272
Education*Tehsil FE	Yes	Yes
Bank*Tehsil FE	Yes	Yes
Tehsil*Preloan FE	Yes	Yes
Education*Bank FE	Yes	Yes
Placebo		X

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table repeats the exercise in the previous table but separates the data by a consumer's education level. This is a triple difference-in-difference specification which examines whether those individuals with loans that mature just after the floods (120 days after the flood) with the least education at the more affected banks were relatively more likely to default on their loans.

The estimates for the relative overdue rates are significantly higher for those individuals with little education.

All standard errors are clustered at the bank level.

TABLE 9. The effect of the funding shock on a bank's likelihood to lend in different risk-weighted categories in the non-flooded area.

	Active Loan	Active Loan
Time*Mortgage	0.000971 (0.00547)	
PostTime*Mortgage	-0.00568 (0.00952)	
Mortgage*Time*Shock	-0.0710 (0.185)	-0.0170 (0.195)
PostTime*Mortgage*Shock	-0.143 (0.282)	-0.229 (0.267)
Time*Shock	0.137*** (0.0266)	
PostTime*Shock	-0.132*** (0.0318)	
Constant	0.491*** (0.00888)	0.662*** (0.0656)
Observations	8080719	156218
Tehsil*Date FE	Yes	Yes
Bank*Borrower*Product FE	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Did banks reduce credit predominantly to those loans with higher capital risk weights? To explore this question, we examine if more exposed banks were more likely to maintain mortgage lending since loans backed by residential property only have a risk weight of 35 percent, whereas all other retail lending has a risk weight of 75 percent (assuming the loans are not overdue).

In column 1, we use a triple-difference-in-difference estimator to examine whether banks which suffered the largest funding shock relatively *increased* mortgage lending following the floods (since these loans have the lowest Basel II risk weights). Our results, clearly show that our 'PostTime \times Mortgage \times Flood Shock' variable, which is dummy variable for whether the loan is a mortgage, interacted with PostTime and the bank specific flood shock, is both negative and not significantly different to zero. This suggests that the banks which were more affected by the floods did not relatively increase their mortgage lending relative to other banks and other non-mortgage lending.

In column 2, we restrict our sample to only mortgage lending. Similar to column 1, we observe that the more affected banks did not increase mortgage lending relative to less affected banks.

All standard errors at clustered at the bank level.

TABLE 10. Did banks' reallocate credit toward those loan categories in which they are heavily specialized or dominant market share.

	Active Loan	Active Loan
PostTime*Bank Product Specialization*Shock	-0.00384 (0.0159)	
PostTime*Bank Product Market Share*Shock		0.0200 (0.0333)
PostTime*Flood Shock	-0.129*** (0.0406)	-0.171* (0.0890)
Time*Bank Product Specialization*Shock	-0.0192 (0.0132)	
Time*Flood Shock	0.158*** (0.0371)	0.194*** (0.0726)
Time*Bank Product Market Share*Shock		-0.0305 (0.0249)
Constant	0.556*** (0.0340)	0.570*** (0.0534)
Observations	8080719	8080719
Tehsil*Date FE	Yes	Yes
Bank*Borrower*Product FE	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table examines whether the more affected banks reallocated credit toward those loan categories in which they are either heavily specialized (column 1) or have a dominant market share (column 2). The bank product specialization and bank product market shares are constructed as in section (6.4.4) .

In column 1 we observe that the more affected banks did not increase lending in those categories for which they are more specialized. In column 2, we observe that the more affected banks did not increase lending in those loan categories for which they have greater market share. All standard errors at clustered at the bank level.

TABLE 11. The effect of the funding shock on a bank's likelihood to lend in differentially affected tehsils.

	Active Loan	Log Loan Size
Time*Funding Shock	0.146*** (0.0343)	0.142 (0.187)
PostTime*Funding Shock	-0.156*** (0.0421)	-0.309 (0.197)
Time*Funding Shock*Tehsil Shock	-0.382 (0.935)	2.313 (4.046)
PostTime*Funding Shock*Tehsil Shock	0.885 (1.425)	-1.080 (3.182)
Constant	0.492*** (0.00945)	10.58*** (0.0461)
Observations	8080719	3463247
Tehsil*Date FE	Yes	Yes
Bank*Borrower*Product FE	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

If a single bank is (or many banks are) unable to distribute credit, one important mechanism to mitigate the reduction in credit would be other banks to increase their supply of credit – in such a way that total credit in the tehsil does not fall. The results suggest there was no substitution of credit from the more affected banks to the less affected banks in those tehsils that were affected the most.

In this table we interact banks' funding shock with the tehsil's shock. The coefficient on 'PostTime \times Funding Shock \times Tehsil Shock' is positive and not statistically significant. If the less affected banks lent more in the more affected tehsils, this coefficient would be negative.

All standard errors are clustered at the bank level.

APPENDIX A. PROOFS

A.1. Proof of Theorem (1), (2) and (3). Theorem: Assuming the bank continues to lend, the bank will reduce lending more to those consumer groups that have a more elastic demand for loans (higher b) following a rise in the bank's funding cost.

Proof. Assuming an interior solution for the banks profit function, the bank's optimal provision of loans, $D^*(b, c, s)$ is:

$$D^*(b_g, \kappa_g c, s) = \frac{1}{3} \left[1 + \left(1 - 3 \frac{b_g \kappa_g c}{s} \right)^{0.5} \right]$$

Differentiating the demand function with respect to c , the change in the provision loans following a rise in a bank's cost is:

$$(8) \quad \frac{\partial D^*(b, c, s)}{\partial c} = -K \frac{b_g}{s} \left(1 - 3 \frac{b_g \kappa_g c}{s} \right)^{-0.5} < 0$$

where K is a positive constant.

To understand how changes in b_g (the parameter that determines the elasticity of demand), we can differentiate equation (8) with respect to b_g :

$$\frac{\partial^2 D_g^*(b_g, \kappa_g c, s)}{\partial b_g \partial c} < 0$$

Therefore the higher the b , the larger the reduction in demand following a rise in costs.

Similarly to prove theorem (2), we can differentiate equation (8) with respect to s :

$$\frac{\partial^2 D_g^*(b_g, \kappa_g c, s)}{\partial s \partial c} > 0$$

Therefore, in those sectors where the problem of adverse selection is the worst (low s) the bank will reduce lending the most.

Similarly to prove theorem (3), we can differentiate equation (8) with respect to κ_g :

$$\frac{\partial^2 D_g^*(b_g, \kappa_g c, s)}{\partial \kappa_g \partial c} < 0$$

Therefore, in those sectors where the costs of lending are the largest (high κ_g) the bank will reduce lending the most. \square

APPENDIX B. EXTRA GRAPHS AND TABLES

TABLE 12. The effect of the flood on a bank's likelihood to lend in flooded areas.

	Active Loan	Log Loan Size
Time*Shock	0.151*** (0.0445)	0.253* (0.137)
PostTime*Shock	-0.0818 (0.0649)	-0.392*** (0.145)
Constant	0.488*** (0.0156)	10.71*** (0.0539)
Observations	2909200	1480161
Tehsil*Date FE	Yes	Yes
Bank*Borrower*Product FE	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

These regressions consider the hypothesis those banks which were exposed more to the flooded area increased lending in the flooded area. For instance, following the flood, you may expect demand for credit to increase in the flooded area due to the flood destroying homes, businesses and livestock.

These regressions show that the banks that were exposed most to the flooded area reduced lending the most in the flooded area, suggesting those banks that were more affected did not reallocate credit to the flooded area. For a 1 percent increase in the funding shock, banks were 0.08 percentage points per quarter less likely to lend to particular a consumer.

All standard errors are clustered at the bank level.

TABLE 13. The effect of the flood on a bank's likelihood to lend in non-flooded areas – omitting non-banking financial institutions.

	Active Loan	Log Loan Size
Time*Shock	0.198*** (0.0600)	0.405** (0.198)
PostTime*Shock	-0.204*** (0.0686)	-0.562*** (0.178)
Constant	0.517*** (0.0143)	10.69*** (0.0592)
Observations	6572070	2872190
Tehsil*Date FE	Yes	Yes
Bank*Borrower*Product FE	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

These regressions duplicate the regressions in table (2), except we omit the non-bank financial institutions. The results are very similar, suggesting that banks and non-bank financial institutions were equally affected by the funding shock.

The full regression is:

$$Y_{bpi} = a_{bpi} + a_{ct} + \beta_1 \times \text{Time}_t \times \text{Funding Shock}_b + \beta_2 \times \text{Post Time}_t \times \text{Funding Shock}_b + \epsilon_{bpi}.$$

All standard errors are clustered at the bank level.