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

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ABSTRACT. We analyze reductions in bank credit using a natural experiment where unprecedented flooding differentially affected banks that were more exposed to flooded regions in Pakistan. Using a unique dataset that covers the universe of consumer loans in Pakistan and this exogenous shock to bank funding, we find two key results. First, banks disproportionately reduce credit to new and less-educated borrowers, following an increase in their funding costs. Second, the credit reduction is not compensated by relatively more lending by less-affected banks. The empirical evidence suggests that adverse selection is the primary cause for banks disproportionately reducing credit to new borrowers.

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1. Introduction

There is substantial evidence that credit access can improve consumer welfare. For instance, greater access to credit can increase income (Karlan and Zinman [2009b]), reduce inequality (Solis [2017]), increase insurance (Udry [1994]), smooth consumption (Gross and Souleles [2002]), and increase entrepreneurship (Banerjee et al. [2015]). Banks are consumers' largest source of credit, and, as such, a small reduction in bank credit can materially reduce consumer's welfare.

Given the important role of banks in intermediating and disbersing credit, there is surprising little evidence for *whom* banks reduce credit to following a credit shock. In this paper, we fill this gap in the banking and household finance literature by answering the following question: Who are banks' marginal borrowers?

Moreover, banks may reduce credit disproportionately to certain consumers for many reasons. For instance, banks may favor pre-existing customers, or favor loans in sectors for which they have a large market share or are product specialists. Understanding why banks reduce credit to certain borrowers may have important implications for consumer welfare, and in turn, for designing policy. Therefore, we also answer the following question: Why are certain borrowers banks' marginal borrowers?

There are two key empirical challenges to answering these questions. First, variation in bank lending is unlikely to be exogenous. For example, recessions will simultaneously cause banks to reduce credit supply and cause households and firms to change credit demand. Second, there are significant data constraints. To determine the marginal borrowers, we need to combine comprehensive loan data with detailed demographic data. To overcome these challenges, we exploit both a natural experiment that exogenously raised banks' funding costs to different extents and detailed loan data that include borrower characteristics.[1]

We have three main results. First, the banks more affected by the funding cost shock disproportionately reduced credit to borrowers with little education and little credit history relative to less-affected banks. Second, the evidence suggests that adverse selection is driving the large relative decreases in lending to these borrowers. Finally, the less-affected banks did not increase lending to compensate for the reduction in credit by the more-affected banks. Therefore, the general equilibrium effects did not mitigate the reduction in credit by the more-affected banks.

The natural experiment comes from Pakistan's 2010 catastrophic floods, which caused exogenous increases in funding costs that differed across banks. The floods affected more

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

than 20 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]). To create a measure of the increase in a bank's funding cost, 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 became more likely to default).

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 the seminal work of Peek and Rosengren [2000], who examined how falls in Japanese stock prices affected Japanese bank branches in the United States, and subsequently U.S. credit markets. Using a difference-in-difference methodology, we compare loan amounts for individuals between different banks, which had different funding shocks, before and after the flood, in the non-flooded area.

We focus on 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.

The first of three datasets we use is supplied by the Space and Upper Atmosphere Research Commission (SUPARCO, Pakistan's space agency) to estimate the flood damage in each tehsil.[2] Then we combine the flood damage data with a bank's loan portfolio in each tehsil to estimate the relative effect of the floods on each bank. Finally, we use detailed loan data and demographic data from the State Bank of Pakistan's credit registry, the Electronic Credit Information Bureau (eCIB) to identify the consumers most affected by the credit reduction and why banks reduce credit disproportionately. The credit registry is a unique dataset that comprises the universe of formal consumer lending in Pakistan and contains information on loan origination dates, maturity dates, product types, and demographic data such as the borrower's education level.

Our empirical strategy follows in five steps. First we show that the floods caused increases in banks' funding costs. Second, we demonstrate that the more-affected banks reduced lending in the non-flooded area relatively more than the less-affected banks. Third, we show that this fall in lending is greater for borrowers with less education and credit history. Fourth, we explore why banks disproportionately reduced lending for these consumers. Finally, we analyze the general equilibrium effects of the bank funding shock. We show

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

that less-affected banks did not compensate for the fall in lending by the more-affected banks.

The first step of our empirical methodology is to show that the floods affected some banks more than others. To do so, we show that the floods had two effects on banks: one, preexisting loans in the flooded area were more likely to default relative to loans in the non-flooded area (a capital shock) and, two, banks that had greater exposure to the flooded area were more likely to have deterioration in deposits as firms and consumers dissaved (liquidity shock).

The second step is to show that more-affected banks reduced lending in the non-flooded areas relatively more than the less-affected banks. To do so, we use the fraction of a bank's portfolio in the flooded area as a measure for the bank's exposure to the floods and, consequently, the size of a bank's funding cost shock. We then use a difference-in-difference methodology to regress this measure of banks' funding cost shocks on a panel dataset of consumer loans, before and after the flood, in the non-flooded area.

The third step is to show that, following the flood, those banks that had larger funding cost shocks, reduced lending in the non-flooded area more for consumers with little education and consumers with no credit history. To do so, we use a triple difference-in-difference methodology and interact the borrower's education level with the size of the bank's funding shock.

The fourth step explores the reasons why banks reduced lending more for certain groups. The evidence suggests that adverse selection was the main driver for the greater reduction in lending for consumers with low education. Adverse selection can cause a disproportionate reduction in credit across consumer groups if the extent of adverse selection is different across such groups. For instance, banks may pass higher funding costs on to consumers through higher interest rates. However, this transmission may cause the pool of borrowers who are willing to take loans at these higher interest rates to be riskier—adverse selection—which causes higher expected rates of default. To cover the higher expected default costs, banks may charge even higher interest rates and subsequently cause even greater reductions in credit (Stiglitz and Weiss [1981]). Therefore, in those consumer groups for which the extent of adverse selection is larger we would expect larger reductions in credit and higher default rates.

To show that adverse selection was driving the disproportionate reduction in credit, we exploit the origination dates of new loans. We look at loans originated just before the floods (120 days before the flood) and loans originated just after the floods (120 days after the flood) in the non-flooded area. We show that, following the flood, the more-affected banks originated loans that were relatively more likely to become overdue than less-affected banks, in the non-flooded area. Furthermore, we show that the relative increase in overdue rates for the more-affected banks was greater for those consumer groups that had the greatest reductions in credit.

We consider alternative reasons for why banks may disproportionately reduce credit to low education groups. We show that the evidence is not consistent with moral hazard. The evidence is also not consistent with bank preferences for pre-existing consumers. Moreover, the evidence is not consistent with bank regulatory restrictions. Nor, is the evidence consistent with a market share or bank specialization motive.

The fifth step of our empirical methodology analyzes the general equilibrium effects of the bank reduction in credit. The previous steps analyzed only the relative changes in lending between more and less-affected banks. It is conceivable that even though *relative* lending by the more-affected banks fell, aggregate lending was unchanged. From a consumer welfare perspective, we are more interested in *aggregate* changes in lending.

To analyze the general equilibrium effects, we exploit the variation in bank concentration in non-flooded tehsils. If the more-affected banks equally reduced lending across each tehsil, those tehsils with a larger concentration of more-affected banks would have larger aggregate reductions in credit. If the less-affected banks compensated for reductions in credit by more-affected banks, we would observe that the less-affected banks relatively increased lending in tehsils with a higher concentration of more-affected banks. To test this possibility, we use a triple difference-in-difference methodology. We find that less-affected banks did not increase lending in the more affected tehsils relative to the less-affected tehsils. This finding suggests that the general equilibrium effects did not mitigate the effects of the bank funding cost shock. We conjecture that this lack of general equilibrium effects is due to the funding cost shock affecting all banks and the difficulty of expanding bank lending to consumers with no credit history.

Our paper is related to a number of strands of literature. A large literature in economics and finance has shown that exogenous shocks to banks can cause changes in lending to firms. These shocks vary from liquidity shocks (Khwaja and Mian [2008], Schnabl [2012], Iyer et al. [2014]), information shocks (Hertzberg et al. [2011], Choudhary and Jain [2015]), capital shocks (Gambacorta and Mistrulli [2004], Aiyar et al. [2014]), and financial crises (Popov and Udell [2012], Cetorelli and Goldberg [2012], De Haas and Van Horen [2012]) to natural disasters (Chavaz [2014], Cortes and Strahan [2014]). In this paper, we add to this literature in three key ways. First, we identify who is most affected by changes in bank credit. Second, we explore the reasons why banks may disproportionately reduce credit to certain consumers. Third, we concentrate on bank credit to consumers, a hitherto, mostly overlooked credit channel in the banking literature.

Our paper complements the literature analyzing the effect of bank credit expansions on credit card usage. Using credit card data, Gross and Souleles [2002] show that consumers with low credit scores are the most credit constrained. Agarwal et al. [2015] demonstrate that during credit expansions, low credit score households increased credit usage the most. We show similar results—during a credit recession, those individuals with the least credit history were most likely to be credit rationed. Furthermore, we extend this work by showing this result also holds in a more general setting using *all* bank consumer credit, which allows us to draw more complete conclusions about credit access. For instance, it is possible that even though certain borrowers had lower credit card limits, these smaller credit lines were supplemented by larger personal loans or overdrafts. Finally, since our unique dataset allows us to match a borrower's credit data with his or her demographic data, we are able to show that the least educated borrowers were the most affected.

Section (2) details the floods and our dataset. Section (3) describes the econometric specifications. Section (4) presents the results and section (5) provides additional robustness tests. Section (6) concludes.

2. Empirical setting

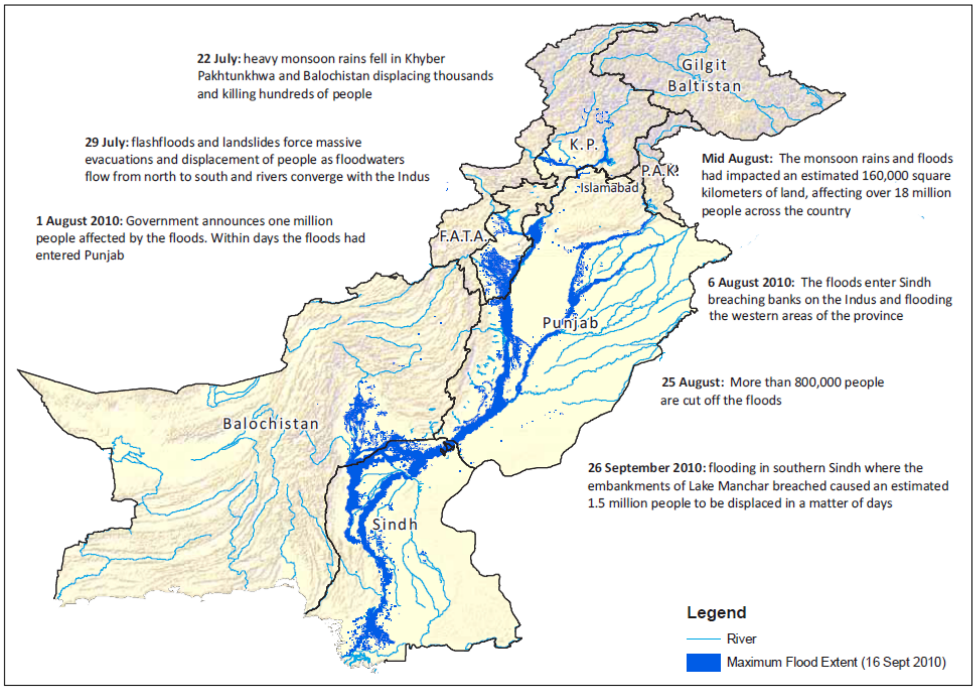
2.1. **Pakistan's 2010 floods.** "The 2010 floods in Pakistan were one of the most devastating natural disasters of our times" (Food and Agriculture Organization [2011]). The floods covered almost 20 percent of Pakistan's land mass, affected more than 20 million people (11.5 percent of Pakistan's population) 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 floods 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 tehsils—out of 591 tehsils in all of Pakistan—were affected by the floods.

2.2. **The effect of the floods on banks.** The effect of the floods on banks came through two different channels: (i) a rise in nonperforming loans (NPLs) (a 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 fact clear:

"The year 2010 saw a continuous rising trend in the industry nonperforming 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]).

Figure 1. Map and timeline of the 2010 Pakistan floods



Source: United Nations [2011].

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 Taraqiati Bank Limited [2010].

The deterioration in banks' loan portfolios was also evidenced by the banks' credit ratings. On September 2, 2010, Moody's changed the financial strength of Pakistan's five biggest banks from stable to negative, noting that "the country's main banks face the threat of a wave of nonperforming 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 (4.1), we show that loans in the flooded area were significantly more likely to default than loans in the non-flooded area following the flood.

Second, like banks in other emerging market economies, Pakistani banks are predominantly deposit financed (with an aggregate loan-to-deposit ratio of 0.7 in 2009 (IMF [2009])). Therefore, those banks that 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 (4.1) 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 that 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 SBP and (ii) the extent of the damage to each tehsil comes from the United Nations and Pakistan's SUPARCO.

The credit and individual data comes from the SBP eCIB, which legally requires all banks and lending institutions to submit data on all borrowers. Some of these data have been used before by Khwaja and Mian [2005, 2008], Mian [2006], Khwaja et al. [2011], Choudhary and Jain [2015]. However, previous economists had access only 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 loan, mortgage loan, car loan, personal loan, small-or-medium enterprise loan, and agricultural loan in Pakistan—averaging 3 million different borrowers and 5 million different loans in any one month.

The credit data include information on origination dates, maturation dates, and performance levels of the loans. Unfortunately, the data do not include interest rates.

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). We retain all borrowers whose unique identification number ends in a certain sequence.

Table (1) shows the loan, lender, and borrower 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. The institutions that were most affected by the floods were relatively more likely to be 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.

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

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 details 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 provides information on the consumer's credit history: how many times the account had been overdue in the last 12 months, and how many payments were late during that period.

3. The effect of the funding shock on bank loans.

3.1. **Econometric specification.** The paper's main question is, what is the effect of a bank funding shock on bank lending? We answer this question using a natural experiment that exogenously increased banks' NPLs and reduced banks' deposits in a way that varied across banks. We argue that this exogenous and unexpected surge in NPLs and reduction in deposits raised a bank's funding cost. We investigate whether banks' compensated for this increase in costs by decreasing leverage and subsequently decreasing lending. If banks did so, to whom did they reduce lending, 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 following form:

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

The unit of observation is at the bank-product-individual-date level, so Y_{bpit} is the variable of interest for bank b, credit-product p and 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 0 and 1, 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 floods (September 2010) and 0 for all quarters before the flood.

All of the main regressions contain a tehsil interacted with a date fixed effect, α_{ct}. This fixed effect ensures that we are estimating the effect of the funding shock using only banks that were differentially affected by funding shocks while controlling for any differences in tehsils over time. For instance, any aggregate demand shifts over time across tehsils would be accounted for 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 (it 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 specification, 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 the rate of existing loans renewed decreases). This expectation suggests that 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 flooding[4]:

(1)

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

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

3.1.1. *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 1 if individual i at bank b in 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 variable 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.

[4]All loan amounts are as of August 2008—24 months before the start of the flood.

4. 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 were more exposed to the flooded area, their deposits relatively decreased (liquidity shock). These two effects suggest that the floods caused a funding shock to banks. Second we show that 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 because of 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.

4.1. **Both capital and liquidity shocks for banks caused an increase in banks' funding costs.** In figure (5), we show that loans in the flooded area were more likely to default immediately after the floods (capital shock). To construct figure (5) we regress whether a loan defaults on the fraction of area in a tehsil that was flooded interacted with a set of time dummies, and additional fixed effects.[5] The figure clearly shows that default rates in the flooded area rapidly climbed following the flood. This result corroborates the information in banks' annual reports and suggests that those banks that were exposed to the flooded area suffered a capital shock.

In figure (6), we show a dramatic, sudden, and sustained relative decrease in liquidity for banks with greater exposure to the floods (liquidity shock).[6] To do so, we show that, following the flood, average deposits for more-affected banks (defined as those banks with an above median funding shock) declined relative to such deposits for less-affected banks. This evidence is consistent with individuals dissaving and reducing deposits at banks.

Overall, a rise in NPLs and fall in deposits would cause banks' funding costs to rise.

4.2. **Those banks with a larger funding shock relatively reduced credit more than those banks with smaller funding shocks.** Those banks that suffered a larger funding shock, immediately following the floods, reduced lending in the non-flooded area. Figure (7) shows the difference in lending, pre- and post- floods between banks with different funding shocks. We plot figure (7) by regressing whether a loan is active on the

[5]Following 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.

[6]Since some non-bank financial institutions do not collect deposits, we show only the change in deposits for those banks that report data on deposits to the SBP.

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 for (i) any bank-borrower specificity and (ii) any aggregate credit changes within the tehsil over time.

In figure (7), we show that prior to the floods, the more-affected banks were expanding the most (as seen by an upward sloping trend line prior to the floods). But immediately after the floods, the more-affected banks reduced lending and stopped expanding relative to the less-affected banks (as seen by an almost flat trend line following the flood). This finding 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 funding shock (weighted by bank size) 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]

4.3. **To whom did banks reduce credit?** The more-affected banks, immediately following the floods relatively reduced lending to borrowers with little credit history and little education in the non-flooded area.

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

In table (4), column 1, we analyze only whether new borrowers (those who 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 relatively less likely, to a statistically significant extent, to offer new loans to new borrowers following the flood. In contrast, 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.

4.4. **Why did banks reduce lending disproportionately to some consumers?**

[7] A total of 2 million borrowers resided in the non-flooded area prior to the flood. Therefore, multiplying 0.7 (causal 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.

4.4.1. *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 transmission 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, these developments may lead banks to charge even higher interest rates and cause even greater reductions in credit. Consistent with this mechanism, those banks with the largest funding shock would also have the largest rises in default rates following the flood.

We first test whether adverse selection was driving the disproportionate reduction in credit across groups. To do so, we test whether loans originated after the floods 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 following form:

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

where "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] "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.

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

To provide further causal evidence for banks changing whom 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, which provides further evidence

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

that it was the banks' funding shock (caused by the floods) that 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, then the larger the relative fall in lending for a consumer group, the larger the relative increase in default rates for that consumer group. 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, following the flood, those loans originated to individuals with little education by the more-affected banks were relatively more likely to default.

In figure (8), we show how the relative reduction in credit across education groups 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 result 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 a disproportionate reduction in lending? If banks raise interest rates, this action will cause a borrower's return to fall, which, may in turn 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 (Karlan and Zinman [2009a]). If moral hazard was driving the reduction in credit to certain borrowers, due to the dynamic repayment incentive, we would expect that the loans at the more-affected banks that matured just after the floods, would be relatively more likely to default.

We test the moral hazard prediction by comparing loans that *matured* 120 days before and 120 days after the flood.

We present our results in tables (7) and (8). Table (7) shows that default rates did not relatively rise for those loans that matured just after the floods for the more-affected banks in the non-flooded area. Table (8) shows that relative default rates for the more-affected banks did not rise systematically for borrowers with low education. Furthermore, in figure (9), we show that default rates did not relatively rise in any pattern that 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.

4.4.2. *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 who 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 who 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 (the second group). 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 (the first group).

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 suggest that the disproportionate reduction in credit to new consumers is being driven neither by the presence of bank-customer specific capital nor by a repeated bank-customer relationship.

4.4.3. *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 the more-affected banks were more likely to increase mortgage lending relative to less-affected banks, since loans collateralized by residential property have a risk weight of only 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 from zero.

[9]Once a consumer has a loan, his or her biographic and credit information would be recorded within the eCIB database, which is accessible to other eligible financial institutions.
[10]In 2010, Pakistan followed the standardized approach when calculating loan's risk weights.

Our results suggest that the disproportionate 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.

4.4.4. *Did banks' preference for specialization or maintaining market share cause them to reduce lending disproportionately to some groups?* The more-affected banks may prefer to reallocate credit to those loan products in which they are heavily specialized or to those products 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 with 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 in 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 the disproportionate reduction in credit for some consumer groups.

In column 2, we examine if the more-affected banks reallocated credit toward those loan products in 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 toward those loan products in which they either are heavily specialized or have a large market share.

4.5. **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, the absense of an aggregate credit shock 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 shock[11].

(2)

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

The tehsil shock corresponds to the mean bank funding shock (weighted by bank lending) in that tehsil. Figure (2) shows the distribution of tehsil shocks across all non-flooded tehsils.

Understanding the general equilibrium effects 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 $\times$ Funding Shock $\times$Tehsil Shock" is positive and not statistically significant. If the less-affected banks lent relatively more in the more affected tehsils, this coefficient would be negative.

Our results demonstrate 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. We conjecture that the lack of additional lending by less-affected banks is due to the funding cost shock affecting all banks and the difficulty of expanding bank lending to consumers with no credit history.

[11]All loan amounts are as of August 2008 – 24 months before the start of the floods.

5. Robustness

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

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

5.1.1. *Is this a credit demand story?* Specifically, did credit fall in the non-flooded area by the most affected banks because of greater credit demand in the flooded area? The large destruction in the flooded region could spur large credit demand in that area—consumers and firms, after all, need to rebuild homes, factories, and inventory. We might expect that banks that 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, and a larger branch network (this result 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 (A) refute this explanation.

The more-affected banks 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 0.05 percentage point less likely to lend to a borrower relative to other banks in the flooded area one year after the flood.

5.1.2. *Are the results distorted by different bank types?* Our dataset has 72 financial institutions that lend to consumers. One potential concern is that our results are driven by a sole bank type. For instance, non-bank financial institutions—such as credit card companies and development agencies—may react differently than banks since they are generally smaller and do not take deposits. Furthermore, public sector banks may react differently to private banks because of different objectives and different governance structures. To explore this possibility, we restrict our dataset by omitting a single bank type (non-bank financial institutions, public banks, domestic private banks, and foreign banks) and replicate the regressions in table (2). Table (13) in Appendix (A) shows that the results are very similar, regardless of whether we exclude any particular bank type. These results suggest that the funding shock affected all financial institutions in similar ways.

5.1.3. *Did banks reduce credit in a single loan category?* Our dataset contains 64 different loan products. To ensure that one loan type is not driving our results we estimate the credit reduction by the more affected banks for each loan category.[12] In table (14), we

[12]For clarity of the results we only include products which have a minimum number of loans as of August 2008. The top eight loan products represent 94 percent of total loans as of August 2008.

regress whether a loan was active on loan product dummies interacted with the bank funding shock and the "PostTime" variable, and other controls. Table (14) shows that, following the floods, the more-affected banks relatively reduced lending in multiple loan products, in the non-flooded area. The largest reductions in credit were for agricultural loans (for capital investments), car loans, and overdraft facilities.

6. 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 United States' quantitative easing program). Analyzing how these potential shocks affect financial intermediation is often complicated by other contemporaneous changes in the economy. To overcome this complication, 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, to whom it lends, and why its lending decisions change.

We have three key empirical results: First, banks rationed credit following a funding shock: those banks that suffered a 1 percent funding shock were 0.7 percentage point less likely to lend to an individual one year after the floods in the non-flooded area. Second, banks disproportionately reduced 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.

Our empirical results 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 in the non-flooded area, by the relatively more-affected banks immediately after the floods 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. These findings are 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 creditworthiness—either through a public credit history or through education—were most likely to be the banks' marginal borrowers. 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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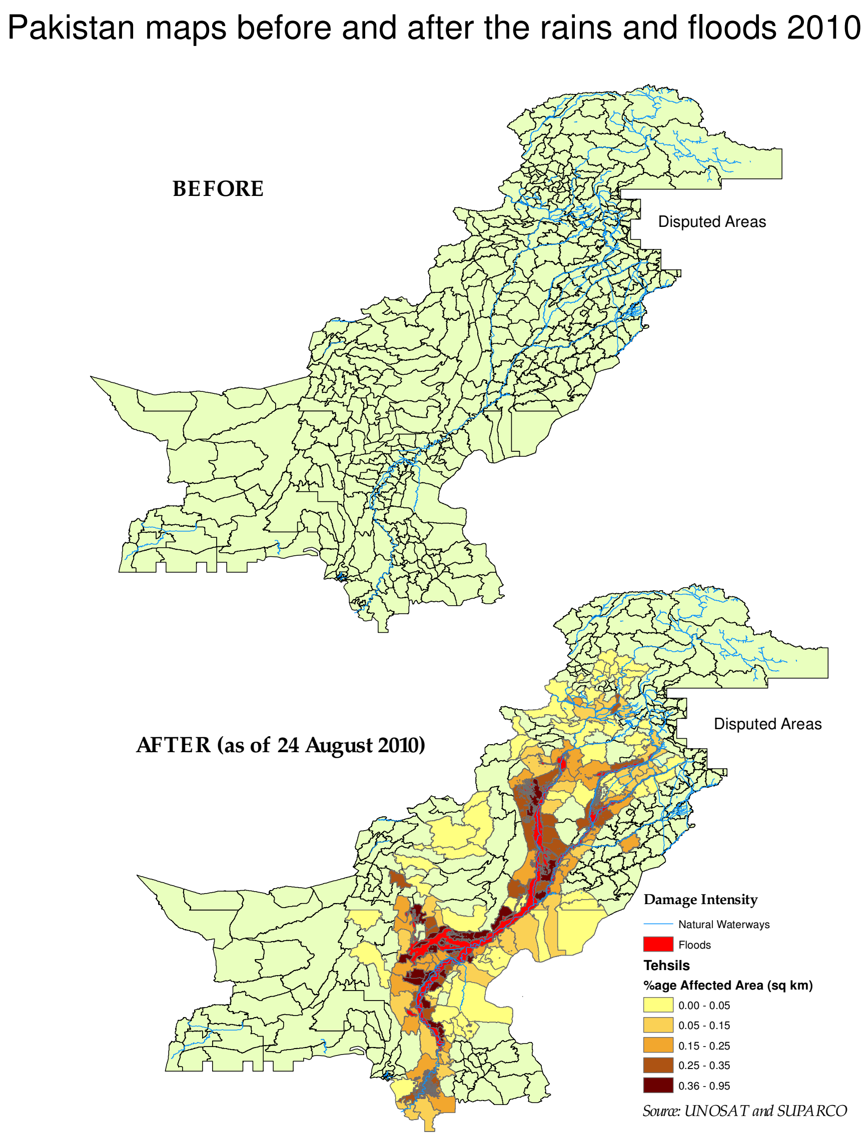
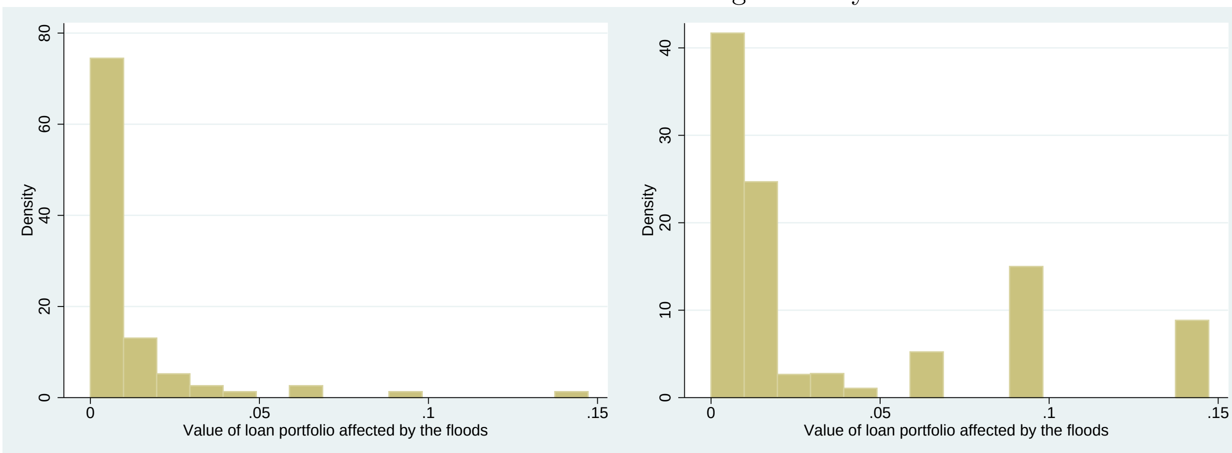
7. Figures and Tables

Figure 2. Effect of the floods by tehsil



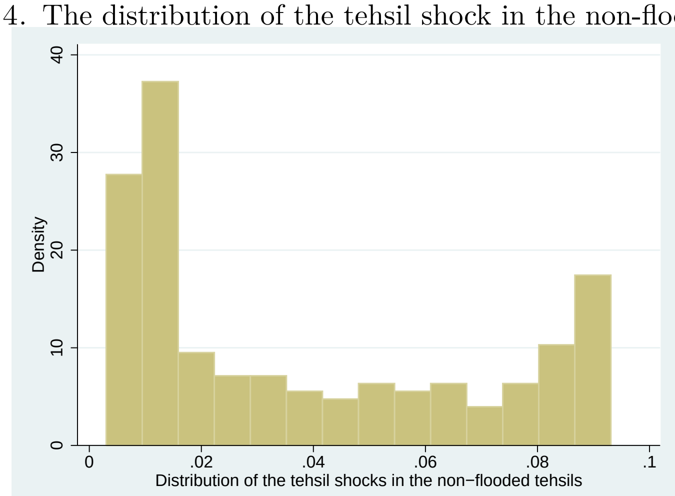
Source: United Nations [2011].

FIGURE 3. The distribution of the funding shock by bank



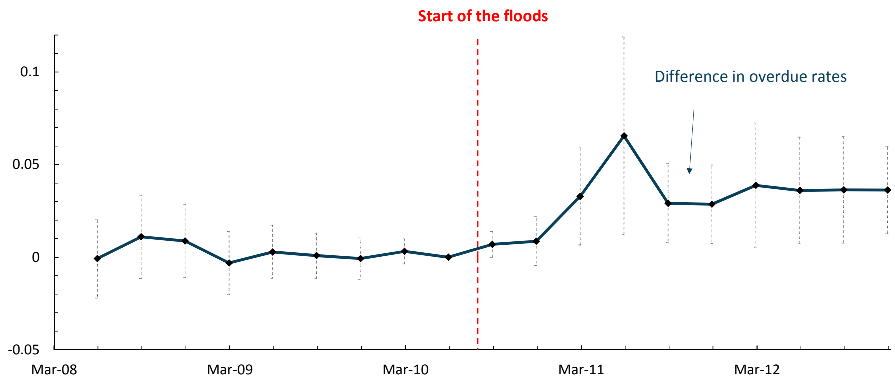
The left panel shows the distribution for the size of the flood shock for each bank. The right panel shows the distribution for the size of the flood shock for each bank, normalized by the number of loans each bank extends. The least affected institutions were the smallest financial institutions since many had a small geographic focus. 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 A).

FIGURE 4. The distribution of the tehsil shock in the non-flooded area



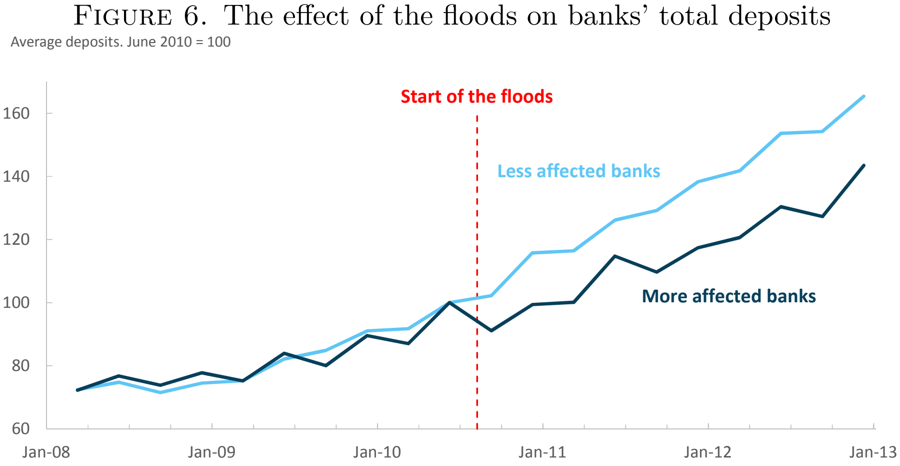
This graph shows the distribution of the "tehsil shock" (see definition (2)) across tehsils in the non-flooded area. The "tehsil shock" is the proportion of total lending in that tehsil affected by the funding shock.

FIGURE 5. The effect of the floods on overdue rates between flooded and non-flooded areas



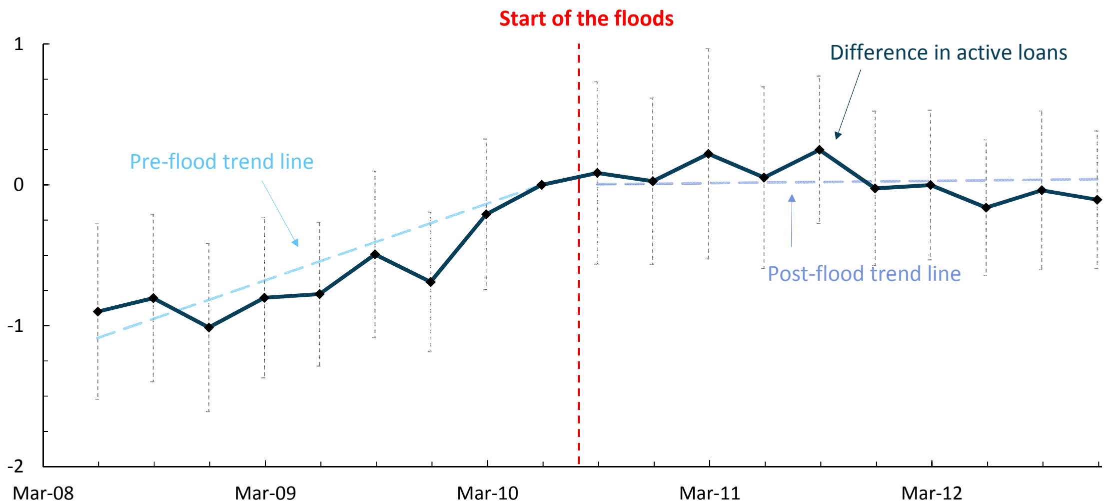
We regress whether a loan is overdue on the percentage of a tehsil that is flooded. The solid blue line is the quarterly coefficient for the increase in overdue rates for a 1 percent rise in the area of a tehsil that was flooded. The regression includes "bank × product × individual" and "bank × date" fixed effects and the standard errors are clustered at the tehsil level. The light blue dotted lines are point-wise 95 percent confidence intervals. The full regression is as follows:
$y_{bict} = a_{bpi} + a_{bt} + \beta \times \mathbf{TimeDummies}_t \times \text{Fraction of tehsil flooded}_c + \epsilon_{bpit}$.
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, in a tehsil that was flooded by 1 percent, the loans were 0.15 - 0.25 percentage point more likely to be overdue every quarter. This increase in the percentage of nonperforming loans in the flooded area is the primary evidence for a sustained increase in a bank's funding costs following the floods in 2010.

FIGURE 6. The effect of the floods on banks' total deposits



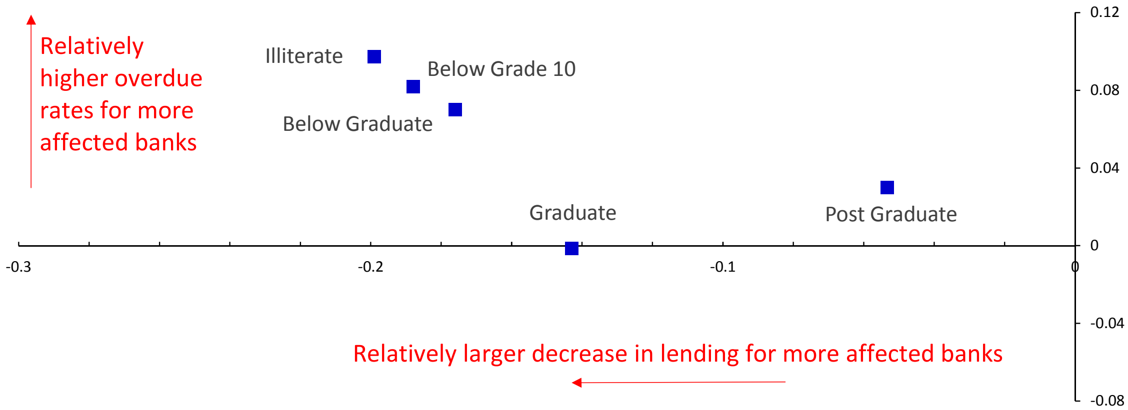
We split banks that take deposits into two groups—those banks that had an above-median exposure to the floods (more-affected banks), and those banks that had a below-median exposure to the floods (less-affected banks). We normalize banks' average deposits in June 2010 to be 100 and show that deposits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

FIGURE 7. The effect of the floods on a bank's likelihood to lend in the non-flooded areas



The blue squares are the quarterly coefficients for the effect of the *funding shock*$_b$ on banks' likelihood to lend in the non-flooded areas 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 as follows:
$y_{bict} = a_{bpi} + a_{bt} + \beta \times \textbf{TimeDummies}_t \times \text{Funding shock}_b + \epsilon_{bpit}$.
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 figure 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 loans on the funding shock interacted with quarter dummies and various controls.

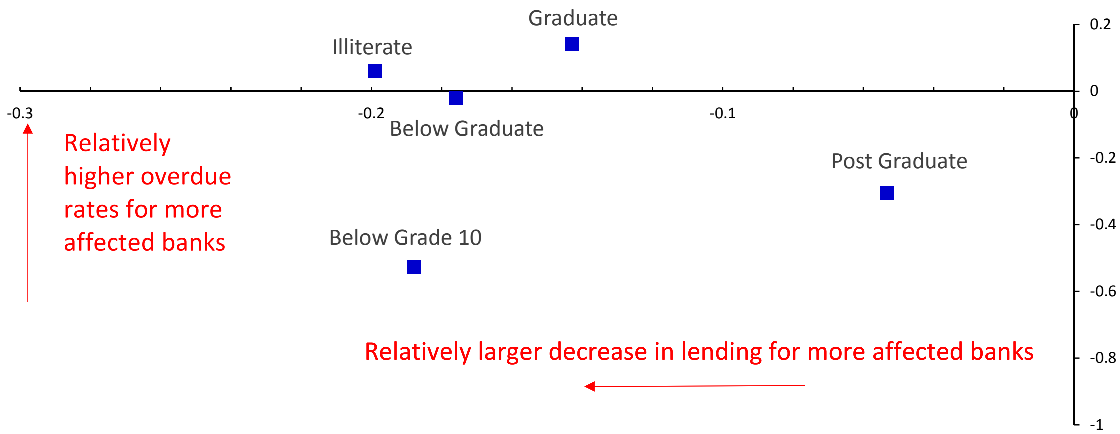
Figure 8. The most affected banks relatively reduced lending the most for those groups that also had the largest rise in relative overdue rates following the flood



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 floods 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 floods (within the first 120 days after the floods) relative to loans originated just before the floods (within the last 120 days before the floods). The coefficients are reported in the regressions in table 6.

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

Figure 9. The overdue rates for loans maturing just after the floods 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 floods 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 floods (within the first 120 days after the flood) relative to loans that *matured* just before the floods (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 floods did not relatively rise. In fact, relative overdue rates *fell* for those consumers who did not finish school ("below grade 10").

Table 1. Loan, lender, and borrower 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%
Lender Characteristics		
Public Bank	13.7%	4.1%
Domestic Private Bank	65.9%	73.5%
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%
Postgraduate	15.1%	9.0%
Total Observations	194296	

This table shows the loan, lender, amd borrower 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 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
PostTime*Shock	-0.133***	-0.341**
	(0.0320)	(0.148)
Time*Shock	0.136***	0.204
	(0.0268)	(0.133)
Observations	8080643	3436498
Number of Borrowers	219785	219785
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 that 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 point per quarter less likely to lend to particular a consumer.

The number of observations in column 2 is fewer than in column 1 since we omit all observations in months where there are no loans. As a robustness check, we have also used the inverted hyperbolic sine function (an exponential function that can handle observations with a zero realization), and the results are similar.

The full regression is as follows: $Y_{bpit} = a_{bpi} + a_{ct} + \beta_1 \times \text{Time}_\text{t} \times$ Funding Cost $\text{Shock}_b + \beta_2 \times \text{Post Time}_\text{t} \times$ Funding Cost $\text{Shock}_b + \epsilon_{bpit}$. 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
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*Postgraduate*Shock	-0.0534
	(0.153)
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*Postgraduate*Shock	0.178
	(0.166)
Observations	6977123
Number of Borrowers	174124
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
PostTime*New Borr*Shock		-0.0807*	-0.378***	
		(0.0420)	(0.102)	
PostTime*Shock	-0.0444		0.232**	-0.0253
	(0.0718)		(0.0940)	(0.0914)
Time*New Borr*Shock		0.0876**	0.211***	
		(0.0408)	(0.0790)	
Time*Shock	0.0512		-0.0843	0.0575
	(0.0491)		(0.0882)	(0.108)
Observations	4281460	2596844	3798917	1201750
Number of Borrowers	118168	100802	137990	37188
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 column 1, we separately analyze whether *new* borrowers (those with no credit history) procured more loans following the floods at more-affected banks. In column 2, we analyze whether *existing borrower-bank relationships* procured more loans following the floods at more-affected banks. Column 1 shows that new consumers were relatively less likely, to a statistically significant extent, to get loans at more-affected banks following the flood. In contrast, 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 so, we exclude the set of preexisting consumer-bank lending relationships (as of August 2008) and separate consumer-bank relationships into two groups: (i) those consumer-bank relationships that did not have a loan relationship in August 2008 but had 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. In constrast, those consumers with some credit history 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: Loans originated just before and after the flood

	Overdue Rate	Overdue Rate	Overdue Rate	Overdue Rate
Originated Post Flood*Bank Shock	0.0544	0.0787*	-0.00562	0.0124
	(0.0369)	(0.0435)	(0.0309)	(0.0186)
Originated Post Flood	-0.00674		0.00245	
	(0.00539)		(0.00375)	
Observations	28227	28227	33840	33840
Number of Borrowers	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 floods (120 days before), and just *after* the floods (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 as follows:

Overdue $\text{Ever}_{bpi} =$

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

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 that a 1 percent increase in a bank's exposure to the flooded area caused the bank to originate loans that were 0.08 percentage point 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*Shock	0.0974**	-0.0651
	(0.0480)	(0.0574)
Or. Post Flood*Below Grade 10*Shock	0.0820	-0.00770
	(0.0602)	(0.0214)
Or. Post Flood*Below Graduate*Shock	0.0702	0.0545
	(0.0473)	(0.0403)
Or. Post Flood*Graduate*Shock	-0.00130	0.152
	(0.143)	(0.120)
Or. Post Flood*Post Graduate*Shock	0.0374	0.0113
	(0.244)	(0.0682)
Or. Post Flood*Illiterate	0.00261	0.0150
	(0.0143)	(0.0102)
Or. Post Flood*Below Grade 10	0.00870	0.00203
	(0.0128)	(0.00468)
Or. Post Flood*Below Graduate	0.00877	-0.00501
	(0.0139)	(0.00894)
Or. Post Flood*Graduate	0.00326	-0.00215
	(0.0112)	(0.00827)
Observations	22518	26293
Number of Borrowers	22518	26293
Education*Tehsil FE	Yes	Yes
Bank*Tehsil FE	Yes	Yes
Tehsil*Preloan FE	Yes	Yes
Education*Bank FE	Yes	Yes
Placebo	Yes	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 that 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 floods 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 that matured just before and after the flood

	Overdue Rate	Overdue Rate	Overdue Rate	Overdue Rate
Matured Post Flood*Shock	-0.200	-0.0568	-0.137	0.104
	(0.229)	(0.104)	(0.248)	(0.127)
Matured Post Flood	0.000656		-0.00913	
	(0.00731)		(0.0176)	
Observations	70886	70886	78909	78909
Number of Borrowers	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 floods (120 days before) and just *after* the floods (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 as follows:

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

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 floods 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*Shock	0.0607	0.264*
	(0.0888)	(0.157)
Mat. Post Flood*Below Grade 10*Shock	-0.526***	-0.260
	(0.123)	(0.273)
Mat. Post Flood*Below Graduate*Shock	-0.0218	0.158
	(0.0691)	(0.108)
Mat. Post Flood*Graduate*Shock	0.141	-0.224
	(0.315)	(0.578)
Mat. Post Flood*Post Graduate*Shock	-0.306	-0.468
	(0.265)	(0.702)
Mat. Post Flood*Illiterate	-0.00541	-0.0411***
	(0.0135)	(0.0145)
Mat. Post Flood*Below Grade 10	-0.00184	-0.0195
	(0.00750)	(0.0168)
Mat. Post Flood*Below Graduate	0.000363	-0.0269***
	(0.00839)	(0.00725)
Mat. Post Flood*Graduate	-0.00305	-0.00879
	(0.00584)	(0.00710)
Observations	60989	70272
Number of Borrowers	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 that examines whether those individuals with the least education with loans at the more affected banks that mature just after the floods (120 days after the flood) 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
PostTime*Mortgage*Flood Shock	-0.143	-0.229
	(0.282)	(0.267)
PostTime*Flood Shock	-0.132***	
	(0.0318)	
PostTime*Mortgage	-0.00568	
	(0.00952)	
Time*Mortgage*Flood Shock	-0.0710	-0.0170
	(0.185)	(0.195)
Time*Flood Shock	0.137***	
	(0.0266)	
Time*Mortgage	0.000971	
	(0.00547)	
Observations	8080719	156218
Number of Borrowers	219785	8209
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 have a risk weight of only 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 that 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 a dummy variable for whether the loan is a mortgage, interacted with PostTime and the bank-specific flood shock, is both negative and not significantly significantly different to zero. This result 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 are clustered at the bank level.

TABLE 10. Did banks reallocate credit toward those loan categories in which they are heavily specialized or have a 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*Shock	-0.129***	-0.171*
	(0.0406)	(0.0890)
Time*Bank Product Specialization*Shock	-0.0192	
	(0.0132)	
Time*Bank Product Market Share*Shock		-0.0305
		(0.0249)
Time*Shock	0.158***	0.194***
	(0.0371)	(0.0726)
Observations	8080719	8080719
Number of Borrowers	219785	219785
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 (4.4.4).

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 a greater market share.

All standard errors are 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
PostTime*Flood Shock*Tehsil Shock	0.885	-1.080
	(1.425)	(3.180)
PostTime*Shock	-0.156***	-0.309
	(0.0421)	(0.197)
Time*Flood Shock*Tehsil Shock	-0.382	2.313
	(0.935)	(4.040)
Time*Shock	0.146***	0.142
	(0.0343)	(0.187)
Observations	8080643	3436498
Number of Borrowers	219785	219785
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 × Funding Shock × Tehsil Shock" is positive and not statistically significant. If the less-affected banks lent relatively more in the more affected tehsils, this coefficient would be negative.

All standard errors are clustered at the bank level.

Appendix A. Extra tables

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

	Active Loan	Log Loan Size
PostTime*Shock	-0.0531	-0.183
	(0.0578)	(0.124)
Time*Shock	0.0838*	0.115
	(0.0418)	(0.103)
Observations	3892530	1757219
Number of Borrowers	140188	140188
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 that those banks that were more exposed 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 floods 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 0.05 percentage point 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 floods on a bank's likelihood to lend in non-flooded areas—omitting different bank types

	Active Loan	Active Loan	Active Loan	Active Loan
PostTime*Flood Shock	-0.177**	-0.114**	-0.134***	-0.129***
	(0.0645)	(0.0436)	(0.0386)	(0.0322)
Time*Flood Shock	0.178***	0.127***	0.141***	0.133***
	(0.0583)	(0.0345)	(0.0314)	(0.0266)
Observations	6881439	7221463	2649854	7489401
Number of Borrowers	177686	97961	105465	213643
Non-Bank Financial Institutions		X	X	X
Public Banks	X		X	X
Domestic Private Banks	X	X		X
Foreign Banks	X	X	X	
Tehsil*Date FE	Yes	Yes	Yes	Yes
Bank*Borrower*Product FE	Yes	Yes	Yes	Yes

Standard errors in parentheses

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

These regressions duplicate the regressions in table (2), except we omit the following types of banks: non-bank financial institutions (column 1), public banks (column 2), private banks (column 3), and foreign banks (column 4). The results are very similar across each sample. These similar results suggests that the effects are similar for all bank types, and the results are not driven by one type of bank.

The full regression is as follows:

$Y_{bpit} = a_{bpi} + a_{ct} + \beta_1 \times$ Time$_{\text{t}}$ $\times$ Funding Shock$_b$ + $\beta_2\times$ PostTime$_{\text{t}}$ $\times$ Funding Shock$_b + \epsilon_{bpit}$.

All standard errors are clustered at the bank level.

TABLE 14. The effect of the funding shock on a bank's loan products in the non-flooded areas

	Active Loan	Active Loan
PostTime*Agricultural Production Loan*Shock	0.0124	0.00958
	(0.0718)	(0.0713)
PostTime*Agricultural Development Loan*Shock	-0.293***	-0.299***
	(0.0864)	(0.0860)
PostTime*Car Loan*Shock	-10.32**	-10.33**
	(4.201)	(4.202)
PostTime*Credit Card Loan*Shock	-0.600	-0.604
	(1.172)	(1.174)
PostTime*Microcredit Loan*Shock	-0.100	-0.105
	(0.0780)	(0.0784)
PostTime*Mortgage Loan*Shock	-0.298	
	(0.295)	
PostTime*Personal Loan*Shock	-1.111	-1.125
	(0.798)	(0.794)
PostTime*Overdraft Cash Facility*Shock	-1.790***	-1.810***
	(0.464)	(0.467)
Observations	7446005	7289806
Number of borrowers	212489	207860
Time*Product	Yes	Yes
Time*Product*Shock	Yes	Yes
PostTime*Product	Yes	Yes
Tehsil*Date FE	Yes	Yes
Bank*Borrower*Product FE	Yes	Yes
Minimum number of loans in August 2008	50,000	100,000

Standard errors in parentheses

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

This table shows that the more-affected banks reduced lending in multiple different products. The largest decreases in lending occured in agricultural lending (for capital investments), car loans, and overdraft facility. To ensure we have sufficient product observations, we restrict our sample to loan products for which there were at least 50,000 loans (column 1) or 100,000 loans (column 2) in August 2008.

Each regression includes a (i) product dummy interacted with time, (ii) a product dummy interacted with the bank shock variable and interacted with the time variable, (iii) a product dummy interacted with the PostTime variable, (iv) a tehsil dummy interacted with a date dummy, (v) a bank dummy interacted with a borrower dummy amd interacted with a product dummy.

All standard errors are clustered at the bank level.