FINANCE AND INEQUALITY: THE DISTRIBUTIONAL IMPACTS OF BANK CREDIT RATIONING

M. ALI CHOUDHARY* AND ANIL JAIN†

Abstract. We analyze reductions in bank credit using a natural experiment where unprecedented flooding differentially affected banks that were more exposed 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 borrowers with little education, little credit history, and seasonal occupations, 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 a reduction in bank monitoring incentives caused the large relative decreases in lending to these borrowers.

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

JEL Codes: G21, G28, 016

Date: April 2021.

*State Bank of Pakistan. Email: `ali.choudhary@sbp.org.pk` and †Board of Governors of the Federal Reserve System. Email: `anil.k.jain@frb.gov`. This paper benefited significantly from the in-depth discussion with Abhijit Banerjee, Bastian von Beschwitz, Mark Carey, Stijn Claessens, Nicholas Coleman, Benjamin Golub, Raj Iyer, Logan Lewis, Conrad Miller, Rodney Ramachandran, Riaz Riazuddin, and Ashish Shenoy. We would like to thank seminar and conference participants at the Annual Economic Association meeting, Darden School of Business, European Financial Association meeting, Federal Reserve Bank of San Francisco, and Financial Management Association Annual Meeting. The findings and conclusions in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System, the views of any other person associated with the Federal Reserve System, or the State Bank of Pakistan.

1. Introduction

There is substantial evidence that credit access can improve consumer welfare.[1] 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 disbursing credit, there is surprisingly little evidence for *whom* banks reduce credit 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?

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.[2]

We have three main results. First, the banks more-affected by the funding cost shock disproportionately reduced credit to borrowers with little education, little credit history,

[1]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]).

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

and seasonal occupations relative to less-affected banks. This reduction in credit is correlated with borrower riskiness with the more-affected banks reducing lending more for credit markets with higher initial overdue rates relative to less-affected banks. Second, the evidence suggests that a reduction in bank monitoring incentives caused 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 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 and potential credit product demand changes in the non-flooded area, we include both county-specific dummies interacted with time fixed effects and credit-product specific dummies interacted with time fixed effects in our specifications.

The first of three datasets we use is supplied by the Space and Upper Atmosphere Research Commission (SUPARCO, Pakistan's space agency) and United Nations' Operational Satellite Applications Programme (UNOSAT) to estimate the flood damage in each tehsil.[3] 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 individual borrowers 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, less credit history, and occupied in seasonal occupations. Fourth, we explore why banks disproportionately reduced lending for these borrowers. Finally, we analyze the general equilibrium effects of the bank funding shock. We show 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 pre-existing loans in the flooded area were more likely to default relative to loans in the non-flooded area (a capital shock for banks) and we show that banks that had greater exposure to the flooded area were more likely to have deterioration in deposits as firms and consumers dissaved (a liquidity shock for banks).

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

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, a proxy for 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, little credit history, and seasonal occupations. To do so, we use a triple difference-in-difference methodology and interact the borrower's demographic information (education, occupation, prior credit history) 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 the results are primarily driven by a reduction in banks' incentives to monitor their loans. Specifically, banks with lower capital ratios may reduce their monitoring effort due to limited liability and moral hazard with respect to monitoring effort (Allen et al. [2011]). Higher capital ratios endogenously lead banks to being more likely to survive to the next period, and consequently, profit from increased monitoring effort today. Moreover, a higher likelihood of a bank surviving increases the value of that bank's existing relationship loan portfolio (borrowers' dynamic incentive to repay is higher as they expect to receive loans in the future), and in turn, induces greater bank monitoring (Mehran and Thakor [2011]). Finally, if the cost of bank monitoring rises differentially across banks—for example, due to lower bank organizational capacity due to the floods—banks that have the largest marginal rise in bank monitoring costs would reduce monitoring the most.

To provide evidence for bank monitoring driving our results, we examine changes in lending, changes in loan performance, and differential changes in lending by institutional type. In terms of lending, we show that the more-affected banks reduced lending more in loans that had higher initial overdue rates compared to less-affected banks, following the floods, in the non-flooded area. Moreover, more-affected banks reduced lending more for unsecured loans than less-affected banks. In terms of loan performance, following the floods, we show overdue rates at more-affected banks rose more, especially for unsecured loans—those loans that require the greatest monitoring. Finally in terms of which financial institutions were most affected, we show some evidence that the size of these effects is attenuated for public banks—those banks that are more likely to survive following negative shocks.

We consider alternative reasons for why banks may disproportionately reduce credit to some groups. We show the evidence is not consistent with a decrease in credit demand (rather than a decrease in credit supply), (ii) an increase in borrower moral hazard, (iii) banks reduced lending due to capital regulation, or (iv) banks reduced lending in a single credit product.

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 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—to differing effects—and the difficulty of expanding bank lending to consumers with no credit history.

Our paper is linked to a few different topics of literature. We add to the expanding literature that examines how the financial system can both amplify or dampen financial shocks from natural disasters. Our paper's finding that banks prioritize their existing customers adds to the large literature on the importance of relationship lending, especially during financial downturns. Finally, our paper adds to the broader literature on how banks react to negative shocks.

There is a large literature that has shown that the adverse economic and health effects from natural disasters are both larger and longer lasting in less economically developed countries, but there is limited evidence on the role of the financial sector in these countries in either amplifying or dampening the economic shocks. For advanced economies, Chavaz [2014], Cortés and Strahan [2017], Bos et al. [2018], Koetter et al. [2020] show that bank lending actually *rose* in areas that suffered natural disasters, and Klomp [2014] shows that large-scale natural disasters have no significant negative effect on the stability of the banking sector in developed countries—but only in emerging countries. For emerging countries, the empirical evidence for the financial system's effectiveness to buffer these shocks is more limited. Consistent with the evidence presented in our paper, Berg and Schrader [2012], show that there were large increases in credit demand *but large decreases in loan supply* following earthquakes in Ecuador in the affected areas. The identified mechanism for reducing credit supply was the increase in credit risks following the earthquake. Finally, following major flooding in Bangladesh, Del Ninno et al. [2003] report increases in demand for credit in the affected areas that was largely met by informal sources, such as friends and neighbors, but not by banks or other formal institutions.

Our main contribution to the literature on the financial effects of natural disasters is to provide additional evidence that the negative effects on the financial sector from natural disasters are larger in emerging economies, and, through the financial sector, can spillover to unaffected areas. Moreover, these effects disproportionately affect disadvantaged individuals in these countries.

Turning to the large literature on relationship lending (starting from Rajan [1992], Petersen and Rajan [1994], Berger and Udell [1995], Boot and Thakor [2000]), we find that the more-affected banks prioritized lending to their pre-existing borrowers and dramatically reduced lending to new borrowers, especially those with little credit history at any bank. Our results are consistent with a number of empirical papers that have shown that during financial downturns relationship banks prioritize their existing corporate borrowers; for example, Sette and Gobbi [2015], Bolton et al. [2016], Beck et al. [2018], Banerjee et al. [2021] show during the global financial crisis. There is significant empirical evidence that banks prioritize their existing borrowers because these borrowers are more profitable due to the bank's informational advantage. Puri et al. [2017] find that retail borrowers who have a relationship with their bank were significantly less likely to default on their loan than other borrowers, and Agarwal et al. [2018]) find that credit card borrowers with other accounts at that bank had lower rates of default, lower rates of attrition, and higher utilization rates. Moreover, we find that less-affected banks did not compensate for the reduction in lending by more-affected banks by increasing their lending to new borrowers, which is consistent with the difficulty of making new lending relationships due to the large information asymmetries.

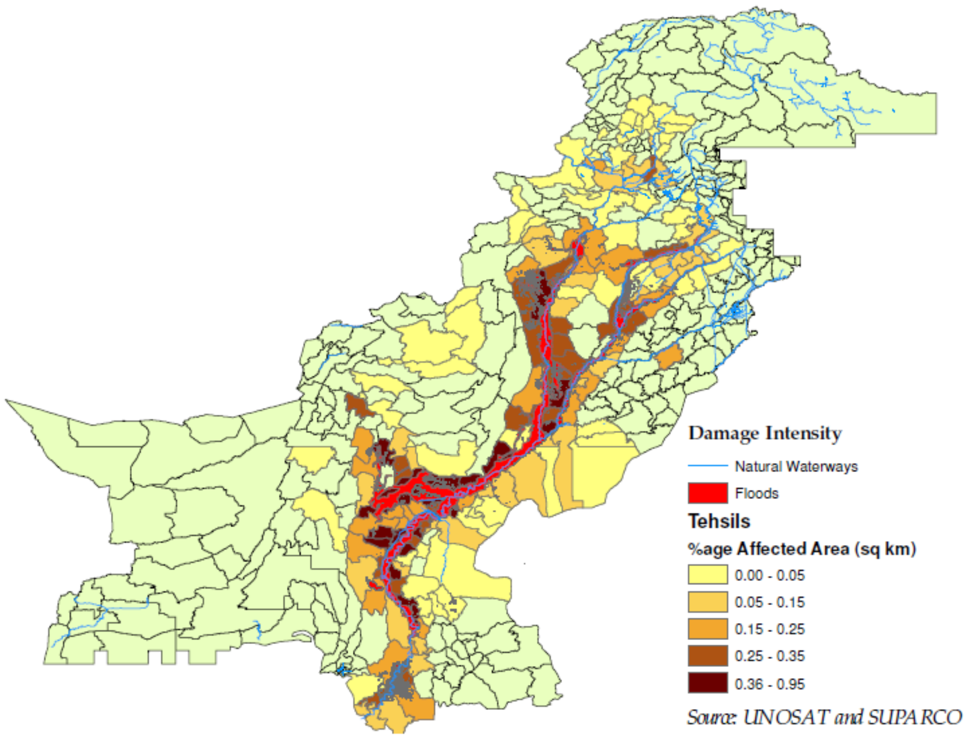
A large literature in economics and finance has shown that exogenous negative shocks to banks can cause changes in lending to firms and households. These shocks vary from liquidity shocks (Khwaja and Mian [2008], Schnabl [2012], Iyer et al. [2014], Gilje et al. [2016]), information shocks (Hertzberg et al. [2011], Choudhary and Jain [2020]), capital shocks (Gambacorta and Mistrulli [2004], Aiyar et al. [2014], Dwenger et al. [2020]), to financial crises (Popov and Udell [2012], Cetorelli and Goldberg [2012], De Haas and Van Horen [2012], Agarwal et al. [2017]). These shocks can cause substantial reduction in lending, and subsequently large negative real effects on employment, investment, and consumption. The closest paper to our paper is Agarwal et al. [2017] that examines changes in consumer credit supply during credit expansions. They show that that banks disproportionately lent less to low-credit score borrowers during the expansion. We show different results: During a credit recession, those individuals with the least credit history were most likely to be credit rationed. Furthermore, we show this result 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. By matching demographic data to our credit data, we are able to inform better-targeted policy responses to credit rationing.

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) 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. The preliminary estimates for the flood's damage was over $10 billion (Asian Development Bank, Government of Pakistan, and World Bank [2010])—over 5 percent of Pakistan's GDP in 2010. Yet, global aid to support Pakistan was both relatively slow and small. As of end-October 2010 (more than two months after the floods), Pakistan had only received $489.5 million, of which $202 million was in-kind transfers (Asian Development Bank et al. [2010]). In total, estimates for pledged global aid (which was a combination of grants, loans, and in-kind transfers), was $ 1.8 billion ((Asian Development Bank et al. [2010]).

FIGURE 1. Effect of the floods by tehsil



This figure shows the fraction of each tehsil that was flooded.

2.2. **The effect of the floods on banks.** Banks felt the impact of the floods through two different channels: (i) a rise in nonperforming loans (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 the incomes of both individuals and firms, and were more likely to default on existing loans. Bank annual reports recorded this trend:

"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]).

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].

Credit ratings of banks across Pakistan revealed the deterioration in their loan portfolios. 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]). Moreover, as a direct indicator for the decrease in Pakistan's financial conditions, Pakistan's sovereign spread increased by 80 basis points against a broadly stable composite index (International Monetary Fund [2010]). Asian Development Bank et al. [2010] preliminary estimates for financial institutions total loan losses from the flood was over USD $1 billion.

As empirical evidence of 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 bank credit to bank deposit ratio of just over 70 percent in 2010 (World Bank [2017]).[4] 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.

[4]In contrast, the bank credit to bank deposit ratio in more developed economies is often larger. That ratio during this same time was 130 percent in Australia, 120 percent in France, 124 percent in Germany, 121 percent in Italy, and 175 percent in Spain. Notably, not all developed economies have high bank credit to bank deposit ratio: in the United States it is 65 percent and in Japan only 50 percent (World Bank [2017]).

2.3. **Data.** We use two main sources in our empirical investigation, using (i) credit data from the State Bank of Pakistan (SBP) and (ii) the extent of the damage to each tehsil as measured by the United Nations and Pakistan's SUPARCO.

The SBP eCIB legally requires all financial institutions to report credit data on all borrowers, both corporate and individual. Some of this data has been used before by Khwaja and Mian [2005, 2008], Mian [2006], Khwaja et al. [2011], Choudhary and Jain [2020]. However, previous researchers had access only to a partial list of corporate borrowers, whereas we have access to *every* loan to an individual for 72 different financial institutions in 2008. 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 dataset does not include interest rates.[5]

The dataset stretches from September 2008 to June 2012. For data management purposes we randomly use 10 percent of the 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 differences in loan and borrower characteristics for loans in September 2008 (the start of our dataset) between the largest five lenders and other lenders. The largest five lenders comprise over half of the total consumer loan market and, overall, have similar lending characteristics as the rest of the lending market. The most noticeable difference between the largest lenders and other lenders, is that the largest lenders have a much larger share of lending to individuals employed in seasonal or contractual occupations, whereas other lenders have a much larger share of salaried employees. As of June 2010, the median loan size was 32,000 Pakistani Rupees (just below USD $400), with the median loan size for borrowers with credit history (defined as borrowers with a loan in June 2008) slightly higher, at 35,000 Pakistani rupees, and the median loan size

[5]The field for interest rates is included in the dataset but the values are mostly missing (more than 90 percent of the data).

for borrowers with no credit history (defined as borrowers with no loan in June 2008) significantly lower, at only 22,000 Pakistani rupees.[6]

TABLE 1. Differences in loan characteristics between the largest five lenders and other lenders in our sample

	Other financial institutions	Five largest financial institutions
Borrower Characteristics (Education)		
Illiterate	7%	1%
Below Grade 10	5%	2%
Below Graduate	16%	14%
Graduate	19%	26%
Post Graduate	12%	14%
Not Reported	40%	22%
Borrower Characteristics (Occupation)		
Business Owner	18%	21%
Salaried	36%	15%
Seasonal / Contractual	4%	24%
Other Occupation	41%	40%
Loan Characteristics		
Overdue Rate	14%	26%
Secured Loan	31%	35%
Loan Size Outstanding (Pkr. Rupees)	148,500	103,262
Total market share	48%	52%

This table shows the differences in loan and borrower characteristics for loans in September 2008 (the start of our dataset) between the largest five lenders and other lenders in the non-flooded area. Column 2 reports statistics for the five largest lenders (defined by the number of loans in the non-flooded area in September 2008), and column 1 reports statistics for the other lenders. All values are weighted by lender size (specifically, the number of loans at that financial institution). The most noticeable difference between the largest lenders and other lenders is that the largest lenders have a much larger share of lending to individuals employed in seasonal or contractual occupations, whereas other lenders have a much larger share of salaried employees.

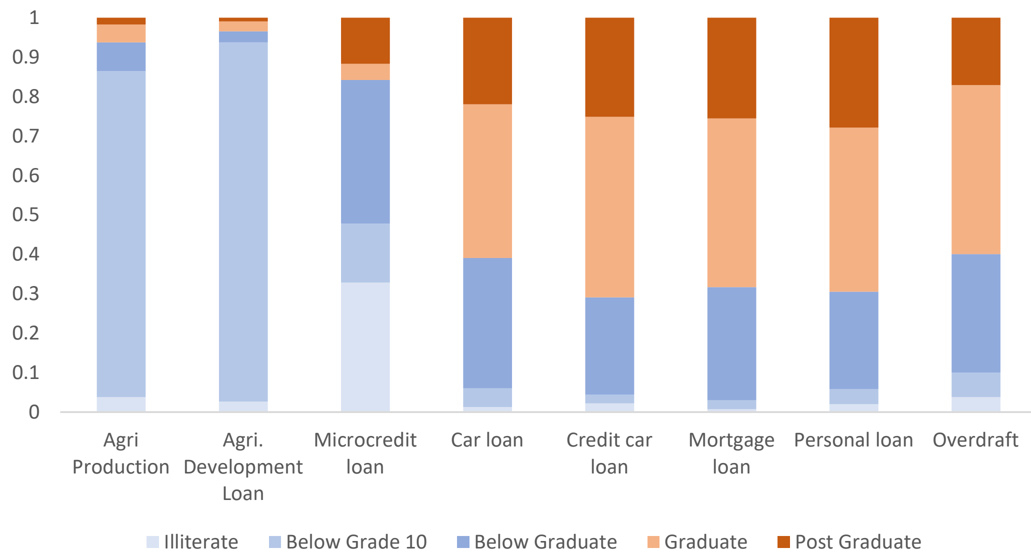
Figure (2) shows the share of lending by education for each loan product in the non-flooded area for September 2008.[7] We observe that the greatest number of agricultural

[6]Moreover, loans to individuals with no credit history were significantly more likely to be secured loans (nearly one-half of these loans were secured) than loans to individuals with credit history (just over one-third of these loans were secured, consistent with the relationship lending literature that finds that collateral and relationship length are negatively correlated (such as Berger and Udell [1995], Harhoff and Körting [1998], Chakraborty and Hu [2006]).

[7]For ease of exposition, Figure (2) only shows the eight largest loan products.

and microfinance borrowers reported very little or no education, and that individuals with greater education are more likely to have loans for credit cards, cars, and mortgages. Figure (3) shows how the education of the average borrower changes over time.

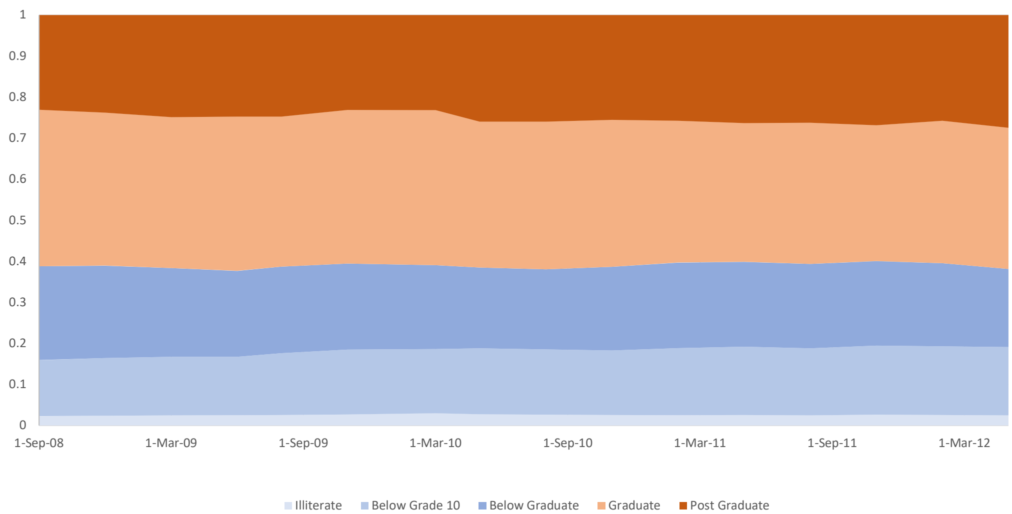
Figure 2. Share (loan value) of lending, by education and product



This figure shows the composition of borrowers' education by loan product in September 2008 for the non-flooded area. For ease of exposition, the figure only shows the eight largest loan products.

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: loan type, loan size, 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.

Figure 3. Share (loan value) of lending, by education, over time



This figure shows how the education level of the average borrower changes over time in the non-flooded area.

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 the paper's identification is comparing loans for individuals between different banks who had different funding shocks, before and after the floods. Moreover, we restrict attention to loans to individuals in the non-flooded part of Pakistan to limit the possibility that loan demand changes due to the floods (additionally, as robustness, in section (5.1), we specifically show results that are consistent with banks rationing credit rather than a reduction in consumers' credit demand).[8]

[8]An additional concern is that the millions of displaced individuals would cause significant net migration to regions that were unaffected by the floods and thereby place additional stress on banks in those areas.

We exploit the time variation in our dataset in two key ways. To examine changes in the recipients of bank loans, we compare active bank loans in June 2010 (just before the flood) and June 2012 (nearly two years after the flood). To examine whether banks changed monitoring practices following the flood, we examine whether loans that originated in a small window (120 days) before and after the flood were more likely to eventually default. Finally, to show that the results are generated by changes in banks' response to the flood, we present placebo regressions, which show no changes in bank or borrower behaviour for placebo shocks for the period before the flood.

To examine changes in active loans we estimate equations of the following form:

$$Y_{bpit} = \beta \times \text{Funding Shock}_b \times \text{Post}_t + \alpha_{bip} + \alpha_{pt} + \alpha_{ct} + \epsilon_{bpit} \tag{1}$$

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, in some regressions it is a binary variable for whether individual i has a mortgage 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. "Post" is a binary variable for whether the observation is after the flood. The standard errors, ϵ_{bpit}, are clustered at the bank level.

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. Moreover, we include a loan product

However, there is some evidence that although there was significant displacement, the majority of those displaced stayed within their home district. A survey of 1,800 households in the most affected districts finds that there was little migration out of the affected districts (Kirsch et al. [2012]). Specifically, the survey finds that even though 90 percent of those surveyed were forced to leave their homes, and that a third moved at least twice, less than 20 percent moved away from their original district. Given that the floods caused significant economic and human damage within the affected areas, which will cause both supply and demand effects for credit, reiterates the importance of focusing our analysis on credit impacts in the non-flooded areas.

dummy interacted with time fixed effect, α_{pt}, that ensures we control for any changes in aggregate demand shifts over time for specific products. Finally, we include a bank dummy interacted with a product dummy interacted with an individual dummy fixed effect, a_{bpi}, that ensures we are controlling for any individual-bank-product specificity (and also ensures we are including a fixed effect for each observation in the panel's cross-section).

In our main regression, the coefficient of interest, β, estimates the causal effect of a 1 percentage point increase in a bank's funding shock on a bank's willingness to lend after controlling for various individual, product, and geographic variables.

To create a measure for the "Funding Shock$_b$" for bank b, we multiply the damage in each tehsil, c, by the fraction of bank b's loan portfolio in tehsil c and sum 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[9]:

(2)

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

Figure (4) shows the distribution of the estimated funding shock by bank. This figure shows that the smallest institutions were the least affected by the floods—most likely because they had the smallest geographic focus. In our robustness results, we demonstrate that excluding the non-banking financial institutions (the smallest financial institutions) do not alter our results (table (19)).

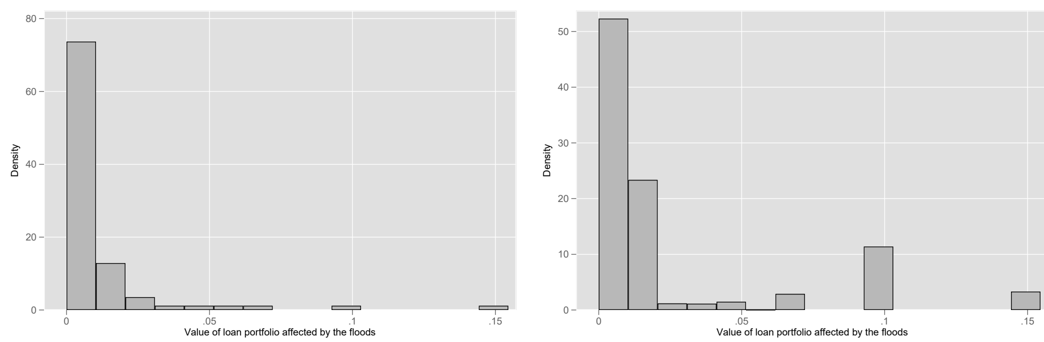
Figure (5) shows how the shock varied across financial institutions of varying size and type by plotting the size of each financial institutions' funding shock by the number of that institution's loans in our sample and financial institution type.[10] Since the floods affected

[9] All loan amounts are as of September 2008—24 months before the start of the flood, that is, the very first month of available data.

[10] In the Appendix, Figure (10) shows the same information as figure (5) but the x-axis is the natural logarithm of a financial institution's loans, rather than the absolute number of a financial institution's loans.

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.

FIGURE 4. The distribution of the funding shock by bank



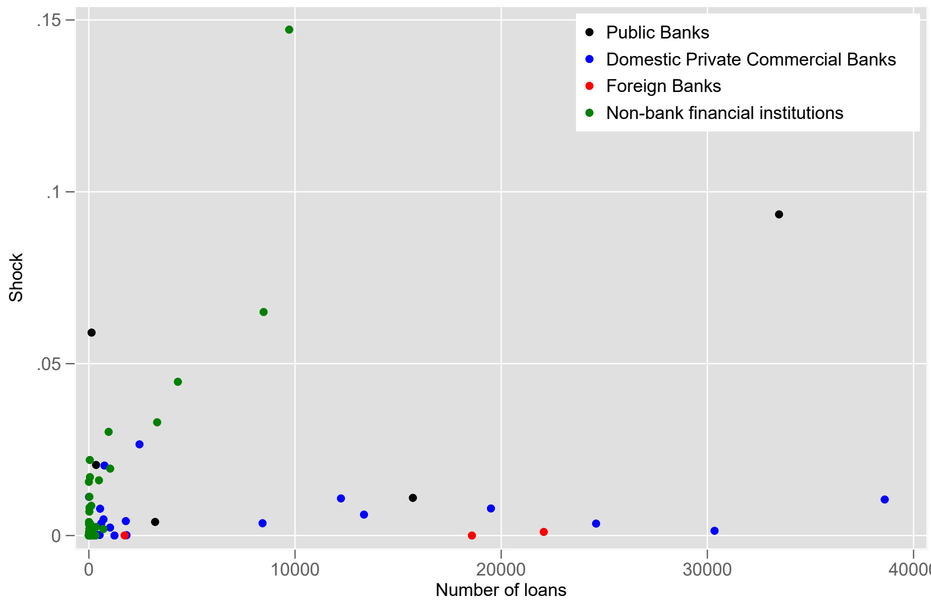
The left panel shows the distribution for the size of the flood shock for each bank. The right panel shows the distribution for the size of the flood shock for each bank, normalized by the number of loans each bank extends. The least-affected institutions were the smallest financial institutions since 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 (19).

Table (2) shows the loan, lender, and borrower characteristics for loans in September 2008 (the start of our dataset). We split our dataset between banks that were more and less-affected by the floods to examine how the set of borrowers differed across these banks. 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.

3.1.1. *Outcomes of interest.* There are three outcomes of interest in the paper:

- Active loan_{bpit}
- Loan size_{bpit}
- Overdue loan_{bpi}

FIGURE 5. The distribution of the funding shock by financial institution



This figure shows how the shock varied across financial institutions of different size by plotting the size of each financial institution's funding shock by the number of that institution's loans in our sample. In the Appendix, figure (10) shows the same information, except that the x-axis is the natural logarithm of a financial institution's loans, rather than the absolute number of a financial institution's loans.

"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.

"Loan size$_{bpit}$" is a continuous measure (inverse hyperbolic sine transformation) of loan size for individual i at bank b in date t for loan product p.[11]

"Overdue loan$_{bpi}$" is a dummy variable equal to 1 if individual i at bank b has an overdue loan in credit product p.

4. RESULTS

First, we 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

[11]Similar to papers Pence [2006], Georgarakos and Pasini [2011], Haushofer and Shapiro [2016], we use the inverse hyperbolic sine transformation, $y = log(y + (y^2 + 1)^{1/2})$, because this transformation approximates the natural logarithm and allows retaining zero-valued observations, that is, individuals with no loans.

TABLE 2. Differences in loan characteristics between the more-affected banks and the less-affected banks in our sample

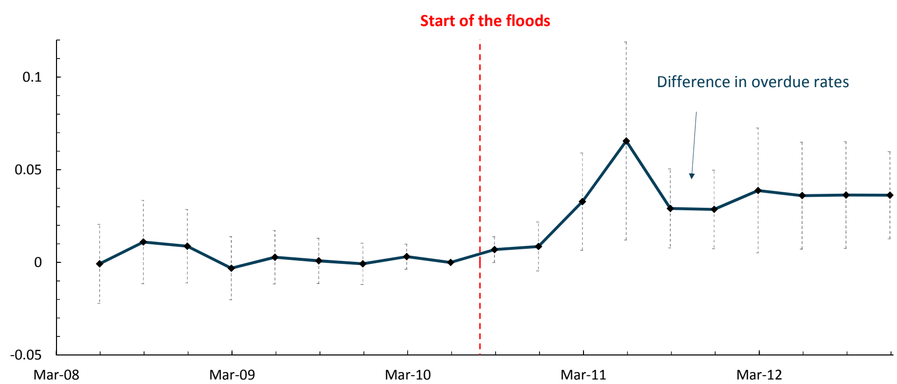
	Less affected financial institutions	More affected financial institutions
Borrower Characteristics (Education)		
Illiterate	3%	5%
Below Grade 10	3%	25%
Below Graduate	17%	13%
Graduate	28%	18%
Post Graduate	16%	11%
Not Reported	33%	28%
Borrower Characteristics (Occupation)		
Business Owner	26%	14%
Salaried	24%	26%
Other Occupation	47%	35%
Seasonal / Contractual	3%	24%
Loan Characteristics		
Overdue Rate	22%	18%
Secured Loan	19%	45%
Loan Size Outstanding (Pkr. Rupees)	150,226	102,463

This table shows the loan, lender, and borrower characteristics for loans in September 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 funding shock. Column 1 has the less-affected banks, and column 2 has the more-affected banks. All values are weighted by lender size (specifically, the number of loans at that financial institution).

the flooded area, their deposits relatively decreased (liquidity shock) (section 4.1). 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 (section 4.2). Third, using these initial results, we show that banks with larger funding shocks reduced credit more to consumers with little education, less credit history, and individuals with seasonal occupations (section 4.3). Fourth, we present evidence that shows that the funding shock led to reduced bank monitoring (section 4.4). 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 (section 4.5).

4.1. **Both capital and liquidity shocks for banks caused 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 the fraction of area in a tehsil that was flooded interacted with a set of time dummies, and additional fixed effects.[12] 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.

FIGURE 6. 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. 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.

In figure (7), we show a dramatic, sudden, and sustained relative decrease in liquidity for banks with greater exposure to the floods (liquidity shock).[13] To do so, we show that,

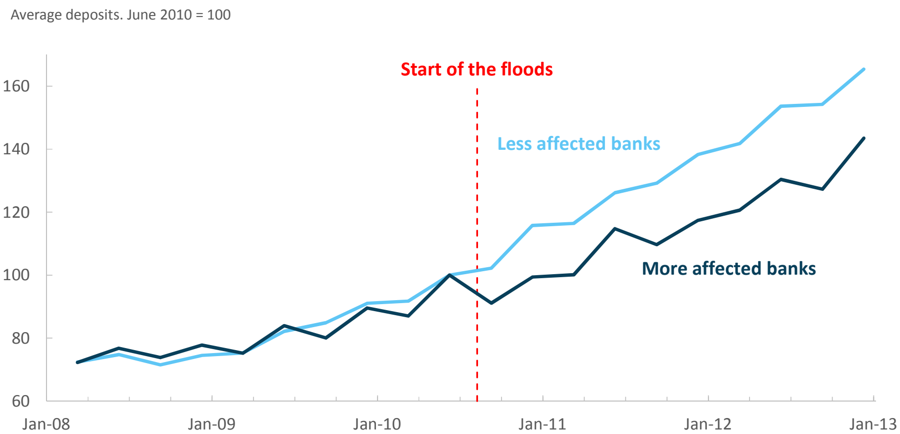
[12]Following Hertzberg et al. [2011], we code a loan to be overdue in only the first quarter it is observed as overdue. To ensure we do not double count our overdue observations we code the loan as missing for all loan observations after this quarter.

[13]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 State Bank of Pakistan.

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.

FIGURE 7. 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.

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. Table (3) demonstrates that the more-affected banks reduced lending relatively more following the flood. Columns 1 and 2 focus on whether banks were more likely to reduce the number of loans, and columns 3 and 4 focus on whether banks were likely to reduce loan size.

In the first column of table (3), we regress whether the loan is active on our variable of interest, "Post x Shock", and various controls. Our controls include (i) a bank dummy interacted with a borrower dummy interacted with a credit product dummy fixed effect (α_{bip}), (ii) a tehsil dummy interacted with a time dummy fixed effect (α_{ct}), and (iii) loan product interacted with time fixed effect, α_{pt}. These fixed effects ensure that we control for bank-borrower specificity, aggregate credit changes within tehsil over time, and aggregate changes in credit product demand over time. For instance, the credit product interacted with time fixed effect ensures that we are controlling for all banks reducing agricultural loans following the flood.

In the second column of table (3), we repeat the exercise from column 1, but conduct a placebo regression using observations for September 2008 and June 2010 (that is, data from before the flood).

The estimates in column 1 show that for a 1 percentage point increase in the funding shock led to just under a 1.5 percentage point decrease in the likelihood a bank will offer a loan to a given borrower two years after the flood. The median funding shock (weighted by bank size) to a bank was just under 1 percent, therefore a back of the envelope calculation suggests that the funding shock caused potentially 30,000 fewer loans in the non-flooded area, two years after the flood.[14]

The results in column 2 show there was no discernible effect from a placebo regression suggesting that the result in column 1 is not driven by pre-existing trends. Moreover, to reinforce evidence for the lack of pre-trends in our outcome of interest, in figure (8), we plot the difference in lending—pre- and post- floods—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 including the same controls as in table (3). Figure (8) clearly shows there were no perceptible differences before the flood for differentially affected banks, but immediately following the flood, lending dramatically fell for those banks with a larger lending shock.

[14]To estimate this statistic we observe that there was a total of 2 million borrowers who resided in the non-flooded area prior to the flood. Therefore, by multiplying the causal effect of the flood shock (1.5) by the median magnitude of the funding shock (1 percent) by the total number of borrowers (2 million) we estimate potentially 30,000 fewer borrowers.

Turning to differences in loan size. Column 3 examines how loan sizes relatively changed for more-affected banks after the flood, in the non-flooded area.[15] The estimates in column 1 show that a 1 percentage point increase in the funding shock led to over a 7 percent decrease in the average loan size two years after the flood. Similar to the results in column 2, we find no evidence of pre-trends in our dataset given the small and non-significant coefficient in our placebo regression for loan size (in column 4).

TABLE 3. The effect of the funding shock on a bank's likelihood to lend in non-flooded areas

	Active loan	Active loan	Loan size	Loan size
Post x Shock	-1.48**		-7.21*	
	(0.66)		(4.16)	
Post x Shock (Placebo)		0.051		-0.14
		(0.77)		(5.54)
Observations	894706	956424	894706	956424
Placebo		X		X
Tehsil x Date FE	Yes	Yes	Yes	Yes
Product x Date FE	Yes	Yes	Yes	Yes
Bank x Borrower x Product FE	Yes	Yes	Yes	Yes

Standard errors in parentheses

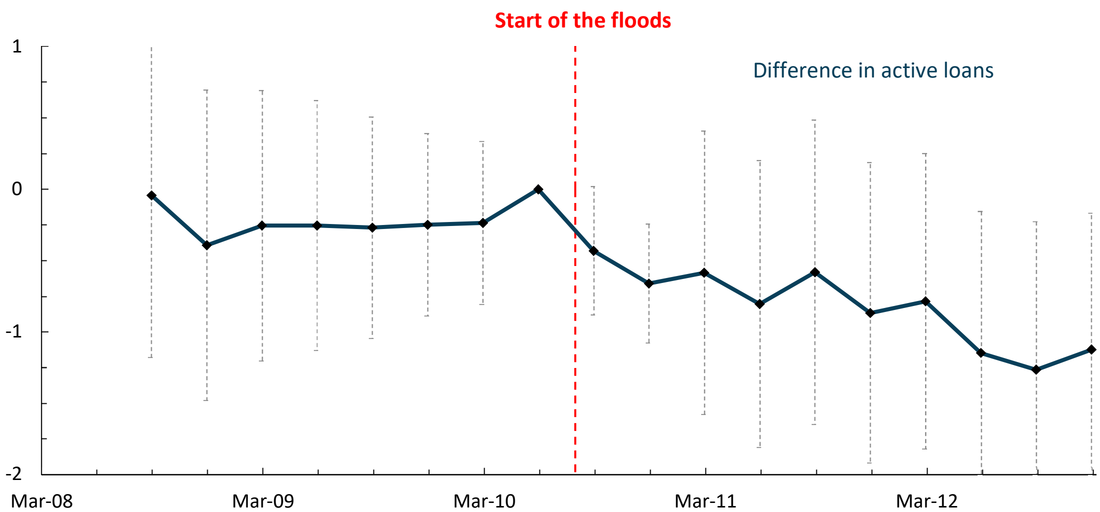
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

These regressions show 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, a bank was 1.48 percentage points less likely to lend to that particular consumer two years after the flood (column 1). The full regression is as follows: $Y_{bpit} = \alpha_{bpi} + \alpha_{ct} + \alpha_{pt} + \beta \times \text{Post}_t \times \text{Funding Cost Shock}_b + \epsilon_{bpit}$. In columns 1 and 3, we use observations from June 2010 and June 2012. Whereas for columns 1 and 3 (placebo regressions), we use observations from September 2008 and June 2010). For robustness, table (21) in the Appendix, shows the results of the same regressions but using June 2010 to calculate the size of the bank's funding shock rather than September 2008. All standard errors are clustered at the bank-level.

4.3. **To whom did banks reduce credit?** Section (4.2) showed that more-affected banks reduced credit. This section provides descriptive evidence on whether specific

[15]As described in section (3.1.1), we use the inverse hyperbolic sine transformation because this transformation approximates the natural logarithm and allows retaining zero-valued observations, that is, individuals with no loans.

FIGURE 8. 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 September 2008. The regression includes "bank×product×individual", "product × time" and "tehsil×time" fixed effects. The black bars are point-wise 95% confidence intervals. The full regression is as follows: $Y_{bpit} = \beta \times \textbf{TimeDummies}_t \times \text{Funding shock}_b + a_{bpi} + a_{pt} + a_{ct} + \epsilon_{bpit}$. 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. This figure is the visual analogue of column 1 in table (3) but including additional time series.

groups were disproportionately affected. We find that the more-affected banks, immediately following the floods, disproportionately reduced lending more to borrowers with little credit history, little education, and individuals with seasonal occupations.

To examine the differential effect of the bank funding shock on borrowers with different credit history and bank relations, we expand on the regressions in table (3) by analysing specific subsets of consumers. In table (4) column 1, we restrict the sample to new borrowers (those who did not have a loan in September 2008). In column 2, we restrict the sample to the set of borrowers with existing bank-borrower relationships (those bank-consumer pairs that had an active loan in September 2008), and finally in column 3, we restrict the sample to new borrower relationships to compare the likelihood of new bank relationships between borrowers with and without credit history.

The results in column 1 of table (4) show that the more-affected banks were relatively less likely, to a statistically significant extent, to offer new loans to new borrowers following the flood, that is, those individuals with no loan in September 2008. In contrast, in column 2, where we analyze banks' existing borrowers, we find no evidence that more-affected banks were less willing to offer these individuals new loans. Therefore, the results in columns 1 and 2 are consistent with the large literature on relationship lending that show that banks prioritize their existing borrowers during financial downturns, such as, Sette and Gobbi [2015], Bolton et al. [2016], Banerjee et al. [2017], and Beck et al. [2018] during the global financial crisis. As shown by Puri et al. [2017] and Agarwal et al. [2018]), these existing borrowers are generally more profitable.

Column (3) analyzes new bank-borrower relationships. Interestingly, we find that borrowers with no bank loans in September 2008 ("new borrowers") were significantly less likely to make a new banking relationship than borrowers with credit history ("existing borrowers") at more-affected banks in the non-flooded area. Therefore, these results show that the more-affected banks prioritized borrowers with credit history over new borrowers.

Tables (5) and (6) examine how individuals with different education levels and different occupations were affected by the reduction in lending, respectively.

Table (5) shows that individuals with lower educational attainment (specifically those with high-school or less) were the individuals that had the largest reductions in credit by the more-affected banks. Moreover, we find no statistically significant effect on individuals that were educated to above high school. Similarly, table (6) shows that individuals with seasonal or contractual occupations were the most affected by the reduction in credit by the more-affected banks, whereas, business owners and salaried employees were less affected.[16]

Overall, we find that the largest effects of the banks' reduction in credit following their funding shock is on individuals with little credit history, less education, and individuals with temporary occupations.

[16] Contractual occupations include fixed-term contracts or piece-rate contracts.

TABLE 4. Individuals with less credit history were less likely to procure loans from more-affected banks following the floods

	(1) Active loan	(2) Active loan	(3) Active loan
Shock x Post	-1.80**	0.34	-2.19***
	(0.86)	(0.74)	(0.74)
Shock x Post x Existing borrower			2.24**
			(1.06)
Observations	164362	560232	334444
Existing Borrower		X	X
New Borrower	X		X
Existing Relationship		X	
New Relationship	X		X
Tehsil x Date FE	Yes	Yes	Yes
Product x Date FE	Yes	Yes	Yes
Bank x Borrower x Product FE	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 table (4) column 1, we restrict the sample to new borrowers (those who did not have a loan in September 2008). In column 2, we restrict the sample to the set of borrowers with existing bank-borrower relationships (those bank-consumer pairs that had an active loan in September 2008), and finally in column 3, we restrict the sample to new borrower relationships to compare the likelihood of new bank relationships between borrowers with and without credit history. Standard errors are clustered at the bank-level.

4.4. **Why did banks reduce lending disproportionately to some consumers?** In section (4.3) we found that the more-affected banks reduced credit disproportionately for some borrowers (even after controlling for loan products and geographic area). This raises the important normative and positive question of "why"? This section presents evidence that banks reduced their riskiest lending due to a reduction in loan monitoring.

Banks with lower capital ratios may reduce their monitoring effort due to limited liability and moral hazard (Allen et al. [2011]). Specifically, higher capital ratios endogenously lead banks to be more likely to survive to the next period, and consequently, profit from increased monitoring effort today. Moreover, a higher likelihood of bank surviving increases the value of that bank's existing relationship loan portfolio (borrowers' dynamic incentive to repay is higher as they expect to receive loans in the future), and in turn,

TABLE 5. Individuals with less education were less likely to procure loans from more-affected banks, following the floods, in the non-flooded area.

	(1) Active loan	(2) Active loan
Post x Shock x High school and below	-0.98*	-1.76**
	(0.58)	(0.79)
Post x Shock x Above high school	0.14	-1.00
	(3.24)	(3.30)
Observations	620648	620642
Tehsil x Date FE	Yes	Yes
Bank x Borrower x Product FE	Yes	Yes
Product x Date FE	No	Yes

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

All individuals for whom education information is not reported are omitted. In this table, we have grouped individuals by whether they completed high school or not ("High school and below") and table (22) in the Appendix shows the results separated by educational level. Standard errors are clustered at the bank-level.

induces greater bank monitoring (Mehran and Thakor [2011]). Finally, if the cost of bank monitoring rises differentially across banks—for example, due to lower bank organizational capacity due to the floods—banks that have the largest marginal rise in bank monitoring costs would reduce monitoring the most.

The theory of bank monitoring provides testable implications. First, banks that monitor less would disproportionately reduce lending more for loans that require greater monitoring. These loans are more likely to be loans that have the greater ex-ante probability of default and loans that are unsecured because these loans have the largest expected loss in the event of loan default. Second, banks that monitor less would have higher overdue rates relative to other banks. Third, public banks due to their implicit government support are more likely to survive even with low capital ratios, and consequently, will reduce monitoring less for the same level of flood shock.

To provide evidence for bank monitoring driving our results, we start by showing that the more-affected banks relatively reduced lending more in loans that had higher initial overdue rates than less-affected banks, following the floods, in the non-flooded area. Moreover,

TABLE 6. Individuals with seasonal occupations were less likely to procure loans from more-affected banks, following the floods, in the non-flooded area.

	(1) Active loan	(2) Active loan
Post x Shock x Business Owner	1.99	1.52
	(1.91)	(1.74)
Post x Shock x Salaried	-0.59	-1.19
	(0.56)	(0.87)
Post x Shock x Seasonal / Contractual	-1.98***	-1.96***
	(0.50)	(0.57)
Post x Shock x Other	0.52	-0.039
	(3.60)	(3.86)
Observations	890300	890294
Tehsil x Date FE	Yes	Yes
Bank x Borrower x Product FE	Yes	Yes
Product x Date FE	No	Yes

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Contractual occupations include fixed-term contracts or piece-rate contracts. Standard errors are clustered at the bank-level.

more-affected banks reduced lending more for unsecured loans than less-affected banks. Second, we show that overdue rates at more-affected banks rose more—especially for unsecured loans—than loans at less-affected banks. Finally, we show some evidence that the size of these effects is attenuated for public banks—those banks that are more likely to survive following negative shocks. Section (5) presents a number of additional robustness test that rule out (i) that a decrease in credit demand (rather than a decrease in credit supply) caused the reduction in lending, (ii) an increase in borrower moral hazard caused the increase in default rates, (iii) banks reduced lending due to capital regulation, (iv) different types of financial institutions respond differently, (v) banks reduced lending in a single credit product.

4.4.1. *Reduction in lending rates are consistent with loans that had the highest initial risk.* To provide evidence that banks reduced lending in markets that had the highest ex-ante risk of default, we create a bank-specific measure of initial (September 2008) overdue rates for different loan markets. Using this measure for initial overdue loans, we assess whether the more-affected banks reduced lending more in loan markets which have higher initial overdue rates than less-affected banks, following the flood, in the non-flooded area.

To calculate a measure of initial overdue rates in different loan markets, we use a broad and flexible definition for a loan market, allowing the loan market to vary at the bank, tehsil, product, and demographic level. For example, in the first column of table (7), we use the definition of a loan market to be bank-product-tehsil specific, where we calculate the bank's initial overdue rate for each loan product in each tehsil.[17] In table (7), we supplement the initial regressions in equation (1), with additional variables that assess whether the more-affected banks reduced lending more in loan markets for which the bank had higher initial overdue rates. Specifically, we conduct the following regression for all loans in the non-flooded area:

$$\begin{aligned}\text{Active Loan}_{bpit} &= \beta_1 \times \text{Post}_t \times \text{Shock}_b \times \text{Initial overdue rate}_{bpit} + \beta_2 \times \text{Post}_t \times \text{Shock}_b \\ &\quad + \beta_3 \times \text{Shock}_b \times \text{Initial overdue rate}_{bpit} + \alpha_{bip} + \alpha_{pt} + \alpha_{ct} + \epsilon_{bpit}\end{aligned}$$

where "Initial overdue rate$_{bpit}$" is the mean initial overdue rate for bank b in different loan markets, and varies at the bank, tehsil, product, and demographic level.

The large negative coefficient on the variable "Post x Shock x Initial overdue rate" in table (7) suggests that the more-affected banks reduced lending in loan markets that had higher overdue rates than other less-affected banks, in the non-flooded area, following the flood. Interestingly, only after conditioning the initial overdue rates on borrower demographics (either education attainment or occupation status), in columns 2 to columns 4, are the coefficients statistically significant (albeit weakly statistically significant at the 10 percent level). Given that the coefficient is similar across all regressions, this finding suggests that borrower demographics are improving the precision of the result.

[17] Similarly, in table (7) we define a loan market as each "Bank x tehsil x product x borrower's education" in column 2; "Bank x tehsil x product x borrower's occupation" in column 3; and "Bank x tehsil x product x borrower's education x borrower's occupation" in column 4.

TABLE 7. more-affected banks reduced lending more in those loan markets that had the highest rates of initial overdue rates

	(1) Active loan	(2) Active loan	(3) Active loan	(4) Active loan
Post x Shock x Initial overdue rate	-5.93	-6.25*	-6.20*	-5.84*
	(3.90)	(3.70)	(3.48)	(3.21)
Post x Shock	0.15	0.26	0.32	0.30
	(1.09)	(1.09)	(1.09)	(1.07)
Shock x Initial overdue rate	0.28	0.27	0.24	0.23
	(0.23)	(0.22)	(0.20)	(0.18)
Observations	798546	790444	786574	759988
Loan category	A	B	C	D
Tehsil x Date FE	Yes	Yes	Yes	Yes
Product x Date FE	Yes	Yes	Yes	Yes
Bank x Borrower x Product FE	Yes	Yes	Yes	Yes

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

These regressions examine whether the more-affected banks reduced lending more in those loan markets where those banks had the highest initial overdue rates. A loan market is defined as "Bank x tehsil x product" (A) in the first column; "Bank x tehsil x product x borrower's education" (B) in the second column; "Bank x tehsil x product x borrower's occupation" (C) in the third column; and "Bank x tehsil x product x borrower's education x borrower's occupation" (D) in the final column. All standard errors are clustered at the bank level.

4.4.2. *More-affected banks increased collateral requirements after the flood.* Unsecured consumer loans require greater monitoring than secured loans because the bank has larger expected loss given default and the borrower has less incentive to repay (and subsequently the borrower may have greater moral hazard).[18] In Pakistan, many banks model expected losses given default from secured loans as 45 percent, and from unsecured loans as 75 percent. Therefore, if banks have less monitoring capacity, we would expect banks to prioritize secured lending.[19] To examine this possibility, we test whether loans originated

[18]Greater collateral can incentivize banks to *increase* monitoring (for example, see theoretical work by Rajan and Winton [1995], Longhofer and Santos [2000], Park [2000] and empirical work by Cerqueiro et al. [2016] and Ono and Uesugi [2009]) but in the case where banks are the sole creditor and loans secured by property—thereby the value of the collateral is generally insensitive to changes in the borrower's solvency—the bank's incentive to monitor is limited given the smaller loss in the event of loan default (Gorton and Winton [2003]).

[19]This result would also be consistent with a rise in adverse selection given the large literature that shows that higher collateral requirements can also be used to screen riskier borrowers and reduce the problem of adverse selection (see, Bester [1985], Besanko and Thakor [1987], Boot and Thakor [1994], Chakraborty and Hu [2006] for theoretical work, and Berger et al. [2011] for a good summary of empirical work).

after the floods by the more-affected banks were relatively more likely to be secured by collateral. Specifically, we examine loans originated within a narrow window around the floods—120 days before, and 120 days after the flood. As before, we examine only loans originated in the non-flooded area. We run regressions of the following form:

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

where "Secured loan$_{bpi}$" is a dummy variable equal to 1 if the originated loan for bank b, in product p, for borrower i is secured.[20] "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.

Table (8) shows that the more-affected banks originated more secured loans following the flood relative to less-affected banks in the non-flooded area. Our preferred specification (column 2), which includes additional time-varying controls, shows that for a 1 percentage point increase in a bank's funding shock, the bank's share of secured lending rose by 15 basis points. Moreover, for robustness, placebo regressions—using observations one year before the flood—in columns 3 and 4, show no statistically significant differences between more and less-affected banks.

4.4.3. *Overdue rates rose more for more-affected banks.* To examine whether more-affected banks had the largest rise in overdue rates, 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. Similar to the regressions in table (8), we examine loans originated only 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:

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

TABLE 8. Collateral requirements rose more for loans originated by the more-affected banks

	(1) Secured Loan	(2) Secured Loan	(3) Secured Loan	(4) Secured Loan
Originated Post Flood * Shock	0.15*	0.15**		
	(0.082)	(0.066)		
Originated Post Flood	-0.013*			
	(0.0072)			
Originated Post Flood * Shock (Placebo)			0.028	0.043
			(0.054)	(0.071)
Originated Post Flood (Placebo)			-0.0014	
			(0.0058)	
Observations	33804	33535	32333	32083
Placebo			X	X
Bank FE	Yes	N/A	Yes	N/A
Tehsil FE	Yes	N/A	Yes	N/A
Product FE	Yes	Yes	Yes	Yes
Tehsil x Preloan FE	No	Yes	No	Yes
Bank x Tehsil FE	No	Yes	No	Yes

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In columns 1 and 2, we use loans that were originated 120 days before the flood and 120 days after the flood. Whereas for columns 3 and 4 (placebo regressions), we use loans that were originated 120 days before September 2009 and 120 days after September 2009, exactly one year before the flood. Standard errors are clustered at the bank-level.

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

where "Overdue Rate" is a dummy variable equal to 1 if the loan goes overdue within the first 600 days of being originated, and 0 otherwise. "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 (9) show weak evidence that overdue rates rose for more-affected banks, following the flood, in the non-flooded area. Our preferred specification (column 2), which includes additional time-varying controls, shows that overdue rates rose relatively more for those loans originated after the floods by the more-affected banks in the non-flooded area, consistent with the more-affected banks monitoring less. Moreover, for robustness, placebo regressions—using observations one year before the flood—in columns 3 and 4, show no statistically significant differences between more and less-affected banks.

Table 9. Overdue rates higher for those loans originated after the flood

	(1) Overdue Rate	(2) Overdue Rate	(3) Overdue Rate	(4) Overdue Rate
Originated Post Flood * Shock	0.085	0.10*		
	(0.13)	(0.057)		
Originated Post Flood	-0.0095			
	(0.0060)			
Originated Post Flood * Shock (Placebo)			0.19	0.24
			(0.25)	(0.15)
Originated Post Flood (Placebo)			-0.021**	
			(0.0088)	
Observations	33804	33535	32333	32083
Placebo			X	X
Bank FE	Yes	N/A	Yes	N/A
Tehsil FE	Yes	N/A	Yes	N/A
Product FE	Yes	Yes	Yes	Yes
Tehsil x Preloan FE	No	Yes	No	Yes
Bank x Tehsil FE	No	Yes	No	Yes

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In columns 1 and 2, we use loans that were originated 120 days before the flood and 120 days after the flood. Whereas for columns 3 and 4 (placebo regressions), we use loans that were originated 120 days before September 2009 and 120 days after September 2009, one year before the flood. Standard errors are clustered at the bank-level.

To extend the results in table (9), we compare secured and unsecured loans. If more-affected banks reduce loan monitoring, you may expect that unsecured loans would have the largest rise in overdue rates because the borrower has the least incentive to repay (no designated collateral). Table (10) includes the triple interacted term “Unsecured x Originated Post Flood x Shock” that measures whether unsecured loans at more-affected banks were more likely to become overdue relative to both secured loans and unsecured loans at other less-affected banks. The large positive statistically significant coefficient for this variable shows that overdue rates for unsecured loans—loans that require the greatest monitoring—originated by more-affected banks, had much higher overdue rates than other loans and other banks.

Table 10. Secured loans by more-affected banks were relatively less likely to be overdue

	(1) Overdue Rate	(2) Overdue Rate
Unsecured x Originated Post Flood x Shock	0.86***	0.48**
	(0.26)	(0.21)
Originated Post Flood x Shock	-0.58**	-0.26*
	(0.22)	(0.13)
Unsecured x Originated Post Flood	-0.034	-0.022
	(0.021)	(0.015)
Unsecured x Shock	-0.37	-0.36
	(0.43)	(0.28)
Originated Post Flood	0.013	
	(0.017)	
Observations	33804	33535
Bank FE	Yes	N/A
Tehsil FE	Yes	N/A
Product FE	Yes	Yes
Tehsil x Preloan FE	No	Yes
Bank x Tehsil FE	No	Yes

Standard errors in parentheses

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

4.4.4. *The effect of the flood was smaller on public banks.* Following adverse shocks, public banks are more likely to survive due to their implicit government support. Therefore, we may expect the effect of the flood on the bank's monitoring incentive to be smaller than for other banks. To test this prediction, in table (11) we examine the reduction in lending by public banks, and in table (12) we examine the increase in overdue rates for these banks relative to other banks.

Table (11) column 1 shows that public banks reduced lending, but the coefficient for public banks is smaller than for other financial institutions. The difference between public banks and other financial institutions is not statistically significant, largely due to the lack of power in our estimates. Table (12) columns 1 and 2 show that the overdue rate for public banks were lower than for other banks. However, again our regressions suffer from a lack of power and the difference in overdue rates between public banks and other financial institutions is only statistically significant for the specification in the first column.

Overall, we find weak evidence that the effect of the flood was smaller on public banks. The results are not statistically significant but the point estimates suggest both, that public banks reduced lending less than other banks in response to the shock, and that the subsequent rise in overdue rates were smaller for public banks.

Table 11. The funding shock's effect was attenuated for public banks (active loan)

	(1) Active loan	(2) Active loan
Post x Shock x Public bank	-1.08***	
	(0.26)	
Post x Shock x Other financial institution	-1.73*	
	(0.96)	
Post x Shock x Public bank (Placebo)		1.08
		(0.73)
Post x Shock x Other financial institution (Placebo)		-0.66
		(0.80)
Observations	894706	956424
Placebo		X
Tehsil x Date FE	Yes	Yes
Product x Date FE	Yes	Yes
Bank x Borrower x Product FE	Yes	Yes

Standard errors in parentheses

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

We use loans that were originated 120 days before the flood and 120 days after the flood. Standard errors are clustered at the bank-level.

Table 12. The funding shock's effect was attenuated for public banks (overdue rates)

	(1) Overdue Rate	(2) Overdue Rate
Public bank x Shock x Originated Post Flood	-0.33***	-0.13
	(0.058)	(0.13)
Other financial insitition x Shock x Originated Post Flood	0.17***	0.12
	(0.054)	(0.074)
Originated Post Flood	-0.0067	
	(0.0054)	
Observations	33804	33535
Bank FE	Yes	N/A
Tehsil FE	Yes	N/A
Product FE	Yes	Yes
Tehsil x Preloan FE	No	Yes
Bank x Tehsil FE	No	Yes

Standard errors in parentheses

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

In column 1, we use observations from June 2010 and June 2012. For column 2 (a placebo regression), we use observations from September 2008 and June 2010. Standard errors are clustered at the bank-level.

To summarize the evidence for bank monitoring, first we find that more-affected banks reduced lending the most in loans that had the highest initial overdue rates, and reduced lending the most for unsecured loans. Second, we show overdue rates at more-affected banks rose the most, especially for unsecured loans—those loans that require the greatest monitoring. Finally, we show weak evidence that the size of these effects is attenuated for public banks—those banks that are more likely to survive following negative shocks.

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, we define a "tehsil shock".

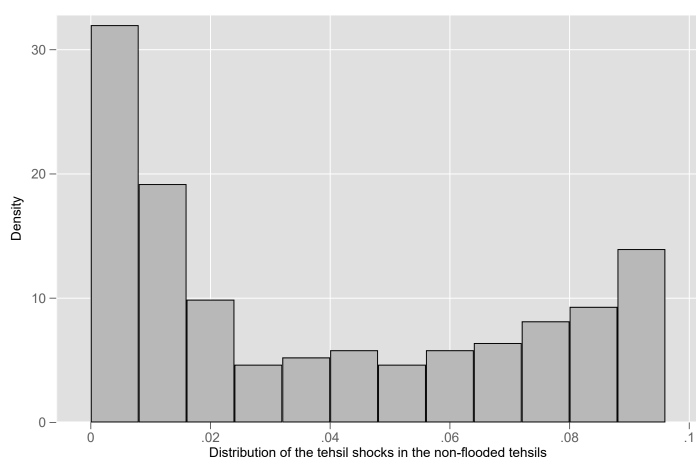
Definition 2. The "*tehsil shock*$_c$" to tehsil c is defined as the fraction of the tehsil's lending (as of September 2008) which was exposed to the funding shock.[21]

(3)

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

The tehsil shock corresponds to the mean bank funding shock (weighted by bank lending) in that tehsil. Figure (9) shows the distribution of tehsil shocks across all non-flooded tehsils.

FIGURE 9. The distribution of the tehsil shock in the non-flooded area



This graph shows the distribution of the "tehsil shock". The "tehsil shock" is the proportion of total lending in that tehsil affected by the funding shock.

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

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 (13), we interact banks' funding shock with the tehsil's shock. The results suggest there was no systematic substitution of credit from the more-affected banks to the less-affected banks in those tehsils that were affected the most. The coefficient on "Time $\times$ Funding Shock $\times$Tehsil Shock" has large standard errors and is not statistically significant.

Our results demonstrate that following banks' funding shock there was no significant 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 flood affecting almost all banks (to differing extents) and, given the importance of banking relationships, the difficulty of expanding bank lending to consumers with little credit history.

5. Robustness

In this section, we examine alternative predictions for how the floods could affect lending in both the flooded and non-flooded areas. Specifically, we rule out that: (i) a decrease in credit demand (rather than a decrease in credit supply) caused the reduction in lending; (ii) an increase in borrower moral hazard caused the increase in default rates, (iii) banks reduced lending due to capital regulation, (iv) different types of financial institutions respond differently, (v) banks reduced lending in a single credit product.

5.1. **Credit demand or credit supply?** One possibility that we have not ruled out is that changes in realized bank lending are due to changes in credit demand, rather than changes in bank supply. For instance, 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—after all, consumers

TABLE 13. The effect of the funding shock on a bank's likelihood to lend in differentially affected tehsils

	(1) Active loan	(2) Active loan
Post x Flood Shock x Tehsil Shock	-12.6	
	(20.8)	
Post x Shock	-1.07	
	(1.28)	
Post x Flood Shock x Tehsil Shock (Placebo)		14.0
		(11.0)
Post x Shock (Placebo)		-0.40
		(0.92)
Observations	894706	956424
Placebo		X
Tehsil x Date FE	Yes	Yes
Product x Date FE	Yes	Yes
Bank x Borrower x 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 for 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 significant 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 not statistically significant. In column 1, we use observations from June 2010 and June 2012. Whereas for column 2 (a placebo regression), we use observations from September 2008 and June 2010. Standard errors are clustered at the bank-level.

and firms, 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], Cortés and Strahan [2017], Bos et al. [2018], Koetter et al. [2020]). 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. Moreover, the large economic shock may cause an increase in precautionary saving, and reduce demand for credit.

The analysis of loan application data, that is loan applications and loan denials, would be the ideal data for identifying whether lower credit demand or lower credit supply cause the observed reduction in credit (such as the German data used in Puri et al. [2011] and Ecuadorian data used in Berg and Schrader [2012]), however, this data is not available. To overcome this constraint, we show four results that suggest credit supply is the key driver of our results. First, we show that more-affected banks did not increase lending in the flooded area suggesting that more-affected banks did not redirect credit from the non-flooded area to the flooded area. Second, we find that closer tehsils to the flooded area do not see greater reductions in total credit. This result suggests that negative economic spillovers from the flooded area did not cause a reduction in credit demand in neighboring tehsils. Third, we do not find that credit utilization rates fell at more-affected banks in the non-flooded area, suggesting that individuals were not reducing their credit usage. Finally, as presented in section (4), we found that the more-affected banks increased their relative share of secured lending, suggesting larger loan collateral requirements. Higher collateral requirements would be consistent with credit rationing given the substantial theoretical and empirical literature showing that greater collateral can attenuate credit rationing (see, Bester [1985], Besanko and Thakor [1987], Boot and Thakor [1994], Chakraborty and Hu [2006] for theoretical work, and Berger et al. [2011] for a good summary of empirical work).

To show that more-affected banks did not relatively increase lending in the flooded area, we replicate the regressions in table (3) but for the flooded area. Table (14) shows this result. Interestingly, our results are different to other papers that have analyzed the bank lending in advanced economies following natural disasters (such as Chavaz [2014], Cortés and Strahan [2017], Bos et al. [2018], Koetter et al. [2020]) that show bank lending *increased* in affected areas. We suspect the differences in outcomes are caused by two key differences in our setting. First, the literature on natural disasters has shown that the adverse effect from natural disasters is both larger and longer-lasting in less economically developed countries.[22] In line with this channel, there is direct evidence from another emerging

[22]Noy [2009] shows that countries with richer, better institutions, and stronger financial systems are more resilient to natural disasters with smaller adverse impacts on future GDP growth rates. Moreover, Kahn [2005] shows that better institutions (democracy level, income inequality and World Bank indicators

market that financial intermediaries reduce lending following a natural disaster.[23] Finally, the scale of the natural disaster in Pakistan was significantly larger than comparable disasters studied in advanced economies.[24]

TABLE 14. The more-affected banks did not relatively increase lending in the flooded area relative to other banks

	(1) Active loan	(2) Active loan
Post x Shock	-0.97	
	(0.71)	
Post x Shock (Placebo)		-0.45
		(0.87)
Observations	354356	388768
Placebo		X
Tehsil x Date FE	Yes	Yes
Product x Date FE	Yes	Yes
Bank x Borrower x Product FE	Yes	Yes

Standard errors in parentheses

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

These regressions show that the banks that were exposed most to the flooded area did not increase lending the most in the flooded area, suggesting those banks that were more-affected did not reallocate credit to the flooded area. In column 1, we use observations from June 2010 and June 2012; in column 2 , we use observations from September 2008 and June 2010 (a placebo regression). Standard errors are clustered at the bank-level.

of good governance) suffer fewer deaths following natural disasters. A key mechanism for these larger adverse effects in less economically developed economies has been the slower reconstruction process in these countries (Felbermayr and Gröschl [2014]). For instance, Kirsch et al. [2012] find that six months after the 2010 floods in Pakistan living standards had greatly fallen relative to living conditions prior to the floods. Finally, there is direct evidence that natural disasters have greater impacts on financial sectors in developing as opposed to developed countries. Klomp [2014] shows that large-scale natural disasters have no significant negative effect on the stability of the banking sector in developed countries—but only in emerging countries.

[23]Consistent with the evidence presented in our paper, Berg and Schrader [2012], using combined loan applications (proxy for loan demand) and loan approvals (proxy for loan supply) show that there was large increases in credit demand but large decreases in loan supply following earthquakes in Ecuador in the affected areas. The key mechanism for reducing credit supply was the increase in credit risks following the earthquake. Finally, following major flooding in Bangladesh, Del Ninno et al. [2003] report increases in demand for credit in the affected areas that was largely met by informal sources, such as friends and neighbors, but not by banks or other formal institutions.

[24]In Pakistan, the 2010 floods are estimated to have caused over USD $10 billion worth of damages (Asian Development Bank et al. [2010], equivalent to just under 6 percent of Pakistani GDP. In contrast, Cortés and Strahan [2017] report that property losses from all natural disasters in the United States between 2001 and 2010 was less than 1 percent of U.S. GDP in 2010.

Turning to the non-flooded area, it is possible that consumers demanded less credit rather than banks supplying less credit. For instance, the negative impacts of the flood would likely spillover to neighboring districts. To investigate this possibility we examine if the fall in credit was larger in non-flooded tehsils that were closest to the flood. Specifically, we conduct the following regression for loans in the non-flooded area.

$$Y_{bpit} = \beta_1 \times \text{Funding Shock}_b \times \text{Post}_t \times \text{Distance to the flood}_c + \beta_2 \times \text{Funding Shock}_b \times \text{Post}_t$$
$$+ \alpha_{bip} + \alpha_{pt} + \alpha_{ct} + \epsilon_{bpit}$$

where "Distance to the flood$_c$" is the distance (in kilometers) from that tehsil to the closest flooded area. This regression is the same as regression (1) but includes an additional interacted term for the distance to the flood. Table (15) shows that there is no evidence that the reduction in credit was larger by the more-affected banks for tehsils closest to the floods. This result provides additional evidence that the reduction in credit was not caused by consumers reducing their demand due to the negative economic spillovers from the flood.

Table 15. No evidence that the effects are larger in closer tehsils

	(1) Active loan	(2) Active loan
Post x Shock	-1.48*	
	(0.79)	
Post x Shock x Distance to flooded tehsil	-0.000012	
	(0.0026)	
Post x Shock (Placebo)		0.22
		(0.87)
Post X Shock x Distance to flooded tehsil (Placebo)		-0.0022
		(0.0019)
Observations	894706	956424
Placebo		X
Tehsil x Date FE	Yes	Yes
Product x Date FE	Yes	Yes
Bank x Borrower x Product FE	Yes	Yes

Standard errors in parentheses

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

In column 1, we use observations from June 2010 and June 2012. Whereas for column 2 (a placebo regression), we use observations from September 2008 and June 2010. Standard errors are clustered at the bank-level.

Finally, we present additional suggestive evidence that our results are not driven by a fall in credit demand by examining credit card balances in the non-flooded area. Specifically, we define two related measures of credit usage. We define the "utilization rate" as the total credit balance divided by the total credit limit, and we define various dummy variables that are equal to one if the utilization rate is greater than a given threshold (80 percent, 90 percent, and 95 percent). Under the assumption that credit limits are a function of credit supply and credit usage is a function of credit demand (similar to Agarwal et al. [2017]), if we observed credit utilization rates falling that would be an indication of credit demand falling. In table (16) we repeat regression (1) but use the various definitions of credit usage as the dependent variable.

Table (16) shows that the utilization rates did not fall, nor were individuals less likely to pay down high balances. Across all the specifications, we find that the coefficient on "Shock x Post" is positive, albeit not statistically significant. A positive coefficient on "Shock x Post" weakly suggests that credit utilization rose at more-affected banks relative to other banks.

TABLE 16. Credit utilization rates did not fall at more-affected banks

	(1) Util. Rate	(2) Util. (> 80%)	(3) Util. (> 90%)	(4) Util. (> 95%)
Shock x Post	2.58	2.75	2.04	1.26
	(1.50)	(1.98)	(1.76)	(1.90)
Observations	78774	78774	78774	78774
Tehsil x Date FE	Yes	Yes	Yes	Yes
Product x Date FE	Yes	Yes	Yes	Yes
Bank x Borrower x Product FE	Yes	Yes	Yes	Yes

Standard errors in parentheses

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

This table analyzes how changes in credit utilization rates for consumer credit cards for the dates June 2010 and June 2012. Column 1 uses a continuous measure of the utilization rate and column 2 to column 4 uses a binary variable that is one if the utilization rate is above a defined threshold (80 percent, 90 percent, and 95 percent). Standard errors are clustered at the bank-level.

In summary, there is substantial evidence that banks reduced credit supply rather than consumers demanded less credit.

5.2. **Did borrower moral hazard cause a reduction in bank lending?** Is the evidence consistent with an increase in borrower moral hazard causing a disproportionate reduction in lending? If banks are reducing access to lending, the borrower's incentive to repay the current loan to ensure they get new loans will also fall (Karlan and Zinman [2009a]), which may in turn cause banks to reduce lending to these individuals. To explore this possibility, we exploit the intertemporal differences in maturity dates. Specifically, we repeat similar regressions in table (9) but instead of using loan origination dates, we concentrate on loan maturity dates by comparing loans that matured 120 days before and 120 days after the flood.

We present our results in table (17). Table (17) 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. This result suggests that borrower moral hazard is not driving the results because we do not see marked increases in default rates for the loans that matured after the flood at the more-affected banks.

TABLE 17. The effect of the funding shock on loan default in the non-flooded area: Loans that matured just before and after the flood

	(1) Overdue Rate	(2) Overdue Rate	(3) Overdue Rate	(4) Overdue Rate
Matured Post Flood x Shock	-0.39	-0.16		
	(0.32)	(0.26)		
Matured Post Flood	0.021			
	(0.017)			
Matured Post Flood x Shock (Placebo)			-0.29	-0.068
			(0.19)	(0.16)
Matured Post Flood (Placebo)			0.0043	
			(0.012)	
Observations	50129	49782	53474	53161
Placebo			X	X
Bank FE	Yes	N/A	Yes	N/A
Tehsil FE	Yes	N/A	Yes	N/A
Product FE	Yes	Yes	Yes	Yes
Tehsil x Preloan FE	No	Yes	No	Yes
Bank x Tehsil FE	No	Yes	No	Yes

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. In columns 1 and 2, 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. Columns 3 and 4 repeat 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. All standard errors are clustered at the bank-level.

5.3. **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 loan products that have the highest Basel II risk weights, the most capital expensive loans.[25] To explore this

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

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 (if the loan is not overdue).

In table (18), 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, show that our "Post×Mortgage ×Shock" variable is both relatively small and not statistically significantly different from zero, suggesting that more-affected banks did not relatively increase their share of mortgage lending.

Table 18. The effect of the funding shock on a bank's likelihood to lend in different risk-weighted products in the non-flooded area

	(1) Active loan	(2) Active loan
Post x Shock x Mortgage Loan	0.70	
	(1.27)	
Post x Shock	-1.52**	
	(0.66)	
Post x Shock x Mortgage Loan (Placebo)		0.16
		(1.36)
Post x Shock (Placebo)		0.083
		(0.78)
Observations	833828	888750
Placebo		X
Tehsil x Date FE	Yes	Yes
Product x Date FE	Yes	Yes
Bank x Borrower x Product FE	Yes	Yes

Standard errors in parentheses

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

In column 1, we use a triple difference-in-difference estimator to examine whether banks that suffered the largest funding shock relatively mortgage lending following the floods (since these loans have the lowest Basel II risk weights). In column 2, we conduct a placebo regression using data for September 2008 and June 2010. Standard errors are clustered at the bank level.

5.4. **Different types of financial institutions respond differently.** 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. To explore this possibility, in table (19), 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 (3). As expected, as we reduce the number of financial institutions in our sample the standard errors increase (this effect is magnified because we are simultaneously reducing the number of clusters), but the coefficient estimates across the various specifications are relatively similar. These results suggest that the funding shock affected all financial institutions and the results are not driven by a specific financial institution type.

TABLE 19. The effect of the floods on a bank's likelihood to lend in non-flooded areas—omitting different bank types

	(1) Active loan	(2) Active loan	(3) Active loan	(4) Active loan	(5) Active loan
Shock x Post	-1.48**	-1.20	-1.77	-1.53**	-1.86***
	(0.66)	(1.20)	(1.09)	(0.58)	(0.66)
Observations	894706	778498	731766	419194	762238
Non-Bank Financial Insitution	X		X	X	X
Public Bank	X	X		X	X
Private Domestic Commercial Bank	X	X	X		X
Foreign Bank	X	X	X	X	
Tehsil x Date FE	Yes	Yes	Yes	Yes	Yes
Product x Date FE	Yes	Yes	Yes	Yes	Yes
Bank x Borrower x Product FE	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

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

These regressions duplicate the regressions in table (3), except we omit the following types of banks: non-bank financial institutions (column 2), public banks (column 3), private domestic commercial banks (column 4), and foreign banks (column 5). 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. All standard errors are clustered at the bank level.

5.5. **Did banks reduce credit in a single loan product?** 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 product.[26] In table (20), we regress whether a loan was active on loan product dummies interacted with the bank funding shock and the "PostTime" variable, and other controls. Table (20) 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) and small loans (microcredit).

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 and amplify inequality. 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: a 1 percentage point increase in the funding shock led to just under a 1.5 percentage point decrease in the likelihood a bank will provide a loan to a given borrower two years after the flood, in the non-flooded area. Second, banks disproportionately reduced credit to certain borrowers; consumers with little education and little credit history were rationed

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

Table 20. The effect of the funding shock on a bank's loan products in the non-flooded areas

	(1) Active loan	(2) Active loan
Post x Shock x Agricultural Production Loan	-1.22***	-1.22***
	(0.31)	(0.31)
Post x Shock x Agricultural Development Loan	-0.39	-0.36
	(0.32)	(0.32)
Post x Shock x Car Loan	-17.5	-17.4
	(27.0)	(27.0)
Post x Shock x Credit Card Loan	-5.38	-5.39
	(21.5)	(21.5)
Post x Shock x Microcredit Loan	-1.74**	-1.76**
	(0.78)	(0.78)
Post x Shock x Mortgage Loan	-0.80	
	(1.54)	
Post x Shock x Personal Loan	-0.084	-0.017
	(18.5)	(18.6)
Post x Shock x Overdraft Cash Facility Loan	5.30	5.32
	(6.40)	(6.41)
Observations	833828	818532
Tehsil x Date FE	Yes	Yes
Product x Date FE	Yes	Yes
Bank x Borrower x Product FE	Yes	Yes

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 production loans), and microcredit. To ensure we have sufficient product observations and for ease of exposition, 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 September 2008. All standard errors are clustered at the bank level.

the most. Third, the reduction in credit was not compensated by more aggregate lending by the less-affected banks.

Our empirical results find that a reduction in banks' incentive to monitor loans is the most likely cause for the disproportionate fall in lending to individuals with low education and seasonal occupations. First, loans originated 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 as opposed to more elastic demand for loans.

References

S. Agarwal, S. Chomsisengphet, N. Mahoney, and J. Stroebel. Do banks pass through credit expansions to consumers who want to borrow? *The Quarterly Journal of Economics*, 133(1):129–190, 2017.

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

S. Aiyar, C. W. Calomiris, J. Hooley, Y. Korniyenko, and T. Wieladek. The international transmission of bank capital requirements: Evidence from the uk. *Journal of Financial Economics*, 113(3):368–382, 2014.

F. Allen, E. Carletti, and R. Marquez. Credit market competition and capital regulation. *The Review of Financial Studies*, 24(4):983–1018, 2011.

Asian Development Bank, Government of Pakistan, and World Bank. Pakistan floods 2010: Preliminary damage and needs assessment. 2010.

A. Banerjee, E. Breza, E. Duflo, and C. Kinnan. Do credit constraints limit entrepreneurship? heterogeneity in the returns to microfinance. *Working paper*, 2015.

R. Banerjee, L. Gambacorta, and E. Sette. The real effects of relationship lending. *Bank of Italy Temi di Discussione (Working Paper) No*, 1133, 2017.

R. N. Banerjee, L. Gambacorta, and E. Sette. The real effects of relationship lending. *Journal of Financial Intermediation*, 48:100923, 2021.

T. Beck, H. Degryse, R. De Haas, and N. Van Horen. When arm's length is too far: Relationship banking over the credit cycle. *Journal of Financial Economics*, 127(1): 174–196, 2018.

G. Berg and J. Schrader. Access to credit, natural disasters, and relationship lending. *Journal of Financial Intermediation*, 21(4):549–568, 2012.

A. N. Berger and G. F. Udell. Relationship lending and lines of credit in small firm finance. *Journal of business*, pages 351–381, 1995.

A. N. Berger, M. A. Espinosa-Vega, W. S. Frame, and N. H. Miller. Why do borrowers pledge collateral? new empirical evidence on the role of asymmetric information. *Journal* *of Financial Intermediation*, 20(1):55–70, 2011.

D. Besanko and A. V. Thakor. Collateral and rationing: sorting equilibria in monopolistic and competitive credit markets. *International economic review*, pages 671–689, 1987.

H. Bester. Screening vs. rationing in credit markets with imperfect information. *The American economic review*, 75(4):850–855, 1985.

P. Bolton, X. Freixas, L. Gambacorta, and P. E. Mistrulli. Relationship and transaction lending in a crisis. *The Review of Financial Studies*, 29(10):2643–2676, 2016.

A. W. Boot and A. V. Thakor. Moral hazard and secured lending in an infinitely repeated credit market game. *International economic review*, pages 899–920, 1994.

A. W. Boot and A. V. Thakor. Can relationship banking survive competition? *The journal of Finance*, 55(2):679–713, 2000.

J. Bos, R. Li, M. Sanders, et al. *Hazardous Lending: The Impact of Natural Disasters on Banks' Asset Portfolio.* Maastricht University, Graduate School of Business and Economics, 2018.

G. Cerqueiro, S. Ongena, and K. Roszbach. Collateralization, bank loan rates, and monitoring. *The Journal of Finance*, 71(3):1295–1322, 2016.

N. Cetorelli and L. S. Goldberg. Follow the money: Quantifying domestic effects of foreign bank shocks in the great recession. *The American Economic Review*, 102(3):213, 2012.

A. Chakraborty and C. X. Hu. Lending relationships in line-of-credit and nonline-of-credit loans: Evidence from collateral use in small business. *Journal of Financial Intermediation*, 15(1):86–107, 2006.

M. Chavaz. Riders of the storm: Economic shock & bank lending in a natural experiment. *Working Paper*, 2014.

M. A. Choudhary and A. K. Jain. How public information affects asymmetrically informed lenders: Evidence from a credit registry reform. *Journal of Development Economics*, 2020.

K. R. Cortés and P. E. Strahan. Tracing out capital flows: How financially integrated banks respond to natural disasters. *Journal of Financial Economics*, 125(1):182–199, 2017.

Dartmouth Flood Observatory (DFO). Global active archive of large flood events. *Electronic Resource*, 2015.

R. De Haas and N. Van Horen. Running for the exit? international bank lending during a financial crisis. *Review of Financial Studies*, 2012.

C. Del Ninno, P. A. Dorosh, and L. C. Smith. Public policy, markets and household coping strategies in bangladesh: Avoiding a food security crisis following the 1998 floods. *World development*, 31(7):1221–1238, 2003.

N. Dwenger, F. M. Fossen, and M. Simmler. Firmsâ financial and real responses to credit supply shocks: Evidence from firm-bank relationships in germany. *Journal of Financial Intermediation*, 41:100773, 2020.

C. C. Fair, P. M. Kuhn, N. Malhotra, and J. N. Shapiro. How natural disasters affect political attitudes and behavior: Evidence from the 2010-11 pakistani floods. *Working Paper*, 2013.

G. Felbermayr and J. Gröschl. Naturally negative: The growth effects of natural disasters. *Journal of development economics*, 111:92–106, 2014.

Financial Times. Pakistan banks at risk from flood impact. September 3rd, 2010.

Food and Agriculture Organization. Pakistan floods one year on. 2011.

L. Gambacorta and P. E. Mistrulli. Does bank capital affect lending behavior? *Journal of Financial intermediation*, 13(4):436–457, 2004.

D. Georgarakos and G. Pasini. Trust, sociability, and stock market participation. *Review of Finance*, 15(4):693–725, 2011.

E. P. Gilje, E. Loutskina, and P. E. Strahan. Exporting liquidity: Branch banking and financial integration. *The Journal of Finance*, 71(3):1159–1184, 2016.

G. Gorton and A. Winton. Financial intermediation. In *Handbook of the Economics of Finance*, volume 1, pages 431–552. Elsevier, 2003.

D. B. Gross and N. S. Souleles. An empirical analysis of personal bankruptcy and delinquency. *Review of financial studies*, 15(1):319–347, 2002.

D. Harhoff and T. Körting. Lending relationships in germany–empirical evidence from survey data. *Journal of Banking & Finance*, 22(10-11):1317–1353, 1998.

J. Haushofer and J. Shapiro. The short-term impact of unconditional cash transfers to the poor: experimental evidence from kenya. *The Quarterly Journal of Economics*, 131 (4):1973–2042, 2016.

A. Hertzberg, J. Liberti, and D. Paravisini. Public information and coordination: Evidence from a credit registry expansion. *The Journal of Finance*, 66(2):379–412, 2011.

International Monetary Fund. Use of fund resourcesârequest for emergency assistance. *IMF Country Report No. 10/295*, 2010.

R. Iyer, J.-L. Peydró, S. da Rocha-Lopes, and A. Schoar. Interbank liquidity crunch and the firm credit crunch: Evidence from the 2007–2009 crisis. *Review of Financial studies*, 27(1):347–372, 2014.

M. E. Kahn. The death toll from natural disasters: the role of income, geography, and institutions. *Review of economics and statistics*, 87(2):271–284, 2005.

D. Karlan and J. Zinman. Observing unobservables: Identifying information asymmetries with a consumer credit field experiment. *Econometrica*, 77(6):1993–2008, 2009a. URL http://onlinelibrary.wiley.com/doi/10.3982/ECTA5781/abstract.

D. Karlan and J. Zinman. Expanding credit access: Using randomized supply decisions to estimate the impacts. *Review of Financial studies*, page hhp092, 2009b.

A. Khwaja, A. Mian, and A. Qamar. Bank credit and business networks. *Working Paper*, 2011.

A. I. Khwaja and A. Mian. Do lenders favor politically connected firms? rent provision in an emerging financial market. *The Quarterly Journal of Economics*, 120(4):1371–1411, 2005.

A. I. Khwaja and A. Mian. Tracing the impact of bank liquidity shocks: Evidence from an emerging market. *The American Economic Review*, pages 1413–1442, 2008.

T. D. Kirsch, C. Wadhwani, L. Sauer, S. Doocy, and C. Catlett. Impact of the 2010 pakistan floods on rural and urban populations at six months. *PLoS currents*, 4, 2012.

J. Klomp. Financial fragility and natural disasters: An empirical analysis. *Journal of Financial Stability*, 13:180–192, 2014.

M. Koetter, F. Noth, and O. Rehbein. Borrowers under water! rare disasters, regional banks, and recovery lending. *Journal of Financial Intermediation*, 43:100811, 2020.

S. D. Longhofer and J. A. Santos. The importance of bank seniority for relationship lending. *Journal of Financial Intermediation*, 9(1):57–89, 2000.

MCB Limited. Annual report. page 67, 2010.

H. Mehran and A. Thakor. Bank capital and value in the cross-section. *The Review of Financial Studies*, 24(4):1019–1067, 2011.

A. Mian. Distance constraints: The limits of foreign lending in poor economies. *The Journal of Finance*, 61(3):1465–1505, 2006.

I. Noy. The macroeconomic consequences of disasters. *Journal of Development economics*, 88(2):221–231, 2009.

A. Ono and I. Uesugi. Role of collateral and personal guarantees in relationship lending: Evidence from japan's sme loan market. *Journal of money, credit and banking*, 41(5): 935–960, 2009.

C. Park. Monitoring and structure of debt contracts. *The Journal of Finance*, 55(5): 2157–2195, 2000.

J. Peek and E. S. Rosengren. Collateral damage: Effects of the japanese bank crisis on real activity in the united states. *American Economic Review*, pages 30–45, 2000.

K. M. Pence. The role of wealth transformations: An application to estimating the effect of tax incentives on saving. *The BE Journal of Economic Analysis & Policy*, 5(1), 2006.

M. A. Petersen and R. G. Rajan. The benefits of lending relationships: Evidence from small business data. *The Journal of Finance*, 49(1):3–37, 1994.

A. Popov and G. F. Udell. Cross-border banking, credit access, and the financial crisis. *Journal of International Economics*, 87(1):147–161, 2012.

M. Puri, J. Rocholl, and S. Steffen. Global retail lending in the aftermath of the us financial crisis: Distinguishing between supply and demand effects. *Journal of Financial Economics*, 100(3):556–578, 2011.

M. Puri, J. Rocholl, and S. Steffen. What do a million observations have to say about loan defaults? opening the black box of relationships. *Journal of Financial Intermediation*, 31:1–15, 2017.

R. Rajan and A. Winton. Covenants and collateral as incentives to monitor. *The Journal of Finance*, 50(4):1113–1146, 1995.

R. G. Rajan. Insiders and outsiders: The choice between informed and arm's-length debt. *The Journal of finance*, 47(4):1367–1400, 1992.

P. Schnabl. The international transmission of bank liquidity shocks: Evidence from an emerging market. *The Journal of Finance*, 67(3):897–932, 2012.

E. Sette and G. Gobbi. Relationship lending during a financial crisis. *Journal of the European Economic Association*, 13(3):453–481, 2015.

A. Solis. Credit access and college enrollment. *Journal of Political Economy*, 125(2): 000–000, 2017.

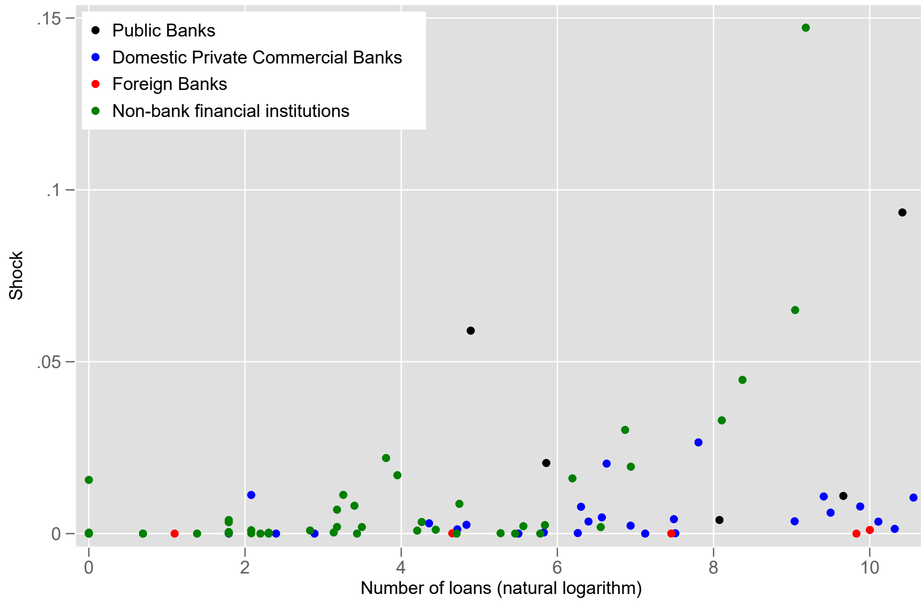
C. Udry. Risk and insurance in a rural credit market: An empirical investigation in northern nigeria. *The Review of Economic Studies*, 61(3):495–526, 1994.

World Bank. The global financial development database. 2017. URL `https://databank.worldbank.org/reports.aspx?source=1250&series=GFDD.SI.04`.

Zarai Taraqiati Bank Limited. Annual report. page 9, 2010.

Appendix

Figure 10. The distribution of the funding shock by financial institution



This figure shows how the shock varied across financial institutions of different size by plotting the size of each financial institutions' funding shock by the number of that institution's loans (after taking the natural logarithm) in our sample.

Table 21. Robustness: Using a different date to calculate the bank's funding shock

	Active loan	Active loan	Loan size	Loan size
Post x Shock	-1.81***		-9.66**	
	(0.65)		(4.67)	
Post x Shock (Placebo)		0.33		0.87
		(0.76)		(5.83)
Observations	894706	956424	894706	956424
Placebo		X		X
Tehsil x Date FE	Yes	Yes	Yes	Yes
Product x Date FE	Yes	Yes	Yes	Yes
Bank x Borrower x Product FE	Yes	Yes	Yes	Yes

Standard errors in parentheses

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

This table repeats the regressions in table (3) but calculates the banks' funding shock using the banks' exposures as of June 2010, rather than September 2008. Standard errors are clustered at the bank-level.

TABLE 22. Individuals with less education were less likely to procure loans from more-affected banks, following the floods, in the non-flooded area.

	(1) Active loan	(2) Active loan
Post x Shock x Illiterate	-0.46	-1.45
	(0.42)	(1.10)
Post x Shock x Below Grade 10	-2.05***	-2.05***
	(0.56)	(0.58)
Post x Shock x Below Graduate	-0.74	-1.63
	(0.54)	(1.14)
Post x Shock x Graduate	-0.27	-0.99
	(3.14)	(3.20)
Post x Shock x Post Graduate	0.45	-0.85
	(3.41)	(3.63)
Observations	620648	620642
Tehsil x Date FE	Yes	Yes
Bank x Borrower x Product FE	Yes	Yes
Product x Date FE	No	Yes

Standard errors in parentheses

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

This table repeats table (5) but separates the results by all educational levels. Individuals for whom education information is not reported are omitted. Standard errors are clustered at the level of the bank.