The Propagation of Idiosyncratic Shocks through Borrower-Lender Networks *

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Abstract

This study examines the extent to which firm-level idiosyncratic shocks propagate in borrower-lender networks. I identify exogenous idiosyncratic shocks with the occurrence of major U.S. natural disasters. I find that the post-disaster lending increases dramatically if a relationship borrower is hit by a natural disaster. This change imposes a substantial decline in loan dollar amounts and an increase in loan pricing on other borrowers outside the disaster area but borrowing from same banks with disaster lending. Subsequently, these borrowers experience a reduction in firm investment and profitability, followed by a slowing sales-growth rate. This spillover effect is more severe for these non-shocked but connected firms in weaker relationships with the common lenders. My estimates are economically large, indicating the importance of credit markets in linking firms. Findings also highlight banks' limited flexibility of allocating capital and the importance of banking frictions in the transmission of credit shocks.

JEL Classification: L14, E23, G21

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1 Introduction

In the context of credit markets, bank shocks coupled with the presence of financing frictions can impact bank lending and certain types of real economic activity. Confronted with the repeated occurrence of financial crisis, researchers have long focused on economic shocks which directly cause deterioration in bank health and then propagate to borrowers (e.g., Slovin, Sushka, and Polonchek, 1993; Kashyap, Lamont, and Stein, 1994; Peek and Rosengren, 2000; Khwaja and Mian, 2008; Chava and Purnanandam, 2011; Chodorow-Reich, 2013; Bord, Ivashina, and Taliaferro, 2017; Amiti and Weinstein, 2018). However, little research has explored borrower-level shocks, which can first cause a demand shock on banks and then develop into a supply shock on non-shocked borrowers (as illustrated in Figure 1). This paper contributes to the literature by exploring the extent to which borrower idiosyncratic shocks spill over to non-shocked borrowers through the credit markets.

Using negative exogenous shocks stemming from 32 major natural disasters (including hurricanes, earthquakes, tornadoes, floods, etc.) in the U.S. for 22 years, I document that banks increase corporate loan lending to the firms experiencing the natural disasters ("**disaster firms**"), especially to the disaster firms with which banks have strong ex-ante relationships. Meanwhile, lending amounts decrease and loan pricing increases for the firms that are not hit by natural disasters but also borrow from theses banks ("**connected firms**"), and this spillover effect is most pronounced for the connected firms with which banks have weak ex-ante relationships. The results are much stronger for loans made by small banks or regional banks, as they are more subject to financial constraints driven by the increase of credit demands from disaster firms. Moreover, after natural disasters hit, connected firms suffer from further outcome losses, including investment decreases, profitability losses, and sales-growth drops due to this capital reallocation. Combined, via borrower-lender networks which are featured in relationship lending, negative idiosyncratic shocks to some borrowers spill over to other borrowers and impose significant output losses.

In the corporate loan market, the transmission of shocks is closely related to bank lending frictions. Bank-borrower relationships matter for 1) how the banks reallocate capital and 2) how deeply borrowers will be affected by the credit crunch. Firstly, the establishment of a relationship with a borrower allows for more efficient information production and processing in offering future loans (Bharath, Dahiya, Saunders, and Srinivasan, 2007). Along with lowering information asymmetries, banks are also able to play a continuing role of managing relationship borrowers' financial needs as they arise (Ongena, Smith, and Michalsen, 2003; Bolton, Freixas, Gambacorta, and Mistrulli, 2016). Therefore, when facing an urgent credit demand, banks will prioritize lending to relationship borrowers, thus they may have to cut financing to non-relationship borrowers. Secondly, many firms face significant costs in switching lenders (Hubbard, Kuttner, and Palia, 2002). If a borrowing firm can easily substitute with other sources of financing in a time of credit crunch, then a credit supply shock will barely affect the firm's real economic activities. However, frictions created by information asymmetry can impede the ability of firms to switch capital sources, especially for informationally opaque firms. As a result, distress may be transmitted across different borrowers: idiosyncratic shocks that affect a group of borrowers can result in the restriction of credit supply as well as real outcome losses on other credit-worthy borrowers.

To track this spillover effect, a big challenge is to identify firm-specific shocks. A common economic shock such as the dot-com bubble or the subprime mortgage crisis cannot be treated as "firm-specific", because it also affects the banking sector. Simply applying these shocks will make it difficult to filter out the negative effect of deterioration in banks' self-health. Instead, I consider major natural disasters —hurricanes, earthquakes, tornadoes, floods, etc.—from 1994 to 2016 across different counties in the United States.[1] These exogenous events have large short-term effects on the firms located in the disaster areas, but do not necessarily directly harm the banking

[1] Studies using natural disasters as exgonenous shocks include Baker and Bloom (2013) for changes in uncertainty, Cortés (2014) for local firms' rebuilding after disasters, Barrot and Sauvagnat (2016) for supplier-customer networks, Cortés and Strahan (2017) for multi-market banks' capital reallocation, Dlugosz, Gam, Gopalan, and Skrastins (2018) for bank branches' ability to set deposit rates locally, etc.

sector. One concern is that some banks are still directly exposed to natural disaster shocks if they are located in disaster areas. To mostly reduce the disturbance caused by such bank-level individual shocks, I exclude bank-year observations for banks headquartered in a given year's disaster area from the test sample, and I also control for each bank's allocation of branches in disaster areas.

Armed with these exogenous firm-level shocks stemming from the natural disasters, I trace out their propagation from natural disaster areas to disaster non-shocked areas. Applying a comprehensive panel dataset of corporate loan originations at the bank-firm-loan level, my analyses focus on two parts: how big the spillover effect is on loan originations outside of natural disaster regions, and whether this effect also causes further real outcome losses on non-shocked firms. When exploring the spillover effect, besides facilitating control of lender- and borrower-characteristics, the rich dataset allows me to saturate models with state$\times$year fixed effects, thus removing confounding local demand effects. Conceptually, my analysis compares corporate loans and firm performance in the same state-year for two otherwise similar firms, one shares common lenders with disaster firms and thus is indirectly exposed to negative natural disaster shocks, while the other does not suffer such exposure.

The tests start by examining the influence of natural disasters on the subsequent loans of disaster firms. Local credit demand increases in response to disasters. Affected firms have new credit demand to help them recover from disrupted production and to rebuild damaged or destroyed plants, equipments or inventories.[2] As a result, I document that the amount of an average disaster loan is about \$28 million higher than loans issued by similar firms in non-disaster areas or during non-disaster periods, and the loan dollar amount difference reaches \$80 million to \$106 million when the disaster firm is in a strong relationship with a bank—this difference is more than one third of loan amount median of the entire loan sample.

In the second step, I examine how the bank lending to non-shocked but connected firms changes after the occurrence of a natural disaster. For connected firms, compared to loans of similar bank-

[2]Similarly, Cortés and Strahan (2017) document the demand increase of mortgages from local residents after natural disasters.

firm pairs with unconnected firms, the post-disaster lending at the loan level on average decreases by \$15.27 to \$18.26 million in dollar amount and increases 42.66 to 48.78 basis points in loan spread. Furthermore, consistent with the notion that lending relationships mitigate contracting friction, disaster lending banks primarily cut post-disaster lending or charge higher loan pricing in weak-relationship connected firms. To further solidify this pattern of the lending change, I directly trace out capital movements from the disaster market to the connected market. After a natural disaster, every one dollar increase in bank lending to disaster firms is associated with 11.5 cents fall on average in bank lending to connected firms; and the fall is 21.8 to 27.3 cents if the connected firm is in a weak relationship with the bank. Moreover, the lending reduction is more severe in small banks or geographically-concentrated banks, which are more easily to experience capital constraints when being confronted with demand shocks. Overall, these findings suggest that lending to non-shocked but connected firms is negatively affected by natural disaster shocks via disaster lending banks, and this spillover effect is most pronounced for firms that banks have weak ex-ante relationships with.

To prove that borrower-level idiosyncratic shocks could result in suboptimal operations of connected borrowers, my third test examines the effect of non-shocked firms' indirect exposure to natural disasters on their investment and performance four quarters after a natural disaster. Compared to other non-shocked firms, a connected firm experiences an average decline in investment of 0.51% of assets, an average loss in profitability of 0.41% of assets, and an average drop of sales-growth rate of 1.27%. In contrast, the sample means are 2.93% of assets in investment, 2.95% of assets in profitability, and 16.38% in sales-growth rate, respectively. The estimates are similar when I control for firm's location, industry, size and age. In addition, I find that this propagation effect is much stronger in the subsample of small firms, whose performance is more sensitive to the change of credit supply. It is worth noting that I incorporate borrower-based relationship strength between non-shocked firms and disaster lending banks when constructing the measure of firm-level indirect exposure to natural disasters. Therefore, these findings also illustrate the importance of borrowing-based relationship, which creates frictions so that firms cannot easily substitute with other sources of financing when their lenders are financially constrained.

This article adds to the large banking literature that studies the frictions in banking and the transmission of credit shocks.[3] The current literature focuses on bank shocks, for instance, the Great Depression (Bernanke, 1983), the Japanese real estate bust (Peek and Rosengren, 2000; Gan, 2007), the Russian sovereign default (Chava and Purnanandam, 2011; Schnabl, 2012), and the 2008–09 financial crisis (Ivashina and Scharfstein, 2010; Chodorow-Reich, 2013). In these studies, economic shocks directly strike the banking sector and develop into a credit supply shock to bank borrowers. The key contribution of this paper is to trace down the propagation of borrower-level idiosyncratic shocks, which drive demand shocks to banks in the first place and then spill over to other borrowers. Equally important, this article provides evidence that, as credit markets become integrated, shocks can propagate across borrowers via financial intermediaries. Echoing the existing literature, my findings underscore the importance of bank-borrower relationships in the propagation of credit shocks, and support the view that shifts in the supply of capital can have significant consequences on firm financing and other real economic activities.

This paper is also closely related to a growing body of work that studies how multi-market banks smooth shocks by reallocating capital. One existing example is that money market mutual funds reduced financing to non-European issuers after suffering large outflows driven by these funds' exposure to European banks (Chernenko and Sunderam, 2014). Two recent studies find that mortgage lending in non-shocked areas gets affected, either by a negative demand shock from banks' response to disaster recovering needs (Gilje, Loutskina, and Strahan, 2016), or by a positive bank liquidity shock from shale booms (Cortés and Strahan, 2017). My study focuses on the corporate loan market. Differing from the mortgage market—which is between banks and households, and the money markets—where arm's length transactions exist, relationship financing plays a much more important role in this arena. Moreover, besides providing a new example about how lenders reallocate capital to adjust to demand shocks, I make a further investigation into

[3]For examples of the research in the transmission of credit shocks, see Peek and Rosengren (1997, 2000); De Haas and Van Horen (2012); Schnabl (2012) for international shock transmission, see Kashyap, Stein, and Wilcox (1993); Kashyap and Stein (2000); Jiménez, Ongena, Peydró, and Saurina (2014) for the transimission of monetary policies.

succeeding real economic outcomes of non-shocked firms.

This article also adds to a broad study in financial economics exploring how firms are linked with each other thereafter are affected by each other. A typical type of firm link is the supplier-customer economic link, which not only induces comovement in stock returns within production networks (Cohen and Frazzini, 2008; Ahern, 2013; Kelly, Lustig, and Van Nieuwerburgh, 2013), but also serves as an important determinant of the propagation of idiosyncratic shocks in the economy (Barrot and Sauvagnat, 2016). Other documented firm linkages are less transparent, such as the connection through common institutional ownership (Anton and Polk, 2014), or the correlation in investment of same-location firms driven by the local agglomeration economies (Dougal, Parsons, and Titman, 2015). My findings propose a new implicit channel: firms are connected if they borrow from the same lenders. The existence of the spillover effect mirrors the important role of the credit markets in linking firms.

The rest of the paper proceeds as follows: Section 2 introduces the data sources and main variables. Section 3 discusses the empirical methods and reports the results. Section 4 concludes.

2 Sample Construction

To trace down the propagation of idiosyncratic shocks in borrower-lender networks, I construct a sample of major natural disasters for identifying exogenous idiosyncratic shocks, a comprehensive sample of syndicated loans matched with firm- and bank-characteristics for testing changes in lending, a sample of firm-quarter observations with firm accounting variables for testing the spillover effect on real outcomes. This section describes how I build and match different samples and construct key variables.

2.1 Data

2.1.1 Corporate Loans

The source of dollar-denominated private corporate loans data is Reuters Loan Pricing Corporation (LPC) Dealscan, which provides loan information at the origination, including loan amount, loan maturity, loan spread, etc. In Dealscan, the basic unit of observation is a loan, which is referred to as a "facility". Loan contracts are referred to as "deals" or "packages", and consist of one or more loans ("facilities"). I match the loan data to Compustat and CRSP for borrower and lender characteristics and stock price information to conduct a final sample of firm-bank-loan observations from 1987 to 2016.

Because DealScan coverage is sparse in earlier years (Schwert, 2017), I start the loan sample from 1989. My test requires five-year time window to construct relationship measures, so the test sample stars from 1994. I exclude loans with either banks or borrowers based outside the United States. I also adjust the loan amount to dollar value in 2016, using the GDP deflator of the Bureau of Economic Analysis.

Syndicated loans have one or more lead arrangers and several participating lenders. Roles of a lead arranger include: originating a loan, holding the largest share of a loan, monitoring the performance of covenants, and administration of collateral (see Dennis and Mullineaux, 2000; Kroszner and Strahan, 2001). A lead lender serves as an administrative agent that has the fiduciary duty to other syndicate members to provide timely information about the borrower, whereas participating lenders are passive investors whose main role is sharing the ownership of a loan. So I restrict my analysis to lead arrangers, as the relationship lender role highlighted in this paper is most appropriate for lead arrangers.[4] Thus, a firm's "bank" or "lender" in this paper refers to the lead arranger on the loan. [5]

[4]Some studies consider all participants of the syndicate. For example, Marchuk (2017) includes partipant lenders when documenting a risk primium on borrowers that is originated from their lenders' risk.

[5]DealScan does not follow a standard rule to report "lender role". My selection criteria of "lead lender" are: 1) "lender role" is reported as "Arranger", "Lead bank", "Agent", "Syndications agent", "Admin agent", "Bookrunner",

2.1.2 Bank Characteristics and Firm-Level Information

Bank characteristics, borrower characteristics, and firm real outcomes are all retrieved from Compustat North America Fundamentals Quarterly database. To merge DealScan with Compustat, I use the DealScan-Compustat link of borrowers from Chava and Roberts (2008) and the DealScan-Compustat link of lenders from Schwert (2017), both cover years to 2012. For years after 2012, I manually construct two similar DealScan-Compustat links, which matches DealScan with Compustat using borrower identifiers and lender identifiers, respectively. When testing the effect on firm real outcomes, I restrict the sample to non-financial firms whose headquarters are located in the United States over the 1994–2016 period; the firm must report in calendar quarters in Compustat, and be traded on NYSE, AMEX, and NASDAQ. To minimize the influence of outliers, I winsorize all firm fundamental variables at the 1% level. Industry dummies are constructed following the 48 Fama-French industry identification from Kenneth French's website.

To identify whether a borrower is hit by a natural disaster, it's important to obtain its location information. I firstly use the location information in DealScan (city, state). For these borrowers whose location is missing in DealScan, if they are public firms that have information in Compustat, I cross-check the historic record of borrowers headquarters information from Compact Disclosure. Unlike Compustat that only reports the current state and county of firms headquarters, Compact Disclosure provides location information (city, state) on an annual basis over the period from 1988 to 2006. For the observations after 2006 of borrowers whose location is missing in DealScan, I use their most recent location information in Compact Disclosure.

Using the Summary of Deposits from the Federal Insurance Deposit Corporation (FDIC), I determine the number of branches and amount of deposits held by each bank in each state-year over the 1994–2016 period. Then I connect this dataset to my loan sample through matching each bank's gvkey with its FDIC certificate number.

"Mandated arranger", "Lead manager" or "Managing agent"; 2) or "lead arrange credit" is "Yes".

2.1.3 Major Natural Disasters

I obtain information on each major natural disaster hitting the U.S. territory from the SHELDUS (Spatial Hazard and Loss Database for the United States) database maintained by the University of South Carolina. For each event, the database provides information on the start date, the end date, and the Federal Information Processing Standards (FIPS) code of all affected counties. I restrict the list to events classified as major disasters that occurred after 1994, which is the start year of my loan sample for testing. I also restrict the sample to major disasters, which make total estimated damages above $1 billion 2016 constant dollars and last less than 30 days.

[Insert Table 1 about here]

As Table 1 shows, from 1994 to 2016, I finally include 32 major disasters, including blizzards, earthquakes, floods, and hurricanes. These disasters affect a broad range of U.S. states and counties over the sample period. However, they are generally very localized. Though some counties are more frequently hit than others, especially those located along the southeast coast of the U.S. mainland, the location of borrowers in borrower-lender networks spans the entire U.S. mainland.

2.2 Classify Borrowers

The prerequisite of studying the propagation of shocks in borrower-lender networks is to identify shock-affected firms.

As Figure 2 shows, in a natural disaster month t, I flag each borrower i as a "disaster firm" if that firm is hit by the natural disaster; lenders that once lent to these firms in the past five years (from month $t-60$ to $t-1$) are "disaster lending banks", otherwise are "non-disaster lending banks"; a borrower not hitting by the natural disaster is a non-shocked firm. If a non-shocked firm also borrows from disaster lending banks in the past five years, it is flagged as a "connected firm" because it is connected with the disaster firms through the historical common lenders; otherwise it is an "unconnected firm". I leave these flags on during the next 12 months and apply them on the bank-firm-loan sample and the firm-quarter sample.

The incremental lending by each bank in the disaster firms provides a proxy for the demand shock experienced by these banks as a consequence of the natural disaster. I consider two time windows: the pre-disaster period which is one to 12 months before the disaster, and the post-disaster period which is one to 12 months after the disaster. For each lender j in a natural disaster d,

$$Disaster\text{-}Lending_{j,d} = \frac{\Delta Lending\text{-}in\text{-}disaster\text{-}states_{j,d}}{N_{j,d}}.$$

The variable $\Delta Lending\text{-}in\text{-}disaster\text{-}states_{j,d}$ is the total dollar-amount of corporate loans between the post-disaster and the pre-disaster periods originated by bank j, summed across all disaster firms hit by the disaster d. $N_{j,d}$ equals the number of non-shocked firms connected to bank j in disaster d. Analytically, I parcel out $\Delta Lending\text{-}in\text{-}disaster\text{-}states_{j,d}$ equally across each of the connected firms.

Similarly, I also measure the decremental lending to each non-shocked firm from each of its lenders surrounding the disaster. Accordingly, the total change of a bank j's lending to a non-shocked firm i between the post- and pre-disaster periods of the disaster d is defined as $\Delta Lending_{i,j,d}$, which is calculated as:

$$\Delta Lending_{i,j,d} = \sum_{t=dt-12}^{dt-1} Loan\ Amount_{i,j,t} - \sum_{t=dt+1}^{dt+12} Loan\ Amount_{i,j,t}$$

2.3 Measures of Relationship

Following the literature on relationship-based lending (e.g., Bharath et al., 2007; Chernenko and Sunderam, 2014), I construct different measures of the strength of the relationship between a borrower and a lender.

Every time when a new loan is originated between firm i and lender j in the month t, I review the borrowing record in the past five years between the borrower and the lender, and capture the *size* and *frequency* of the lender-borrower pair's past lending.

$$\textit{Lending Size}_{i,j,t} = \frac{\text{\$ Amount of loans to borrower } i \text{ by bank } j}{\text{Total \$ amount of loans by lender } j},$$

$$\textit{Lending Freq}_{i,j,t} = \frac{\text{Number of loans to borrower } i \text{ by bank } j}{\text{Total number of loans by lender } j},$$

$$\textit{Borrowing Size}_{i,j,t} = \frac{\text{\$ Amount of loans to borrower } i \text{ by bank } j}{\text{Total \$ amount of loans by borrower } i},$$

$$\textit{Borrowing Freq}_{i,j,t} = \frac{\text{Number of loans to borrower } i \text{ by bank } j}{\text{Total number of loans by borrower } i}$$

All the four measures range from 0 to 1. $\textit{Borrowing Size}_{i,j,t}$ and $\textit{Borrowing Freq}_{i,j,t}$ are borrower-based measures, representing how big in size and how frequently a given borrower i borrowing from a lender j comparing with i's borrowing from other lenders. $\textit{Lending Size}_{i,j,t}$ and $\textit{Lending Freq}_{i,j,t}$ are lender-based measures, representing how big in size and how frequently a given lender j lend to a borrower i comparing with j's lending to other borrowers. [6]

Given that the establishment of strong lender-borrower relationships can generate significant benefits for both the borrower and the lender, the *size* and *frequency* of the past lending would be positively correlated with the existence of a strong relationship: a given lender lend in larger loan size and higher frequency to relationship borrowers, a given borrower borrow in larger loan size and higher frequency from relationship lenders. Thus, I construct four relationship strength dummies: $\textit{Strong-Relation}^{size}$, $\textit{Strong-Relation}^{freq}$, $\textit{Weak-Relation}^{size}$, and $\textit{Weak-Relation}^{freq}$. A borrower-

[6] The original measures in Bharath et al. (2007) are lender-based only. I follow Chernenko and Sunderam (2014), who make a similar adapation by taking the lender's view and the borrower's view seperatetly when studying shadow banking relationship.

lender pair (i, j) is considered to have a **strong** relationship in the month t if $Lending\ Size_{i,j,t}$ or $Lending\ Freq_{i,j,t}$ is **above** the median for that lender i in the past five years; otherwise a weak relationship. These four lender-based relationship strength variables represent how important a borrower is for a given lender comparing with its other borrowers.

2.4 Exposure to Natural Disasters

Natural disasters create idiosyncratic shocks on disaster-firms. To measure the extent to which banks and connected-firms are also exposed to these shocks through the borrower-lender networks, I apply the above relationship measures to construct a series of indirect-exposure variables.

I firstly construct the measure of bank j's exposure to a natural disaster d through ex-ante loan lending, which I call $Bank\text{-}Disaster\text{-}Exposure_{j,d}$. Suppose a natural disaster d occurs in the month dt, and I^d is the set of disaster firms, then

$$Bank\text{-}Disaster\text{-}Exposure^{size}_{j,d} = \sum_{i \in I^d} Lending\ Size_{i,j,dt},$$
$$Bank\text{-}Disaster\text{-}Exposure^{freq}_{j,d} = \sum_{i \in I^d} Lending\ Freq_{i,j,dt};$$

otherwise

$$Bank\text{-}Disaster\text{-}Exposure^{size}_{j,d} = 0, \text{and } Bank\text{-}Disaster\text{-}Exposure^{freq}_{j,d} = 0.$$

$Lending\ Size_{i,j,dt}$ and $Lending\ Freq_{i,j,dt}$ are the lending size and frequency of bank j to a disaster firm in I^d. *Bank-Disaster-Exposure* is simply the fraction, raging from 0 to 1, of the bank's lending to firms in the disaster area, based on its lending history in the prior five years. Before a natural disaster occurs, a bank lend in larger loan size and higher frequency to the disaster area has built stronger relationships with local firms, and thus is more exposed to the disaster after it hits the area.

In addition I construct a measure of non-shocked firm i's indirect exposure to a natural disaster

d in the month t through their common lenders with disaster firms: $Firm\text{-}Disaster\text{-}Exposure_{i,t}$,

$$
\begin{aligned}
& Firm\text{-}Disaster\text{-}Exposure^{size}_{i,d} \\
& = \sum_j Borrowing\ Size_{i,j,dt} \times \frac{Bank\text{-}Disaster\text{-}Exposure^{size}_{j,d}}{N_{j,d}}, \\
& Firm\text{-}Disaster\text{-}Exposure^{freq}_{i,d} \\
& = \sum_j Borrowing\ Freq_{i,j,dt} \times \frac{Bank\text{-}Disaster\text{-}Exposure^{freq}_{j,d}}{N_{j,d}}.
\end{aligned}
$$

This is the average of *Bank-Disaster-Exposure* across banks that provide financing to firm i, weighted by the firm's historical borrowing size or frequency from these banks, where $N_{j,d}$ is the total number of bank j's non-shocked but connected firms when the disaster d occurs. This exposure measure not only measures how exposed the banks that provide financing to firm i are to a disaster, but also considers how heavily the non-shocked firm i's borrowing relies on these banks before the disaster. if the month t is within the 12-month window after a disaster, *Firm-Disaster-Exposure* is 0 for unconnected firms, and it is larger than 0 for connected firms. The more a connected firm's lenders are exposed to the disaster, and the stronger the relation the firm has with these lenders, the higher this firm's indirect exposure to a disaster will be.

A similar measure based on the changes of banks' disaster lending, which I call $Firm\text{-}Dis\widehat{aster}\text{-}Exposure_{i,d}$, gives more intuitive measurement about how non-disaster firm i is indirectly affected by a natural disaster d via borrower-lender networks. Suppose a natural disaster d occurs in the month dt, then

$$
\begin{aligned}
Firm\text{-}Disa\widehat{ster\text{-}E}xposure^{size}_{i,d} &= \sum_j Borrowing\ Size_{i,j,dt} \times \frac{Disaster\text{-}Lending_{j,d}}{Asset_{i,dt}}, \\
Firm\text{-}Disa\widehat{ster\text{-}E}xposure^{freq}_{i,d} &= \sum_j Borrowing\ Freq_{i,j,dt} \times \frac{Disaster\text{-}Lending_{j,d}}{Asset_{i,dt}}.
\end{aligned}
$$

This is the weighted average of the ratio of $Disaster\text{-}Lending_{j,d}$ relative to firm i's asset, across banks that provide financing to firm i. The weight is based on the firm's historical borrowing size or frequency from these banks. After a disaster hit, the more a connected firm's lenders increase their lending to the disaster area, and the more heavily the firm's ex-ante borrowing relies on these lenders, the higher this firm's indirect exposure to the disaster will be.

2.5 Sample Characteristics

Table 2 presents summary statistics for my samples. Loan variables are presented at the firm-bank-loan level. Bank variables are presented at the bank-loan level. Borrower variables are presented at the firm-loan level. Firm real outcomes are presented at the firm-quarter level.

[Insert Table 2 about here]

Panel A in Table 2 covers all the loans in my sample, including both loans issued in non-disaster periods and loans issued within the 12-month period after a disaster. Across the entire sample, the median loan is a $234-million credit package with 4.3-year maturity, a credit spread of 185 basis points, and 10.28 participant lenders; about two-thirds of the loans are revolving credit facilities and about one-thirds are term loans. At the firm-bank pair level, 29.8% (36.5%) of pairs have a strong ex-ante lender-based relationship according to historical lending size (frequency); and the median firm-bank pair does not have a strong lender-based relationship. At the bank-year level, an average lender's ex-ante lending size to disaster firms is 13.18%, and its ex-ante lending frequency to disater firms is 12.38%.

The banks in the sample have an median of $183 billion in assets. An average bank has deposits of 63.5% of its assets, operates in 10.8 states with 985 branches in total; regarding to the level of the geographical concentration, its Herfindahl-Hirschman Index is 0.5 by deposits and 0.4 by branches. When a natural disaster hits: around 18% of an average bank's branches or deposits are in the disaster regions; 13% of its lending amounts or 12% of its loan numbers are from the disaster area in the preceding five-year window; the bank increases lending to disaster firms by 103 million dollars.

The median borrowers in the sample have \$1.12 billion in assets, with an ROA of 0.13 and an age of 15 years since its IPO. An average non-shocked borrower's indirect linkage to a natural disaster is 0.158 (0.142) when measured in common lenders' lending size (frequency), or 0.122 (0.098) of its assets when measured in common lenders' disaster lending.

For firm real outcomes in Panel B, the main variables of interest are $Investment$ (quarterly investments scaled by lagged assets), $Profitability$ (quarterly operating income to total asset ratio), and $\Delta Sales$ (the sales growth between the current quarter and the same quarter in the previous year). The sample averages for these variables are 2.93% of assets, 2.95% of assets, and 16.38% of one-year lagged sales.

3 Methods and Results

3.1 Natural disasters as a Negative Demand Shock

My analyses start from examining how natural disasters affect loans of disaster firms, which is the onset of the propagation. The hypothesis is that banks increase lending to disaster firms whom they have strong relationships with.

Loans are defined as "disaster loans" if the loan is issued during the 12-month window after the firm is hit by a natural disaster. I do so by constructing a panel data set at the loan level (firm-bank-month) which includes disaster loans, loans issued by unconnected firms during the 12-month window after a natural disaster, and loans issued in non-disaster period. I drop "connected loans" –loans issued by connected firms during the 12-month window after a disaster– from this sample, because their amount may also be affected by natural disasters based on my hypothesis. I report the regression as follows (firm i, bank j, month t, year y, and state s):

$$\begin{aligned} Loan\ Amount_{i,j,t} =& \beta_1 Disaster\text{-}Loan_{i,t} + \beta_2 Strong\text{-}Relation_{i,j,t} \\ &+ \beta_3 Disaster\text{-}Loan_{i,t} \times Strong\text{-}Relation_{i,j,t} \\ &+ \beta_4 Control_{i,j,t} + \alpha_i + \gamma_{j,y} + \mu_t + \varepsilon_{i,j,t}. \end{aligned} \tag{1}$$

The dependent variable $Loan\ Amount_{i,j,t}$ is each loan's dollar amount in million dollar value of 2016. $Disaster\text{-}Loan_{i,t}$ is a firm-loan-level dummy equals one to denote disaster loans. $Strong\text{-}Relation_{i,j,t}$ is the lender-based strong relationship variable introduced in the section 2.3, measured either in lending size or in lending frequency. The vector $Control_{i,j,t}$ contains bank- and firm-specific control variables. To ensure the relationship strength variable and the control variables are ex-ante thus not affected by a natural disaster shock, for disaster loans, namely loans originated during $(dt+1, dt+12)$ (dt is the month that a natural disaster occurs), I use the relationship strength variable measured at the time when the disaster occurs ($Strong\text{-}Relation_{i,j,dt}$), and the control variables from the most recent quarter before the disaster occurs.

In all regressions, I control for bank size and the ratio of a bank's branches locating in a natural disaster region, so that the results are less likely to be affected by big banks or banks' direct losses caused by natural disasters. In some regressions that only contain public firms, which can be matched with Compustat, I further control for borrower characteristics of size, return of asset, years since IPO, and industry, to mitigate the impact of omitted factors that are correlated with the borrower quality. I also control for borrowers' state location which can also lead to difference in lending. Finally, I include loan-type fixed effects to control loan attributes, firm fixed effects α_i to remove time-invariant factors that drive lending to a given firm, calendar month fixed effects μ_t to remove time trends, and bank$\times$year fixed effects $\gamma_{j,y}$ to sweep out potentially confounding factors affecting all borrowers of a given bank in a giving year. Conceptually, with the control of these fixed effects, I compare disaster loans with other loans of the same firm-bank pair but originated in the non-disaster period, or loans issued in the same period but by non-shocked firms. I cluster by bank and firm in building standard errors.

[Insert Table 4 about here]

Table 4 reports the regression estimates. The coefficient on the disaster loan indicator is positive, indicating that banks lending increases to a firm increases within 12 months after the firm is hit by natural disaster. Column (1) of Panel A implies that the amount of an average disaster loan is about $29 million higher. Narrowing down the sample to public firms being borrower and controlling for more borrower characteristics in Column (3) increase the coefficient magnitude and statistical significance. In Column (4) to (9), I decompose the effect of *Disaster-Loan* based on whether the firm-bank pair has a strong relationship ex-ante. When facing urgent lending demand, banks will tilt to relationship borrowers because of information advantage. The results prove that the increase of disaster loans are mainly reflected on the ones of strong relation firm-bank pairs. When strong relationship is measured by historical loan size (frequency), the lending to disaster firms increase by $80 million to $106 million ($69 million to $85 million) per loan. Given the median loan amount is $234 million in my sample, the above increases are economically high.

The sample period has some overlapping with the periods that the financial markets also suffer turmoils. If the pre-disaster months are also the financial crisis period, its average loan size could be smaller than that in the post-disaster months. To ensure findings in Table 4 are not driven by the influences of market-wise shocks, I make robustness tests excluding bank crisis periods of 1998-2001 and 2008-2009, which cover the time windows of the Russian crisis, the dotcom bubble, and the Great Recession. This exclusion does not change the above main findings.[7]

Taken together, the results in Section 3.1 support the hypothesis that banks increases lending to firms that experienced urgent capital needs because of damages from natural disasters, and this increasing concentrates on firms who have a strong relation with these banks even before a natural disaster occurs.

[7] See Table A.1 for detailed results.

3.2 Spillover Effects on Connected Firms

In this section, I explore the spillover effect on non-shocked but connected firms. The spillover effect includes two parts. First, as part of the shock propagation, it will affect the lending to connected firms. I examine how the amount and the pricing of connected firms' loans change after a natural disaster comparing with unconnected firms' loans. Second, the negative loan change will trigger further influence on connected firms' real outcome. To show the first-order evidence of how influential this propagation could be, I focus on non-shocked firms' investment, profitability and sales growth. In this part, I also consider other channels that can affect firm performance, including firms' time variant or constant characteristics, industry-, year-quarter, or state-wise influence, as well as the other possible links between firms, such as supply-demand links.

3.2.1 The loan-level evidence

I build a panel data set at the loan level (firm-bank-month) including all the firm-bank-month triplets in which that bank once lent to the firm in the prior five calendar year. With lending history, these firms are assumed to be the relevant lending markets for each bank to start a new loan. I drop disaster loans from this data set because the aim here to test how the shock affects lending in non-shocked markets.

A. Baseline results: loan amount

I firstly test whether the loan amount of connected firms is abnormally low in the months following natural disasters. I report the regression as follows (firm i, bank j, month t, year y, and state s):

$$\begin{aligned} \textit{Loan Amount}_{i,j,t} = & \beta_1 \textit{Bank-Disaster-Exposure}_{j,t} + \beta_2 \textit{Weak-Relation}_{i,j,t} \\ & + \beta_3 \textit{Bank-Disaster-Exposure}_{j,t} \times \textit{Weak-Relation}_{i,j,t} \\ & + \beta_4 \textit{Control}_{i,j,t} + \alpha_i + \gamma_j + \mu_t + \eta_{s,y} + \varepsilon_{i,j,t}. \end{aligned} \quad (2)$$

The dependent variable *Loan Amount*$_{i,j,t}$ is each loan's dollar amount in million dollar value of 2016. *Bank-Disaster-Loan*$_{j,t}$ is a bank-month-level variable to measure the bank j's exposure to natural disasters in the month t through ex-ante lending. It's zero for all banks in non-disaster periods and for banks not lending to disaster firms in disaster periods. For "connected loans" –the loan issued during the 12-month window after a natural disaster, with the borrower being connected firm regarding to that disaster– *Bank-Disaster-Exposure* must be nonzero. *Weak-Relation*$_{i,j,t}$ is the lender-based weak relationship variable introduced in the section 2.3, measured either in lending size or in lending frequency. The vector *Control*$_{i,j,t}$ contains bank- and firm-specific control variables. To ensure the relationship strength variable and the control variables are ex-ante thus not affected by a natural disaster shock, for disaster loans, namely loans originated during $(dt+1, dt+12)$ (dt is the month that a natural disaster occurs), I use the relationship strength variable measured at the time when the disaster occurs (*Weak-Relation*$_{i,j,dt}$), and the control variables from the most recent quarter before the disaster occurs.

In all regressions, I control for bank size and the ratio of a bank's branches locating in a natural disaster region, so that the results are less likely to be affected by big banks or banks' direct losses caused by natural disasters. In some regressions that only contain public firms, which can be matched with Compustat, I further control for borrower characteristics of size, return of asset, years since IPO, and industry, to mitigate the impact of omitted factors that are correlated with the borrower quality. Finally, I include loan-type fixed effects to control loan attributes, firm fixed effects α_i to remove time-invariant factors that drive lending to a given firm, calendar month fixed effects μ_t to remove time trends, bank fixed effects γ_j to sweep out potentially confounding factors affecting all borrowers of a given bank, and state-year fixed effects $\eta_{s,y}$ that affect lending to a give state in a certain year. Conceptually, my analysis compares loan amount of loans in the same state-year for two otherwise similar firm-bank pairs, one with nonzero *Bank-Disaster-Exposure* (connected firm) and the other without such exposure (unconnected firm).

[Insert Table 5 about here]

Table 5 reports estimates of the regression in Eq.(2). In Panel A, Column 1–2 and Column 5–6 show a statistically significant negative relation between banks' ex-ante exposure to natural disasters and the decrease of loan amount of non-shocked connected firms after a natural disaster hit disaster firms. Given $Bank\text{-}Disaster\text{-}Exposure^{size}$ ($Bank\text{-}Disaster\text{-}Exposure^{freq}$) of 13.18% (12.39%), the post-disaster loan amount of per non-shocked connected firm on average decrease by \$15.27 million to \$18.26 million (\$22.58 million to \$31.25 million).

Column 3–4 and Column 7–8 decompose the above negative effect by introducing the weak relationship measure and its interaction with the bank-level disaster exposure measure, which allow for the amount by which lending falls with exposure to shocks to vary across borrower-bank relationship strength. According to the sign and statistical significance of coefficients estimations, the negative effect of banks' aggregated exposure to disaster firms on non-shocked connected firms is concentrated on weak-relationship firms. With the control of bank-characteristics and other fixed effects, an average disaster-lending bank decreases its post-disaster lending to per weak-relationship and connected firms by \$31.76 million (testing with size-based *Bank-Disaster-Exposure* and *Weak-Relation*) or \$26.67 million (testing with frequency-based *Bank-Disaster-Exposure* and *Weak-Relation*). In contrast, the marginal effect of banks' exposure to disasters is not significantly negative on non-weak-relationship firms. These results show that banks cut post-disaster lending sharply in none-shocked weak-relationship firms.

In Panel B, I add more borrower-characteristics when only testing loans whose borrowers are public firms. Though the loan amount is positively correlated with borrowers' size, ROA, and age, the effect of *Bank-Disaster-Exposure* is still significantly negative for weak-relationship connected firms, with larger magnitude in the corresponding coefficients estimations: an average disaster-lending bank decreases its post-disaster lending to per weak-relationship and connected firms by \$47.41 million (testing with size-based *Bank-Disaster-Exposure* and *Weak-Relation*) or \$38.69 million (testing with frequency-based *Bank-Disaster-Exposure* and *Weak-Relation*).

B. Baseline results: loan pricing

I then test whether the loan pricing of connected firms is abnormally high in the months following natural disasters. I report the regression as follows (firm i, bank j, month t, year y, and state s):

$$
\begin{aligned}
Loan\ Spread_{i,j,t} = & \beta_1 Bank\text{-}Disaster\text{-}Exposure_{j,t} + \beta_2 Weak\text{-}Relation_{i,j,t} \\
& + \beta_3 Bank\text{-}Disaster\text{-}Exposure_{j,t} \times Weak\text{-}Relation_{i,j,t} \\
& + \beta_4 Control_{i,j,t} + \alpha_i + \gamma_j + \mu_t + \eta_{s,y} + \varepsilon_{i,j,t}.
\end{aligned} \tag{3}
$$

The dependent variable $Loan\ Spread_{i,j,t}$ is the all-in-drawn spread in basis points. Other variables are the same with the ones in Eq.(2).

[Insert Table 6 about here]

Table 6 reports estimates of the regression in Eq.(2). In Panel A, Column 1–2 and Column 5–6 show a statistically significant negative relation between banks' ex-ante exposure to natural disasters and the increase of loan spread of non-shocked connected firms after a natural disaster hit disaster firms. Given $Bank\text{-}Disaster\text{-}Exposure^{size}$ ($Bank\text{-}Disaster\text{-}Exposure^{freq}$) of 13.18% (12.39%), the post-disaster all-in-drawn spread of per non-shocked connected loan on average increase by 42.66 basis points to 48.78 basis points (28.80 basis points to 31.68 basis points).

Column 3–4 and Column 7–8 decompose the above positive effect by introducing the weak relationship measure and its interaction with the bank-level disaster exposure measure, which allow for the amount by which pricing hikes with exposure to shocks to vary across borrower-bank relationship strength. According to the sign and statistical significance of coefficients estimations, the positive effect of banks' aggregated exposure to disaster firms on non-shocked connected firms is concentrated on weak-relationship firms. With the control of bank-characteristics and other fixed effects, an average disaster-lending bank decreases its post-disaster lending to per weak-relationship and connected firms by 54.71 basis points (testing with size-based *Bank-Disaster-Exposure* and *Weak-Relation*) or 62.94 basis points (testing with frequency-based

Bank-Disaster-Exposure and *Weak-Relation*). In contrast, the marginal effect of banks' exposure to disasters is not significantly positive on non-weak-relationship firms. These results show that banks increase post-disaster loan pricing sharply in none-shocked weak-relationship firms.

In Panel B, I add more borrower-characteristics when only testing loans whose borrowers are public firms. Though the loan pricing is negatively correlated with borrowers' size, ROA, and age, the effect of *Bank-Disaster-Exposure* is still significantly negative for weak-relationship connected firms, although the magnitude of the coefficients estimations gets reduced slightly: an average disaster-lending bank decreases its post-disaster lending to per weak-relationship and connected firms by 38.26 basis points (testing with size-based *Bank-Disaster-Exposure* and *Weak-Relation*) or 28.19 basis points (testing with frequency-based *Bank-Disaster-Exposure* and *Weak-Relation*).

C. Small bank and geographically-concentrated bank

The above impact of natural disaster shocks on disaster firms' connected firms through the borrower-lender networks should be stronger when the financial intermediary is smaller, or less dispersed, and thus easier for the bank to run into short-term financial constraints when facing negative demand shock. I use our three variables to measure the extent to which banks will run into financial constraints. I report the regression as follows (firm i, bank j, month t, year y, and state s):

$$\begin{aligned}
Loan\ Lendingi, j, t =& \beta_1 Bank\text{-}Disaster\text{-}Exposure_{j,t} + \beta_2 Weak\text{-}Relation_{i,j,t} \\
&+ \beta_3 Bank\text{-}Disaster\text{-}Exposure_{j,t} \times Weak\text{-}Relation_{i,j,t} \\
&+ \beta_4 Bank\text{-}Disaster\text{-}Exposure_{j,t} \times Weak\text{-}Relation_{i,j,t} \times Bank\text{-}Constraint_{j,t} \\
&+ \beta_5 Bank\text{-}Constraint_{j,t} + \beta_6 Control_{i,j,t} + \alpha_i + \gamma_j + \mu_t + \eta_{s,y} + \varepsilon_{i,j,t}.
\end{aligned} \tag{4}$$

The dependent variable $Loan\ Lending_{i,j,t}$ is either $Loan\ Amount_{i,j,t}$ in Eq.(2) or $Loan\ Spread_{i,j,t}$ in Eq.(3). $Bank\text{-}Constraint_{j,t}$ is measured by three different dummies: *Small Bank* if a bank's asset is below the sample mean, $Regional\ Bank^{branches}$ if the Herfindahl-Hirschman index of a bank's numbers of branches across all the states is below the sample mean, $Regional\ Bank^{deposits}$ if the

Herfindahl-Hirschman index of a bank's deposits across all the states is below the sample mean. Other variables are the same with the ones in Eq.(2) and in Eq.(3).

[Insert Table 7 about here]

The results are presented in Table 7. Overall, the above baseline results are indeed much stronger when the bank is small or geographically concentrated, or when the bank is a state bank. Hence, the results suggest how strongly a bank's balance sheet can be affected by a natural-disaster-induced demand shock is a key driver of the propagation of shocks from disaster firms to their connected firms.

3.2.2 Trace out capital flows: the firm-bank level lending change

As a further test of the spillover effect on lending to connected firms from banks with disaster lending, in this section I directly study capital movements from the disaster market to the connected market. I build a panel data set at the firm-bank-disaster level with the change of the total dollar amount that each firm i borrows from bank j between 12-month-after and -before a natural disaster d. I drop from this sample the firm-bank-disaster triplets where the firm is a disaster firm. Using this three-dimensional panel, I estimate the effect of each bank's change of lending surrounding natural disasters in the shocked areas on the change of its lending to connected firms surrounding the same disaster:

$$\begin{aligned}\frac{\Delta Lending_{i,j,d}}{Total\text{-}Lending_{j,d}} =& \beta_1 \frac{Disaster\text{-}Lending_{j,d}}{Total\text{-}Lending_{j,d}} + \beta_2 Weak\text{-}Relation_{i,j,d} \\ &+ \beta_3 \frac{Disaster\text{-}lending_{j,d}}{Total\text{-}Lending_{j,d}} \times Weak\text{-}Relation_{i,j,d} \\ &+ \beta_4 Control_{i,j,d} + \alpha_i + \mu_y + \gamma_j + \eta_{s,y} + \varepsilon_{i,j,d},\end{aligned} \tag{5}$$

where the dependent variable $\Delta Lending_{i,j,d}$ and the independent variable $Disaster\text{-}Lending_{j,d}$ are calculated as the change of the lender j's lending to connected firm i and to all firms experiencing the disaster d, respectively, surrounding the natural disaster. $Total\text{-}Lending_{j,d}$ is bank j's total loan lending within one year right before the natural disaster d. I divide both the dependent and key explanatory variables by $Total\text{-}Lending_{j,d}$ as a normalization that will help reduce heteroskedasticity. The dividing does not affect the units of measurement and hence does not change the interpretation of β_1 and β_3. $Weak\text{-}Relation_{i,j,d}$ is the lender-based weak relationship variable, either by loan size or by loan frequency, measured at the time when the disaster occurs. The vector $Control_{i,j,d}$ contains bank- and firm-specific control variables measured in the most recent quarter before the disaster occurs.

In all regressions, I include firm fixed effects α_i to remove time-invariant factors that drive lending to a given firm, and calendar year fixed effects μ_y to remove time trends. I also sweep out bank fixed effects γ_j and state-year fixed effects $\eta_{s,y}$ that affect lending to a give state in a certain year. Conceptually, my analysis compares the change of lending amount of firm-bank pairs in the same state-year with non-shocked firms for two otherwise similar pairs: the bank of one pair is also the lender to disaster areas and thus has nonzero *Disaster-Lending*, while the bank of the other pair is not. I cluster by bank and firm in building standard errors.

[Insert Table 8 about here]

Table 8 reports the regression estimates. Columns (1) and (2) in Panel A show the results without considering lender-based relationships. The coefficients are negative, indicating that the change of borrowing in non-shocked firms from banks with disaster lending is in the opposite direction of the change of these banks' lending to disaster areas. With the control of bank size and the ratio of bank branches in disaster areas, I find that per dollar increase in bank lending to disaster firms is associated with 11.5 cents decrease of bank lending to per connected firm. Columns (3) to (6) includes weak relationship measures. The $Weak\text{-}Relation \times Disaster\text{-}Lending$ interaction terms obtain negative and significant coefficients. which show that lending to per connected and weak-relationship firm falls by 21.8 to 27.3 cents for per dollar lending increase to disaster firms. The effect is statistically significant. Economically speaking, given the *Disaster-Lending* mean of 103.4 million dollars and the average number of loans a bank has with a connected firm is 1.17, the

27.3 cents connected lending fall to one dollar disaster lending increase means a reduction of 24.1 million dollars in a connected loan, which is close to the same loan amount estimation in 3.2.1. The magnitude of the above negative effect of lending reallocation is much larger when adding more borrower-characteristics as controls in Panel B. Lending of per bank to per connected and weak relationship firm drops by 35.5 to 46.6 cents for per dollar increasing of disaster lending.

3.3 Real Outcomes of Connected Firms

In this section, I further estimate the effect on firms' real outcomes of their connection with disaster firms through common lenders. The tests compare the post-disaster performance of non-shocked but connected firms with the performance of other firms—either the same firms in different periods or other non-shocked firms in the same post-disaster period. I do so by constructing a panel data set at the firm-quarter level of real outcome measures related to investment, profitability and sales growth. This sample excludes the firm-quarter pairs of disaster firms in the eight-quarter window after a disaster hit. Specifically, I estimate the effect of each firm's indirect exposure to natural disasters on its post-disaster performance, as follows:

$$Real\ Outcome_{i,q} = \alpha_i + \gamma_q + \beta Firm\text{-}Disaster\text{-}Exposure_{i,q-4} + \varepsilon_{i,q}, \tag{6}$$

$Real\ Outcome_{i,q}$ is the real outcome of firm i in the quarter q, measured by $Investment_{i,q}$ (quarterly investments scaled by lagged assets), $Profitability_{i,q}$ (quarterly operating income to total asset ratio), and $\Delta Sales_{i,q,q-4}$ (the sales growth between the current quarter and the same quarter in the previous year). $Firm\text{-}Disaster\text{-}Exposure$ is the firm-level average of banks' pre-disaster exposure to disaster areas, weighted by the connected firm's historical borrowing size or frequency from these banks. All tests control for firm fixed effects and fiscal quarter fixed effects. In some specifications, I include state×year fixed effects and industry×year fixed effects. To ensures that the estimates are not driven by heterogeneous trends among large or old firms, I also set lagged controls for size, ages, and profitability by interacting year-quarter dummies with terciles of firms's assets, age, ROA on one years prior to the quarter q. In all regressions, standard errors are clustered at the firm level.

[Insert Table 9 about here]

The baseline results are presented in Panel A and Panel B of Table 9. A firm's indirect exposure to natural disasters is measured based on the overlapped banks' historical lending size in Panel A and the overlapped banks' historical lending frequency in Panel B. In Columns 2–3 and Columns 5–6, I include state by year fixed effects and 48 Fama-French industry fixed effects; In Column 3 and Column 6, I introduce controls for lagged size, age, and profitability. The coefficient estimates of *Firm-Disaster-Exposure* keep negative at the statistical significance level no more than 10% across all the columns in Panel A and Panel B. Given that an average non-shocked firm has a size-based *Firm-Disaster-Exposure* of 0.158 and a frequency-based *Firm-Disaster-Exposure* of 0.142, when everything else equal, Column(3) indicates a drop in investment of 0.37% (Panel A) or 0.48% (Panel B) of assets, for an average connected firm four quarters after a natural disaster hit. Relative an average *Investment* of 2.93% of assets in the sample, the two estimates translate into a relative decrease in capital expenditures of 12% and 16%, respectively. Similarly, Column(6) indicates a loss in profitability of 0.37% (Panel A) or 0.43% (Panel B) of assets; and Column(9) indicates a reduction in sales-growth rate of 1.33% (Panel A) or 1.28% (Panel B). Given the sample means of $Profitability$ and $\Delta Sales$ are 2.95% and 16.38%, respectively, both estimates are economically large.

As a more direct test of the above spillover effect that is caused by banks' disaster lending, in Panel C and D, I use $\textit{Firm-Dis}\widehat{\textit{aster}}\textit{-Exposure}$, which is based on the change of overlapped banks' lending to disaster areas, as the regressor. As shown in Table 9, the coefficient estimates of $\textit{Firm-Dis}\widehat{\textit{aster}}\textit{-Exposure}$ keep negative at the statistical significance level less than 5% across all the columns. Given that an average non-shocked firm has a size-based $\textit{Firm-Dis}\widehat{\textit{aster}}\textit{-Exposure}$ of 0.122 and a frequency-based one of 0.098, when everything else equal, Column(3) indicates a drop in investment of 0.51% (Panel A) or 0.49% (Panel B) of assets, for an average connected firm four quarters after a natural disaster hit. Similarly, a loss in profitability of 0.41% (Panel A) or 0.38% (Panel B) of assets is estimated from Column(6), and a reduction in sales-growth of rate of 1.27% (Panel A) or 1.40% (Panel B) is estimated in Column(9). These estimations are quite close to the one indicated in Panel A and B, and are also economically large compared with the sample means listed above.

The effect from the indirect exposure to natural disaster shocks should be stronger when the non-shocked firms are more sensitive to the change of credit supply, such as small firms or bank dependent firms. To test whether this is the case, I conduct the above spillover tests with the consideration of firm size or firm's dependence on banks. A firm is defined as small if its one-year lagged total asset is smaller than the cross-sectional sample median. I use the absence of public debt rating as the proxy for bank-dependence.

[Insert Table 10 about here]

Overall, the effect is indeed much stronger for small firms or bank dependent firms. Hence, the results suggest that firm size or firms' bank dependence is a important factor to determine how heavily connected firms are affect by the natural disaster shocks.

4 Conclusion

In this paper, I propose a new channel of firm linkage: firms are connected if they borrow from the same lenders in the credit markets. I test the transmission of firm-level idiosyncratic shocks via borrower-lender networks. Relying on the exogenous occurrence of natural disasters in the U.S. for almost 30 years, I identify firm-level idiosyncratic shocks, and trace out their influence via banks with disaster lending. Disaster-affected borrowers who are in strong relationships with these banks are found to receive more loans after the disaster. As consequences of a subsequent spillover effect, their connected peers who are not affected by the natural disaster suffer substantial loan declines, output losses and equity value drops. This spillover effect is more severe for these connected borrowers in weaker relationships with the lenders. My estimates are economically large, suggesting that this type of firm connection in the credit markt is an important determinant of the propagation of idiosyncratic shocks in the economy. The findings emphasize the importance of the credit markets in bonding firms, and highlight the role of relationship financing in credit markets in the contagion credit fluctuations.

It's interesting to notice that the findings are against financial intermediaries' role as risk buffers. Banks should have been capable of organizing their operations to avoid temporary disruption propagating across borrowers. The fact that idiosyncratic shocks transmit via borrower-lender networks indicates the limitation of financial intermediaries in risk management.

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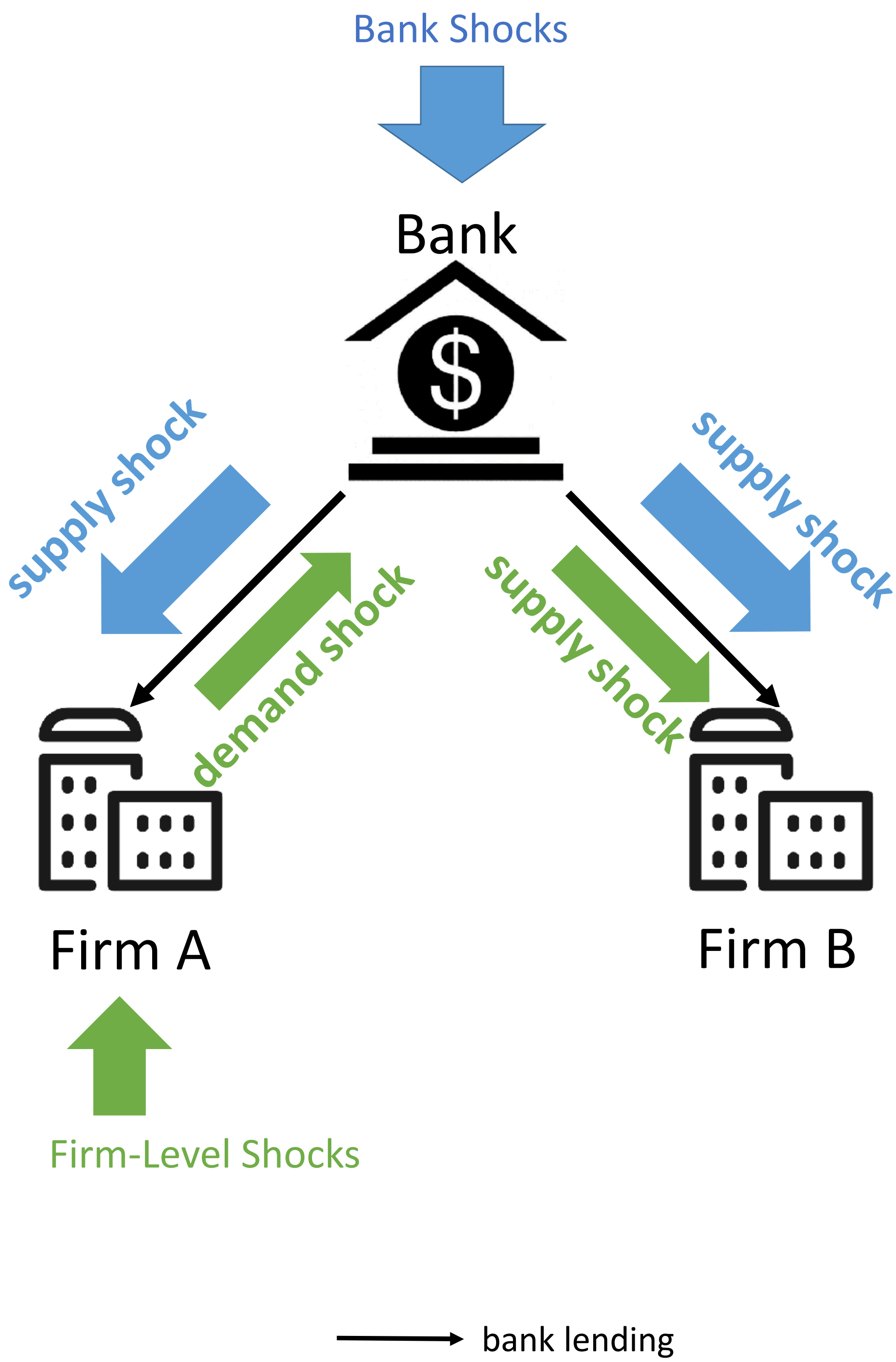

Figure 1: Credit shocks transmission through lender-borrower networks

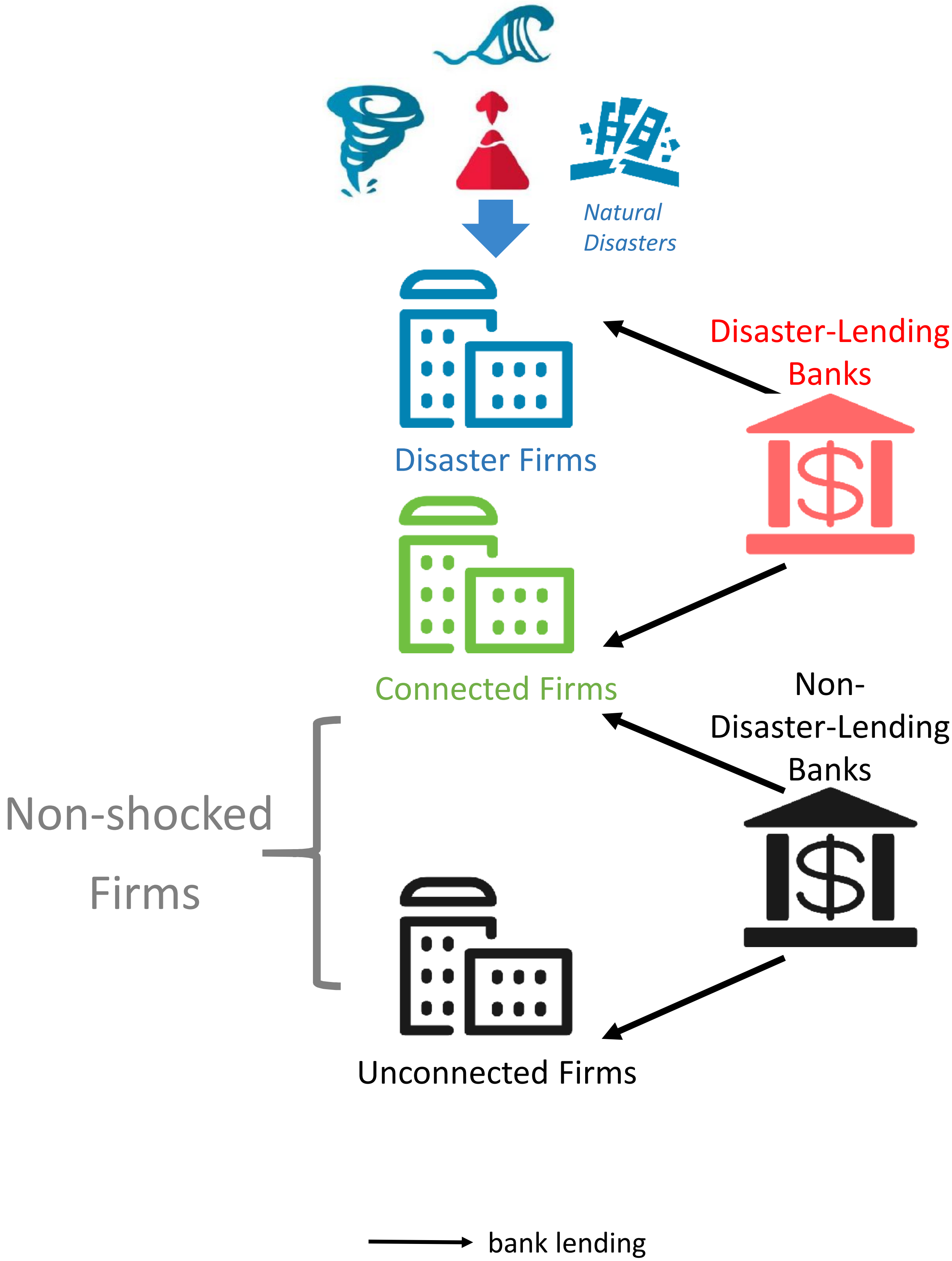

Figure 2: Borrowers and lenders when regional natural disasters hit

Table 1: Major Natural Disasters from 1989-2016

Disaster	Date	States
Northridge earthquake	Jan-94	CA
Hurricane Alberto	Jul-94	AL, FL, GA
Hurricane Opal	Oct-95	AL, FL, GA, LA, MS, NC, SC
Blizzard	Jan-96	CT, DE, IN, KY, MA, MD, NC, NJ, NY, PA, VA, WV
Hurricane Fran	Sep-96	NC, SC, VA, WV
Ice storm Janu	Jan-98	ME, NH, NY, VT
Hurricane Bonnie	Aug-98	NC, VA
Hurricane Georges	Sep-98	AL, FL, LA, MS
Hurricane Floyd	Sep-99	CT, DC, DE, FL, MD, ME, NC, NH, NJ, NY, PA, SC, VA, VT
Hurricane Allison	Jun-01	FL, GA, LA, MS, PA, TX
Hurricane Isabel	Sep-03	DE, MD, NC, NJ, NY, PA, RI, VA, VT
Southern California wildfires	Oct-03	CA
Hurricane Charley	Aug-04	FL, GA, NC, SC
Hurricane Frances, Ivan, Jean	Sep-04	AL, FL,DE, GA, KY, MD, NC, NY, OH, PA, SC, VA, WV, LA, MA, MS, NC, NH, NJ, PA, SC, TN
Hurricane Dennis	Jul-05	AL, FL, GA, MS, NC
Hurricane Katrina	Aug-05	AL, AR, FL, GA, IN, KY, LA, MI, MS, OH, TN
Hurricane Rita	Sep-05	AL, AR, FL, LA, MS
Hurricane Wilma	Oct-05	FL
Midwest floods	Jun-08	IA, IL, IN, MN, MO, NE, WI
Hurricane Gust, Ikeav	Sep-08	AR, LA, MS, MO, TN, TX
Blizzard, Groundhog Day	Feb-11	CT, IA, IL, IN, KS, MA, MO, NJ, NM, NY, OH, OK, PA, TX, WI
Hurricane Irene	Aug-11	CT,MA, MD, NC, NJ, NY, VA, VT
Tropical Storm Lee	Sep-11	AL, CT, GA, LA, MD, MS, NJ, NY, PA, TN, VA
Isaac	Aug-12	FL, LA, MS
Hurricane Sandy	Oct-12	CT, DE, MA, MD, NC, NH, NJ, NY, OH, PA, RI, VA, WV
Flooding and severe weather	Apr-13	IL, IN, MO
Flooding	Sep-13	CO
Winter Storm	Jan-14	AL, GA, IL, IN, KY, MD, MI, MO, MS, NC, NJ, NY, OH, PA, SC, TN, VA
Tornadoes and Flooding	Apr-14	AL, AR, DE, FL, GA, KS, MD, MO, MS, NC, NJ, NY, PA, TN, VA
Severe Weather	May-14	CO, MT, IA, IL, IN, OH, SC, VA, PA, DE, NY
Flood	May-15	AR, CO, GA, KS, LA, OH, OK, SC, TX
Hurricane Matthew	Sep-16	GA, FL, NC, SC

This table describes the 32 natural disasters included in the sample. The sample period is from January 1994 to December 2016.

Table 2: Descriptive statistics

This table presents the summary statistics for the sample of loans merged with borrower and bank characteristics in Panel A and the sample of firm real outcomes in Panel B. The sample period is from 1994 to 2016. The loan sample contains new loan originations matched with lead lenders; bank- and borrower-characteristics are observed from the most recent filing before loan origination. The firm real outcomes sample contains the quarterly firm performance information from Compustat for U.S. non-financial firms, excluding firm-quarter pairs of disaster firms. For loan variables, observations are counted by loan. For bank variables, observations are counted by bank-quarter. For firm variables, observations are counted by firm-quarter. *Amount* is the dollar amount of a loan in million dollar value of 2016. *Maturity* is the number of years between loan start and end dates. *Credit Spread* is the all-in-drawn spread in basis points. *Revolving-Loan* and *Term-Loan* are indicators for loan type. *Participant Count* is the number of participant lenders in a loan contract. *Strong-Relation* is a dummy equals one if the *Lending Size* or *Lending Freq* of a lender-borrower pair is above the median for that of the lender during the five-year window before a loan is issued. *Book Asset* is a bank's book assets in billion dollars. *Tier 1 Capital* is the risk-weighted Tier 1 capital ratio in percentage. *Number of Branches* and *Number of States* are the total number of bank branches or states that a bank assigns a branch, respectively. $HHI^{deposits}$ or $HHI^{branches}$ are the Herfindahl-Hirschman index based on either banks' deposits in each state or bank branch numbers in each state. *%Disaster-deposits* or *%Disaster-branches* are the ratio of a bank's deposits in disaster areas over its total deposits, or the ratio of a bank's branch number in disaster areas over its total branch number. $Bank\text{-}Disaster\text{-}Exposure^{size}$ and $Bank\text{-}Disaster\text{-}Exposure^{freq}$ are a bank's exposure to a natural disaster through ex-ante loan lending. *Disaster-Lending* is the incremental lending by each bank in the disaster firms. *Bank-Dependent* is an indicator equals one if the firm does not have an S&P long-term issuer rating. *Firm-Disaster-Exposure* and $Firm\text{-}Dis\widehat{aster}\text{-}Exposure$ are the borrower-level average of *Bank-Disaster-Exposure* or *Disaster-Lending* across all banks that provide financing to a firm, weighted by the firm's historical borrowing size or frequency from these banks. *Investment* is quarterly investments scaled by lagged asset. *Profitability* is the ratio of operating income before depreciation to book assets. $\Delta Sales$ is the sales growth between the current quarter and the same quarter in the previous year.

	Obs.	Mean	*SD*	p25	p50	p75
Panel A: Loan lending						
Loan Variables						
Amount ($MM)	44958	587.117	956.785	84.522	233.544	639.907
Maturity (Years)	42298	3.947	2.033	2.667	4.333	5.000
Credit Spread (bps)	37018	212.765	146.122	100	185	300
Revolving Loan	44958	0.634	0.435	0.119	1.000	1.000
Term Loan	44958	0.302	0.409	0.000	0.000	0.750
Participant Count	44958	10.280	16.882	2	5	12
Strong-Relation^{size}	44958	0.298	0.457	0.000	0.000	1.000
Strong-Relation^{freq}	44958	0.365	0.482	0.000	0.000	1.000

	Obs.	Mean	*SD*	p25	p50	p75
Bank Variables						
Bank Assets ($B)	1813	464.079	570.153	53.013	183.010	693.575
Tier 1 Capital (%)	1759	9.805	2.406	7.980	9.230	11.540
Deposits/Assets	1813	0.635	0.133	0.591	0.658	0.710
Number of Branches	1897	984.800	1431.690	36	441	1249
Number of States	1897	10.768	10.260	3	7	15
HHI^{deposits}	1897	0.500	0.322	0.211	0.409	0.822
HHI^{branches}	1897	0.409	0.308	0.150	0.311	0.556
%Disaster-deposits	1897	17.974	27.883	0.000	0.149	25.325
%Disaster-branches	1897	17.808	25.451	0.000	0.634	32.749
Bank-Disaster-Exposure^{size}(%)	2273	13.183	18.180	0.000	4.775	19.375
Bank-Disaster-Exposure^{freq}(%)	2273	12.387	16.005	0.000	6.061	18.182
Disaster-Lending($MM)	2273	103.388	69.398	12.446	87.652	173.558
Borrower Variables						
Book Assets ($B)	23763	7.637	22.584	0.286	1.122	4.378
ROA	18778	0.133	0.108	0.080	0.128	0.185
Years since IPO	23824	20.945	17.037	7.000	15.000	33.000
Bank-Dependent	24091	0.469	0.499	0.000	0.000	1.000
Firm-Disaster-Exposure^{size}	23763	0.158	0.154	0.040	0.100	0.233
Firm-Disaster-Exposure^{freq}	23763	0.142	0.126	0.047	0.097	0.208
$\widehat{\text{Firm-Disaster-Exposure}}^{size}$	23763	0.122	0.408	0.000	0.000	0.046
$\widehat{\text{Firm-Disaster-Exposure}}^{freq}$	23763	0.098	0.335	0.000	0.001	0.035

Panel B: Firm real outcomes

Investment (%)	172239	2.930	4.410	0.168	0.743	1.885
Profitability (%)	161985	2.951	2.299	0.359	2.279	4.568
ΔSales(%)	170744	16.379	40.867	-5.624	7.075	25.000

Table 4: The effect of natuaral disasters on loan amounts

This table examines how natural disasters affect lending amount to disaster firms. The sample excludes the loans of connected firms that are issued within the 12-month time window after a natural disaster because their amount may also be affected by natural disasters.

$$\begin{aligned} Loan\ Amount_{i,j,t} = & \beta_1 Disaster\text{-}Loan_{i,t} + \beta_2 Strong\text{-}Relation_{i,j,t} \\ & + \beta_3 Disaster\text{-}Loan_{i,t} \times Strong\text{-}Relation_{i,j,t} \\ & + \beta_4 Control_{i,j,t} + \alpha_i + \gamma_{j,y} + \mu_t + \varepsilon_{i,j,t}. \end{aligned}$$

The dependent variable $Loan\ Amount_{i,j,t}$ is each loan's dollar amount in million dollar value of 2016. $Disaster\text{-}Loan_{i,t}$ is a firm-loan-level dummy equals one to denote loans issued during the 12-month window after the firm is hit by a natural disaster. $Strong\text{-}Relation_{i,j,t}$ is the lender-based strong relationship variable measured either in lending size or in lending frequency. $Control_{i,j,t}$ include bank size, ratio of bank branches hit by a natural disaster, borrower size, profitability, years since IPO, industry and state dummies, and loan type dummies. t-statistics based on two-way clustered standard errors by firm and bank are reported in brackets. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Disaster-Loan	28.708*	78.884***	42.200**	18.483	65.061	48.172	18.371	56.965	50.658
	(1.820)	(2.819)	(2.402)	(1.194)	(1.625)	(1.424)	(1.403)	(1.524)	(1.437)
Strong-Relation^{size}				54.205***	34.554*	58.210***			
				(3.019)	(1.642)	(3.018)			
Strong-Relation^{size} $\times$Disaster-Loan				82.147**	79.651*	105.568**			
				(3.087)	(1.864)	(2.363)			
Strong-Relation^{freq}							46.852***	15.293**	23.823***
							(3.350)	(2.315)	(2.870)
Strong-Relation^{freq} $\times$Disaster-Loan							73.712***	69.434**	85.534*
							(3.443)	(2.029)	(1.747)
Bank Size	8.809		6.231	8.627		5.623	9.282		6.882
	(1.441)		(1.522)	(1.425)		(1.471)	(1.500)		(1.556)
%Disaster-branches	-1.485		-2.848	-1.848		-2.484			-4.787
	(-0.083)		(-0.104)	(-0.104)		(-0.090)			(-0.180)
Borrower Size		3.767***	2.470***		3.033***	2.937***		3.628***	2.554***
		(5.041)	(3.705)		(5.172)	(3.811)		(5.162)	(3.749)
Borrower ROA		8.308***	5.506***		8.237***	5.471***		8.268***	5.459***
		(2.980)	(2.766)		(2.961)	(2.765)		(2.966)	(2.743)
Borrower Age		8.735	1.978		8.593	2.192		8.402	2.199
		(1.188)	(1.208)		(1.159)	(1.227)		(1.131)	(1.228)
Industry FE	N	Y	Y	N	Y	Y	N	Y	Y
Loan Type FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
Month FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
Borrower FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
Bank$\times$Year FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
State FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations8	22598	17185	17185	22598	17185	17185	22598	17185	17185
Adjusted R^2	0.609	0.705	0.715	0.638	0.724	0.747	0.627	0.718	0.746

Table 5: The effect of natuaral disasters on loan amounts of non-shocked firms

This table reports regressions of the loan amount in non-shocked areas on banks' exposure to natural disasters through ex-ante lending activities. The sample includes all loans of firm-bank-month triplets in which the bank has lending history with the firm in the prior five calendar years, with the exclusion of disaster loans. Panel B excludes borrowers that cannot be matched to Compustat.

$$\begin{aligned} Loan\ Amount_{i,j,t} =& \beta_1 Bank\text{-}Disaster\text{-}Exposure_{j,t} + \beta_2 Weak\text{-}Relation_{i,j,t} \\ &+ \beta_3 Bank\text{-}Disaster\text{-}Exposure_{j,t} \times Weak\text{-}Relation_{i,j,t} \\ &+ \beta_4 Control_{i,j,t} + \alpha_i + \gamma_j + \mu_t + \eta_{s,y} + \varepsilon_{i,j,t}. \end{aligned}$$

The dependent variable $Loan\ Amount_{i,j,t}$ is each loan's dollar amount in million dollar value of 2016. $Bank\text{-}Disaster\text{-}Loan_{j,t}$ is a bank-month-level variable to measure the bank j's exposure to natural disasters in the month t through ex-ante lending. It's zero for all banks in non-disaster periods and for banks not lending to disaster firms in disaster periods. $Weak\text{-}Relation_{i,j,t}$ is the lender-based weak relationship variable measured either in lending size or in lending frequency. The vector $Control_{i,j,t}$ contains bank- and firm-specific control, including bank size, ratio of bank branches hit by a natural disaster, borrower size, profitability, years since IPO, industry, state×year dummies, and loan type dummies. t-statistics based on two-way clustered standard errors by firm and bank are reported in brackets. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: The entire sample								
Bank-Disaster-Exposure^{size}	-1.385**	-1.158**	-0.815*	-0.520				
	(-2.461)	(-2.334)	(-1.696)	(-1.593)				
Weak-Relation^{size}			-50.099***	-47.911***				
			(-6.251)	(-7.245)				
Bank-Disaster-Exposure^{size}			-2.409***	-2.795***				
×Weak-Relation^{size}			(-4.220)	(-3.426)				
Bank-Disaster-Exposure^{freq}					-2.523***	-1.823**	-0.871	-0.689
					(-2.693)	(-2.442)	(-1.033)	(-1.484)
Weak-Relation^{freq}							-37.241**	-22.544**
							(-2.204)	(-2.387)
Bank-Disaster-Exposure^{freq}							-2.155***	-2.153**
×Weak-Relation^{freq}							(-3.357)	(-2.405)
Bank Size		8.800***		9.279***		8.781***		7.792***
		(2.713)		(2.585)		(2.717)		(2.623)
%Disaster-branches		-1.341		-1.648		-1.285		-1.893
		(-0.106)		(-0.161)		(-0.142)		(-0.153)
Loan Type FEs	Y	Y	Y	Y	Y	Y	Y	Y
Month FEs	Y	Y	Y	Y	Y	Y	Y	Y
Borrower FEs	Y	Y	Y	Y	Y	Y	Y	Y
Bank FEs	Y	Y	Y	Y	Y	Y	Y	Y
State×Year	Y	Y	Y	Y	Y	Y	Y	Y
Observations	35322	35322	35322	35322	35322	35322	35322	35322
Adjusted R^2	0.651	0.682	0.699	0.784	0.635	0.678	0.691	0.781

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel B: Borrwers being public firms								
Bank-Disaster-Exposure^{size}	-1.458*	-1.641*	-0.745**	-0.857*				
	(-1.758)	(-1.892)	(-1.991)	(-1.700)				
Weak-Relation^{size}			-40.025***	-66.439***				
			(-4.501)	(-4.745)				
Bank-Disaster-Exposure^{size}			-3.727***	-3.596***				
$\times$Weak-Relation^{size}			(-3.594)	(-2.631)				
Bank-Disaster-Exposure^{freq}					-1.063*	-1.237	-0.747	-0.748
					(-1.859)	(-1.205)	(-1.226)	(-0.457)
Weak-Relation^{freq}							-40.161**	-22.852**
							(-2.151)	(-2.850)
Bank-Disaster-Exposure^{freq}							-3.168**	-3.123**
$\times$Weak-Relation^{freq}							(-2.500)	(-2.395)
Borrower Size	5.566***	4.570***	5.211***	4.995***	5.731***	5.819***	5.351***	4.020***
	(5.782)	(5.814)	(5.638)	(5.691)	(5.911)	(6.282)	(5.892)	(6.264)
Borrower ROA	5.193	7.141**	5.432	7.442**	5.445*	7.402**	5.407	7.420**
	(1.568)	(2.224)	(1.631)	(2.311)	(1.665)	(2.353)	(1.655)	(2.336)
Borrower Age	6.287**	1.697**	6.163**	1.127**	4.156***	2.275***	3.936***	2.039***
	(2.473)	(2.098)	(2.418)	(2.080)	(3.188)	(3.543)	(3.126)	(3.396)
Bank Size		8.415***		6.882**		8.135**		6.646**
		(2.994)		(2.179)		(2.505)		(2.286)
%Disaster-branches		-1.264		-1.506		-1.448		-1.077
		(-0.184)		(-0.090)		(-0.115)		(-0.198)
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Loan Type FEs	Y	Y	Y	Y	Y	Y	Y	Y
Month FEs	Y	Y	Y	Y	Y	Y	Y	Y
Borrower FEs	Y	Y	Y	Y	Y	Y	Y	Y
Bank FEs	Y	Y	Y	Y	Y	Y	Y	Y
State$\times$Year	Y	Y	Y	Y	Y	Y	Y	Y
Observations	21748	21748	21748	21748	21748	21748	21748	21748
Adjusted R^2	0.703	0.754	0.816	0.824	0.702	0.720	0.781	0.820

Table 6: The effect of natuaral disasters on loan pricing of firms in non-schocked areas

This table reports regressions of the loan spread in non-shocked areas on banks' exposure to natural disasters through ex-ante lending activities. The sample includes all loans of firm-bank-month triplets in which the bank has lending history with the firm in the prior five calendar years, with the exclusion of disaster loans. Panel B excludes borrowers that cannot be matched to Compustat.

$$\begin{aligned} Loan\ Spread_{i,j,t} =& \beta_1 Bank\text{-}Disaster\text{-}Exposure_{j,t} + \beta_2 Weak\text{-}Relation_{i,j,t} \\ &+ \beta_3 Bank\text{-}Disaster\text{-}Exposure_{j,t} \times Weak\text{-}Relation_{i,j,t} \\ &+ \beta_4 Control_{i,j,t} + \alpha_i + \gamma_j + \mu_t + \eta_{s,y} + \varepsilon_{i,j,t}. \end{aligned}$$

The dependent variable $Loan\ Spread_{i,j,t}$ is the all-in-drawn spread in basis points. $Bank\text{-}Disaster\text{-}Loan_{j,t}$ is a bank-month-level variable to measure the bank j's exposure to natural disasters in the month t through ex-ante lending. It's zero for all banks in non-disaster periods and for banks not lending to disaster firms in disaster periods. $Weak\text{-}Relation_{i,j,t}$ is the lender-based weak relationship variable measured either in lending size or in lending frequency. The vector $Control_{i,j,t}$ contains bank- and firm-specific control variables, including bank size, ratio of bank branches hit by a natural disaster, borrower size, profitability, years since IPO, industry, state$\times$year dummies, and loan type dummies. t-statistics based on two-way clustered standard errors by firm and bank are reported in brackets. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: The entire sample								
Bank-Disaster-Exposure^{size}	3.700**	3.236*	1.162*	2.121				
	(2.090)	(1.858)	(1.890)	(1.028)				
Weak-Relation^{size}			11.331*	11.950*				
			(1.683)	(1.857)				
Bank-Disaster-Exposure^{size}			3.960**	4.150**				
$\times$Weak-Relation^{size}			(2.054)	(2.387)				
Bank-Disaster-Exposure^{freq}					2.325*	2.557*	1.601	2.487
					(1.749)	(1.708)	(1.530)	(1.241)
Weak-Relation^{freq}							10.692	11.545*
							(1.367)	(1.947)
Bank-Disaster-Exposure^{freq}							3.836**	4.774**
$\times$Weak-Relation^{freq}							(2.061)	(2.550)
Bank Size		3.397		7.298		3.357		5.471
		(0.604)		(0.814)		(0.703)		(0.769)
%Disaster-branches		-1.860		-1.255		-1.435		-1.878
		(-0.128)		(-0.187)		(-0.161)		(-0.144)
Loan Type FEs	Y	Y	Y	Y	Y	Y	Y	Y
Month FEs	Y	Y	Y	Y	Y	Y	Y	Y
Borrower FEs	Y	Y	Y	Y	Y	Y	Y	Y
Bank FEs	Y	Y	Y	Y	Y	Y	Y	Y
State$\times$Year	Y	Y	Y	Y	Y	Y	Y	Y
Observations	31727	31727	31727	31727	31727	31727	31727	31727
Adjusted R^2	0.613	0.661	0.686	0.712	0.594	0.653	0.672	0.702

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel B: Borrwers being public firms								
Bank-Disaster-Exposure^{size}	1.879**	1.667*	0.959	1.190				
	(2.318)	(1.911)	(1.213)	(1.004)				
Weak-Relation^{size}			14.907	15.265*				
			(1.183)	(1.831)				
Bank-Disaster-Exposure^{size}			2.815**	2.902**				
$\times$Weak-Relation^{size}			(2.130)	(2.308)				
Bank-Disaster-Exposure^{freq}					1.624*	1.476*	1.036	1.154
					(1.816)	(1.731)	(1.335)	(1.628)
Weak-Relation^{freq}							9.676*	12.535*
							(1.691)	(1.762)
Bank-Disaster-Exposure^{freq}							2.617***	2.276***
$\times$Weak-Relation^{freq}							(2.852)	(2.766)
Borrower Size	-20.156***	-22.143***	-20.280***	-22.036***	-20.159***	-22.168***	-20.306***	-22.265***
	(-5.094)	(-5.721)	(-5.129)	(-5.710)	(-5.100)	(-5.748)	(-5.222)	(-5.901)
Borrower ROA	-1.877***	-1.780***	-1.873***	-1.778***	-1.878***	-1.779***	-1.878***	-1.784***
	(-5.458)	(-4.486)	(-5.473)	(-4.506)	(-5.459)	(-4.492)	(-5.456)	(-4.520)
Borrower Age	-2.115**	-1.116	-2.128**	-1.132	-2.115**	-1.117	-2.123**	-1.131
	(-2.051)	(-1.374)	(-2.069)	(-1.396)	(-2.051)	(-1.375)	(-2.066)	(-1.399)
Bank Size		4.569		4.152		4.438		5.576
		(1.506)		(1.636)		(1.502)		(1.638)
%Disaster-branches		-1.863		-1.551		-1.746		-1.285
		(-0.139)		(-0.122)		(-0.186)		(-0.155)
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Loan Type FEs	Y	Y	Y	Y	Y	Y	Y	Y
Month FEs	Y	Y	Y	Y	Y	Y	Y	Y
Borrower FEs	Y	Y	Y	Y	Y	Y	Y	Y
Bank FEs	Y	Y	Y	Y	Y	Y	Y	Y
State$\times$Year	Y	Y	Y	Y	Y	Y	Y	Y
Observations	20048	20048	20048	20048	20048	20048	20048	20048
Adjusted R^2	0.715	0.781	0.829	0.870	0.700	0.742	0.813	0.859

Table 7: The effect of natuaral disasters on firms in non-schocked areass: small bank, and geographically concentrated bank

This table reports regressions of loan lending, either the loan amount or the loan spread, in non-shocked areas on banks' exposure to natural disasters through ex-ante lending activities. The sample includes all loans of firm-bank-month triplets in which the bank has lending history with the firm in the prior five calendar years, with the exclusion of disaster loans.

$$\begin{aligned} Loan\ Lendingi, j, t = & \beta_1 Bank\text{-}Disaster\text{-}Exposure_{j,t} + \beta_2 Weak\text{-}Relation_{i,j,t} \\ & + \beta_3 Bank\text{-}Disaster\text{-}Exposure_{j,t} \times Weak\text{-}Relation_{i,j,t} \\ & + \beta_4 Bank\text{-}Disaster\text{-}Exposure_{j,t} \times Weak\text{-}Relation_{i,j,t} \times Bank\text{-}Constraint_{j,t} \\ & + \beta_5 Bank\text{-}Constraint_{j,t} + \beta_6 Control_{i,j,t} + \alpha_i + \gamma_j + \mu_t + \eta_{s,y} + \varepsilon_{i,j,t} \end{aligned}$$

The dependent variable $Loan\ Lending_{i,j,t}$ is either $Loan\ Amount_{i,j,t}$ in Eq.(2) or $Loan\ Spread_{i,j,t}$ in Eq.(3). $Bank\text{-}Constraint_{j,t}$ is measured by three different dummies: *Small Bank* if a bank's asset is below the sample mean, $Regional\ Bank^{branches}$ if the Herfindahl-Hirschman index of a bank's numbers of branches across all states is below the sample mean, $Regional\ Bank^{deposits}$ if the Herfindahl-Hirschman index of a bank's deposits across all states is below the sample mean. Other variables are the same with the ones in Table 5 and Table 6. t-statistics based on two-way clustered standard errors by firm and bank are reported in brackets. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Loan Amount		Loan Spread		Loan Amount		Loan Spread	
Panel A: Small Bank								
Bank-Disaster-Exposure^{size}	-0.511	-0.986*	1.872	1.005				
	(-1.483)	(-1.733)	(0.883)	(1.013)				
Weak-Relation^{size}	-48.314***	-68.480***	11.967*	15.107*				
	(-4.384)	(-4.689)	(1.864)	(1.859)				
Bank-Disaster-Exposure^{size}	-1.044	-1.170*	0.173	0.159*				
$\times$Weak-Relation^{size}	(-1.013)	(-1.732)	(1.464)	(1.989)				
Bank-Disaster-Exposure^{size}	-4.005***	-7.298***	5.137***	3.164***				
$\times$Weak-Relation^{size} $\times$Small Bank	(-2.656)	(3.022)	(2.619)	(2.641)				
Bank-Disaster-Exposure^{freq}					-0.603	-0.841	2.505	1.157
					(-1.463)	(-0.483)	(1.223)	(1.633)
Weak-Relation^{freq}					-22.890**	-54.203***	11.585**	12.497*
					(-2.401)	(-2.842)	(1.968)	(1.829)
Bank-Disaster-Exposure^{freq}					-2.495	-1.367	0.176	0.233*
$\times$Weak-Relation^{freq}					(-1.052)	(-1.234)	(1.475)	(1.814)
Bank-Disaster-Exposure^{freq}					-2.576**	-5.617**	5.361***	2.467***
$\times$Weak-Relation^{freq} $\times$Small Bank					(-2.405)	(-2.473)	(2.620)	(2.819)
Small Bank	-20.957*	-17.072*	-7.699	-1.844	-29.270*	-17.098*	-7.484	-1.199
	(-1.764)	(-1.793)	(-1.391)	(-1.259)	(-1.772)	(-1.844)	(-1.264)	(-1.383)
Borrower Size		4.963***		-21.846***		4.811***		-22.060***
		(5.733)		(-5.658)		(6.103)		(-5.854)
Borrower ROA		7.409**		-1.807***		7.126**		-1.813***
		(2.302)		(-4.524)		(2.205)		(-4.544)
Borrower Age		1.144**		-1.462		1.817**		-1.466
		(2.076)		(-1.394)		(2.099)		(-1.396)
Bank Size	4.831**	6.927*	7.012	4.330	5.759**	6.018**	5.891	5.382*
	(2.343)	(1.941)	(0.870)	(1.515)	(2.243)	(1.999)	(0.784)	(1.681)
%Disaster-branches	-1.297	-1.834	-1.240	-1.446	-1.124	-1.950	-1.914	-1.374
	(-0.171)	(-0.183)	(-0.147)	(-0.176)	(-0.119)	(-0.094)	(-0.109)	(-0.140)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Loan Amount		Loan Spread		Loan Amount		Loan Spread	
Industry FE	N	Y	N	Y	N	Y	N	Y
Loan Type FEs	Y	Y	Y	Y	Y	Y	Y	Y
Month FEs	Y	Y	Y	Y	Y	Y	Y	Y
Borrower FEs	Y	Y	Y	Y	Y	Y	Y	Y
BankFEs	Y	Y	Y	Y	Y	Y	Y	Y
State$\times$Year	Y	Y	Y	Y	Y	Y	Y	Y
Observations	35322	21748	31727	20048	35322	21748	31727	20048
Adjusted R^2	0.785	0.825	0.713	0.871	0.782	0.824	0.705	0.861
Panel B: High level of geoprahical concentration (in branches)								
Bank-Disaster-Exposure^{size}	-0.522	-0.834*	1.762	1.052				
	(-1.606)	(-1.709)	(0.879)	(1.009)				
Weak-Relation^{size}	-47.801***	-67.203**	11.877*	15.986				
	(-4.253)	(-2.062)	(1.813)	(1.340)				
Bank-Disaster-Exposure^{size}	-1.779	-1.253	0.114	0.131				
$\times$Weak-Relation^{size}	(-0.386)	(-0.591)	(1.249)	(1.141)				
Bank-Disaster-Exposure^{size}	-3.959***	-5.819***	4.359**	3.458***				
$\times$Weak-Relation^{size}$\times$Regional Bank^{branches}	(-2.821)	(-2.800)	(2.498)	(2.905)				
Bank-Disaster-Exposure^{freq}					-0.615	-0.784	2.146	1.533*
					(-1.488)	(-0.477)	(1.132)	(1.655)
Weak-Relation^{freq}					-22.626**	-52.919***	11.658*	12.186*
					(-2.322)	(-2.827)	(1.904)	(1.735)
Bank-Disaster-Exposure^{freq}					-1.697	-1.110	0.102	0.128
$\times$Weak-Relation^{freq}					(-0.295)	(-0.349)	(1.015)	(0.965)
Bank-Disaster-Exposure^{freq}					-2.640***	-3.196**	4.630***	2.561***
$\times$Weak-Relation^{freq}$\times$Regional Bank^{branches}					(-2.685)	(2.455)	(2.957)	(3.094)
Regional Bank^{branches}	-22.272**	-16.957**	-25.283*	-13.754	-22.968**	-15.543**	-25.110	-11.852
	(-2.324)	(-2.454)	(-1.672)	(-1.483)	(-2.363)	(-2.393)	(-1.555)	(-1.469)
Borrower Size		4.838***		-21.883***		4.325***		-21.885***
		(5.799)		(-5.666)		(6.133)		(-5.750)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Loan Amount		Loan Spread		Loan Amount		Loan Spread	
Borrower ROA		7.426**		-1.803***		7.152**		-1.805***
		(2.311)		(-4.490)		(2.202)		(-4.479)
Borrower Age		1.091**		-1.447		1.803**		-1.451
		(2.095)		(-1.395)		(2.099)		(-1.398)
Bank Size	8.219***	6.983*	7.334	5.983*	7.096***	6.537**	5.982	5.643*
	(2.928)	(1.938)	(0.831)	(1.908)	(3.093)	(2.138)	(0.736)	(1.920)
%Disaster-branches	-1.740	-1.938	-1.252	-1.254	-1.032	-1.315	-1.978	-1.652
	(-0.220)	(-0.188)	(-0.186)	(-0.138)	(-0.115)	(-0.157)	(-0.172)	(-0.187)
Industry FE	N	Y	N	Y	N	Y	N	Y
Loan Type FEs	Y	Y	Y	Y	Y	Y	Y	Y
Month FEs	Y	Y	Y	Y	Y	Y	Y	Y
Borrower FEs	Y	Y	Y	Y	Y	Y	Y	Y
BankFEs	Y	Y	Y	Y	Y	Y	Y	Y
State $\times$ Year	Y	Y	Y	Y	Y	Y	Y	Y
Observations	35322	21748	31727	20048	35322	21748	31727	20048
Adjusted R^2	0.789	0.829	0.720	0.874	0.786	0.828	0.706	0.867
Panel C: State bank								
Bank-Disaster-Exposure^{size}	-0.514	-0.805	1.866	1.511				
	(-1.596)	(-1.532)	(0.882)	(1.014)				
Weak-Relation^{size}	-47.684***	-67.353***	11.903*	15.987				
	(-4.762)	(-4.490)	(1.828)	(1.338)				
Bank-Disaster-Exposure^{size}	-1.583	-1.324	0.130	0.138				
$\times$Weak-Relation^{size}	(-0.762)	(-0.627)	(1.206)	(1.177)				
Bank-Disaster-Exposure^{size}	-4.116***	-5.777***	4.288**	3.466***				
$\times$Weak-Relation^{size}$\times$Regional Bank^{deposits}	(-4.234)	(-4.802)	(2.520)	(2.910)				
Bank-Disaster-Exposure^{freq}					-0.608	-0.778	2.428	1.818*
					(-1.476)	(-0.469)	(1.129)	(1.658)
Weak-Relation^{freq}					-22.879**	-53.014**	11.663	12.186
					(-2.461)	(-2.244)	(1.909)	(1.582)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Loan Amount		Loan Spread		Loan Amount		Loan Spread	
Bank-Disaster-Exposure^{freq}					-1.186	-1.136	0.113	0.133
$\times$Weak-Relation^{freq}					(-0.407)	(-0.583)	(1.081)	(1.002)
Bank-Disaster-Exposure^{freq}					-2.497***	-3.363***	4.538**	2.564***
$\times$Weak-Relation^{freq}$\times$Regional Bank^{deposits}					(-2.984)	(-3.162)	(2.564)	(2.911)
Regional Bank^{deposits}	-23.044**	-14.537**	-32.312*	-21.250	-22.687**	-17.872***	-28.397*	-21.978
	(-2.096)	(-2.237)	(-1.675)	(-1.477)	(-2.132)	(-2.652)	(-1.855)	(-1.480)
Borrower Size		4.750***		-21.873***		4.261***		-21.905***
		(6.146)		(-5.654)		(6.246)		(-5.748)
Borrower ROA		7.421**		-1.803***		7.150**		-1.805***
		(2.134)		(-4.484)		(2.088)		(-4.282)
Borrower Age		1.089**		-1.449		1.801*		-1.453
		(2.034)		(-1.396)		(1.975)		(-1.398)
Bank Size	8.066**	6.223**	7.603	5.355*	7.930**	6.774**	5.247	5.790*
	(2.471)	(2.043)	(0.809)	(1.923)	(2.502)	(2.090)	(0.715)	(1.929)
%Disaster-branches	-1.288	-1.130	-1.233	-1.238	-1.841	-1.460	-1.800	-1.560
	(-0.158)	(-0.170)	(-0.192)	(-0.104)	(-0.147)	(-0.184)	(-0.152)	(-0.158)
Industry FE	N	Y	N	Y	N	Y	N	Y
Loan Type FEs	Y	Y	Y	Y	Y	Y	Y	Y
Month FEs	Y	Y	Y	Y	Y	Y	Y	Y
Borrower FEs	Y	Y	Y	Y	Y	Y	Y	Y
BankFEs	Y	Y	Y	Y	Y	Y	Y	Y
State$\times$Year	Y	Y	Y	Y	Y	Y	Y	Y
Observations	35322	21748	31727	20048	35322	21748	31727	20048
Adjusted R^2	0.789	0.827	0.721	0.875	0.786	0.831	0.709	0.867

Table 8: Trace out capital flows: from the change of bank lending in disaster areas to the change of banking lending to non-shocked firms

This table reports regressions of $\Delta Lending$, the total change of lending of each firm-bank pair surrounding natural disasters, on *Disaster-Lending*, the total change of lending of each bank to disaster areas surrounding natural disasters. I divide both dependent and the key explanatory variables by *Total-Lending* as a normalization that will help reduce heteroskedasticity. The data are measured at the firm-bank-disaster level. The sample drops firm-bank-disaster triplets with disaster firms.

$$\begin{aligned}\frac{\Delta Lending_{i,j,d}}{Total\text{-}Lending_{j,d}} =& \beta_1 \frac{Disaster\text{-}Lending_{j,d}}{Total\text{-}Lending_{j,d}} + \beta_2 Weak\text{-}Relation_{i,j,d} \\ &+ \beta_3 \frac{Disaster\text{-}lending_{j,d}}{Total\text{-}Lending_{j,d}} \times Weak\text{-}Relation_{i,j,d} \\ &+ \beta_4 Control_{i,j,d} + \alpha_i + \mu_y + \gamma_j + \eta_{s,y} + \varepsilon_{i,j,d},\end{aligned}$$

$Weak\text{-}Relation_{i,j,d}$ is the lender-based weak relationship variable measured either in lending size or in lending frequency. The vector $Control_{i,j,d}$ contains bank- and firm-specific control variable, including bank size, ratio of bank branches hit by a natural disaster, borrower size, profitability, years since IPO, industry, state×year dummies, and loan type dummies. t-statistics based on two-way clustered standard errors by firm and bank are reported in brackets. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: The entire sample						
Disaster-Lending/Total-Lending	-0.140***	-0.115***	-0.017	-0.011	-0.069	-0.047
	(-2.958)	(-3.148)	(-1.058)	(-1.191)	(-1.481)	(-1.066)
Weak Relation^{size}			-0.470	-0.376		
			(-0.833)	(-0.758)		
Disaster-Lending/Total-Lending			-0.243***	-0.256***		
×Weak Relation^{size}			(-6.742)	(-6.670)		
Weak Relation^{freq}					-0.557	-0.581
					(-1.004)	(-1.005)
Disaster-Lending/Total-Lending					-0.273***	-0.218***
×Weak Relation^{freq}					(-4.570)	(-4.197)
Bank Size		1.371***		1.424***		1.371***
		(5.247)		(5.182)		(5.216)
%Disaster-branches		-0.008		-0.008		-0.010
		(-1.309)		(-1.259)		(-1.591)
Month FEs	Y	Y	Y	Y	Y	Y
Borrower FEs	Y	Y	Y	Y	Y	Y
Bank FEs	Y	Y	Y	Y	Y	Y
State×Year	Y	Y	Y	Y	Y	Y
Observations	6023	6023	6023	6023	6023	6023
Adjusted R^2	0.356	0.408	0.510	0.674	0.457	0.633

	(1)	(2)	(3)	(4)	(5)	(6)
Panel B: Borrowers being public firms						
Disaster-Lending/Total-Lending	-0.321**	-0.335**	-0.025	-0.028***	-0.071	-0.059
	(-2.322)	(-2.351)	(-1.000)	(-1.202)	(-1.016)	(-1.188)
Weak Relation^{size}			-0.323	-0.309		
			(-0.898)	(-0.864)		
Disaster-Lending/Total-Lending $\times$Weak Relation^{size}			-0.435***	-0.466***		
			(-4.242)	(-4.207)		
Weak Relation^{freq}					-0.447	-0.411
					(-1.175)	(-1.151)
Disaster-Lending/Total-Lending $\times$Weak Relation^{freq}					-0.355***	-0.368***
					(3.650)	(-3.440)
Borrower Size	-3.075***	-1.378**	-3.116***	-1.418**	-3.070***	-1.350**
	(-3.499)	(-2.517)	(-3.386)	(-2.605)	(-3.490)	(-2.442)
Borrower ROA	0.025	-0.064	0.024	-0.062	0.025	-0.061
	(0.891)	(-1.042)	(0.881)	(-1.054)	(0.900)	(-1.055)
Borrower Age	0.125	0.215***	0.126	0.215***	0.122	0.208***
	(1.426)	(3.970)	(1.424)	(4.023)	(1.394)	(3.804)
Bank Size		1.709***		1.766***		1.692***
		(4.042)		(4.068)		(3.984)
%Disaster-branches		-0.008		-0.008		-0.011
		(-0.903)		(-0.904)		(-1.241)
Industry FE	Y	Y	Y	Y	Y	Y
Loan Type FEs	Y	Y	Y	Y	Y	Y
Month FEs	Y	Y	Y	Y	Y	Y
Borrower FEs	Y	Y	Y	Y	Y	Y
Bank FEs	Y	Y	Y	Y	Y	Y
State$\times$Year	Y	Y	Y	Y	Y	Y
Observations	5905	5905	5905	5905	5905	5905
Adjusted R^2	0.419	0.547	0.593	0.744	0.591	0.738

Table 9: The effect of natuaral disasters on real outcomes of non-shocked firms

This table presents regression results for the effect on firms' real outcomes of their connection with disaster firms through common lenders. The data are measured at the firm-quarter level, excluding firm-quarter pairs of disaster firms.

$$Real\ Outcome_{i,q} = \alpha_i + \gamma_q + \beta Firm\text{-}Disaster\text{-}Exposure_{i,q-4} + \varepsilon_{i,q},$$

$Real\ Outcome_{i,q}$ is measured by $Investment_{i,q}$ (quarterly investments scaled by lagged assets) in Column (1) to (3), by $Profitability_{i,q}$ (quarterly operating income to total asset ratio) in Column (4) to (6), and by $\Delta Sales_{i,q,q-4}$ (the sales growth between the current quarter and the same quarter in the previous year) in Column (7) to (9), respectively. The regressor *Firm-Disaster-Exposure* is the the firm-level average of bank disaster exposures, weighted by a firm's borrowing size or frequency. Bank disaster exposures is measured by banks' post-disaster lending relationships with disaster firms in Panel A and B, and is measured by banks' disaster lending in Panel C and D. t-statistics based on clustered standard errors by firm are reported in brackets. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Investment (%)			Profitability (%)			Sales-Growth Rate (%)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year-quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Size-, Age-, ROA-tercile×Year FE	N	N	Y	N	N	Y	N	N	Y
State×Year FE	N	Y	Y	N	Y	Y	N	Y	Y
Industry×Year FE	N	Y	Y	N	Y	Y	N	Y	Y
Panel A: Size-based firm disaster exposure									
Firm-Disaster-Exposure^{size}	-6.446***	-5.312***	-2.339*	-3.999***	-2.885**	-2.372**	-23.273***	-19.309***	-8.406***
	(-3.268)	(-3.243)	(-1.653)	(4.515)	(-2.047)	(-2.075)	(-6.296)	(-5.999)	(-2.723)
Observations	172239	172239	172239	161985	161985	161985	170744	170744	170744
Adjusted R^2	0.133	0.191	0.229	0.229	0.302	0.415	0.186	0.205	0.233
Panel B: Frequency-based firm disaster exposure									
Firm-Disaster-Exposure^{freq}	-8.452***	-6.830***	-3.396**	5.043***	-3.774**	-3.086**	-28.652***	-23.273***	-9.030**
	(-3.081)	(-3.003)	(-1.985)	(4.520)	(-2.019)	(-2.072)	(-6.339)	(-6.295)	(-2.516)
Observations	172239	172239	172239	161985	161985	161985	170744	170744	170744
Adjusted R^2	0.178	0.200	0.238	0.270	0.360	0.496	0.192	0.212	0.246
Panel C: Size-based firm disaster exposure through disaster lending									
$\widehat{\text{Firm-Disaster-Exposure}}^{size}$	-6.524***	-4.928**	-4.192**	-4.367***	-3.341**	-3.364**	-35.225***	-24.537***	-10.370***
	(-2.703)	(-2.449)	(-2.426)	(-4.887)	(-2.130)	(-2.147)	(-6.851)	(-5.520)	(-2.607)
Observations	172239	172239	172239	161985	161985	161985	170744	170744	170744
Adjusted R^2	0.137	0.151	0.276	0.359	0.446	0.531	0.151	0.227	0.239
Panel D: Frequency-based firm disaster exposure through disaster lending									
$\widehat{\text{Firm-Disaster-Exposure}}^{freq}$	-8.616***	-5.004**	-4.976**	-5.962***	-3.883**	-3.907**	-33.621***	-25.749***	14.284**
	(-2.765)	(-2.154)	(-2.159)	(5.262)	(-2.010)	(-2.031)	(-10.430)	(-5.332)	(-2.271)
Observations	172239	172239	172239	161985	161985	161985	170744	170744	170744
Adjusted R^2	0.142	0.156	0.251	0.396	0.468	0.557	0.195	0.230	0.242

Table 10: Investment, profitability, and sales growth of connected firms: small firms versus big firms

This table presents regression results for the effect on firms' real outcomes of their connection with disaster firms through common lenders, with the consideration of firm size or firm's dependence on banks. The data are measured at the firm-quarter level, excluding firm-quarter pairs of disaster firms.

$$
\begin{aligned}
Real\ Outcome_{i,q} &= \alpha_i + \gamma_q + \beta_1 Firm\text{-}Disaster\text{-}Exposure_{i,q-4} + \beta_2 Firm\text{-}Disaster\text{-}Exposure_{i,q-4} \times Small\text{-}Firm_{i,q} + \beta_3 Small\text{-}Firm_{i,q} + \varepsilon_{i,q},\\
Real\ Outcome_{i,q} &= \alpha_i + \gamma_q + \beta_1 Firm\text{-}Disaster\text{-}Exposure_{i,q-4} + \beta_2 Firm\text{-}Disaster\text{-}Exposure_{i,q-4} \times Bank\text{-}Dependent_{i,q} + \beta_3 Bank\text{-}Dependent_{i,q} + \varepsilon_{i,q},
\end{aligned}
$$

A firm is defined as small if its one-year lagged total asset is smaller than the cross-sectional sample median. I use the absence of public debt rating as the proxy for bank-dependence. Other variables are the same with the ones in Table 9. t-statistics based on clustered standard errors by firm are reported in brackets. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Investment (%)				Profitability (%)				Sales Growth (%)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Firm size												
Firm-Disaster-Exposure^{size}	-0.810*				-2.268*				-8.949**			
	(-1.651)				(-1.798)				(-2.514)			
Firm-Disaster-Exposure^{size}	-3.145**				-10.145**				-11.851***			
× Small-Firm	(-2.213)				(-2.188)				(-3.060)			
Firm-Disaster-Exposure^{freq}		-1.106*				-2.803*				-8.049**		
		(-1.762)				(-1.753)				(-2.083)		
Firm-Disaster-Exposure^{freq}		-3.332**				-8.759**				-18.203***		
× Small-Firm		(-2.125)				(-2.479)				(-2.705)		
$\widehat{\text{Firm-Disaster-Exposure}}^{size}$			-1.201**				-2.995*				-9.851*	
			(-2.299)				(-1.779)				(-1.721)	
$\widehat{\text{Firm-Disaster-Exposure}}^{size}$			-4.293***				-7.269**				-13.267***	
× Small-Firm			(-2.666)				(-2.326)				(2.770)	
$\widehat{\text{Firm-Disaster-Exposure}}^{freq}$				-1.418*				-3.810*				-12.266
				(-1.894)				(-1.672)				(-1.349)
$\widehat{\text{Firm-Disaster-Exposure}}^{freq}$				-5.594***				-5.582**				-16.614**
× Small-Firm				(-2.866)				(-2.227)				(-2.360)
Small-Firm	1.799***	1.798***	1.851***	1.850***	0.037**	0.037**	0.037**	0.037**	28.647***	28.713***	29.045***	28.994***
	(8.802)	(8.795)	(8.894)	(8.896)	(2.018)	(2.019)	(2.004)	(1.973)	(16.486)	(16.516)	(16.306)	(16.290)
Observations	172239	172239	172239	172239	161985	161985	161985	161985	170744	170744	170744	170744
Adjusted R^2	0.233	0.243	0.282	0.254	0.428	0.468	0.425	0.467	0.241	0.255	0.240	0.252
Fixed effects: Year-quarter, Firm, Size–tercile×Year, Age-tercile×Year, ROA-tercile×Year, State×Year, Industry×Year												

	Investment (%)				Profitability (%)				Sales Growth (%)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel B: Dependence on banks												
Firm-Disaster-Exposure^{size}	-1.153				-2.577				-7.414			
	(0.541)				(-0.988)				(-0.951)			
Firm-Disaster-Exposure^{size}	-3.957***				-8.842***				-16.789***			
× Bank-Dependent	(-2.917)				(-3.267)				(-3.099)			
Firm-Disaster-Exposure^{freq}		-1.126				-2.560				-5.029		
		(-1.334)				(-0.796)				(-0.995)		
Firm-Disaster-Exposure^{freq}		-4.187***				-0.839***				-17.328***		
× Bank-Dependent		(-2.748)				(-2.954)				(-2.942)		
$\widehat{\text{Firm-Disaster-Exposure}}^{size}$			-2.075				-2.254				-8.387	
			(-0.839)				(-1.541)				(-1.217)	
$\widehat{\text{Firm-Disaster-Exposure}}^{size}$			-5.079**				-8.602***				-18.575***	
× Bank-Dependent			(-2.274)				(-3.161)				(-2.957)	
$\widehat{\text{Firm-Disaster-Exposure}}^{freq}$				-2.014				-1.452				-6.783*
				(-1.232)				(-1.671)				(-1.676)
$\widehat{\text{Firm-Disaster-Exposure}}^{freq}$				-5.053***				-8.038***				-21.440***
× Bank-Dependent				(-2.865)				(-2.741)				(-2.991)
Bank-Dependent	-0.609***	-0.606***	-0.600***	-0.603***	-0.609***	-0.606***	0.127***	0.127***	-10.542***	-10.469***	-10.876***	-10.775***
	(-2.673)	(-2.654)	(-2.580)	(-2.595)	(-2.673)	(-2.654)	(5.518)	(5.503)	(-6.118)	(-6.069)	(-6.312)	(-6.227)
Observations	172239	172239	172239	172239	161985	161985	161985	161985	170744	170744	170744	170744
Adjusted R^2	0.241	0.251	0.281	0.252	0.529	0.570	0.537	0.569	0.247	0.256	0.246	0.257
Fixed effects: Year-quarter, Firm, Size–tercile×Year, Age-tercile×Year, ROA-tercile×Year, State×Year, Industry×Year												

Appendix

A. Variable Definitions

Loan Variables	
Loan Amount	The loan amount in million dollar value of 2016
Maturity (Years)	The number of years between loan start and end dates
Credit Spread (bps)	The all-in-drawn spread in basis points
Term Loan	A dummy equals one if the loan type is term loan
Revolving Loan	A dummy equals one if the loan type is revolver
Participant Count	The number of participant lenders in a loan contract
Firm-Bank-Pair Variables	
$Disaster\text{-}Loan_{i,t}$	A firm-loan-level dummy equals one if the loan is issued in the month t , and the firm i is hit by a natural disaster at the month dt, where $dt < t \leq dt + 12$.
$Strong\text{-}Relation^{size}_{i,j,t}$	A lender-based strong-relationship-dummy equals one if $Lending\ Size_{i,j,t}$ is above the median for that lender j during the five-year window preceding the month t
$Strong\text{-}Relation^{freq}_{i,j,t}$	A lender-based strong-relationship-dummy equals one if $Lending\ Freq_{i,j,t}$ is above the median for that lender j during the five-year window preceding the month t
$Weak\text{-}Relation^{size}_{i,j,t}$	A lender-based weak-relationship-dummy equals one if $Lending\ Size_{i,j,t}$ is below the median for that lender j during the five-year window preceding the month t
$Weak\text{-}Relation^{freq}_{i,j,t}$	A lender-based weak-relationship-dummy equals one if $Lending\ Freq_{i,j,t}$ is below the median for that lender j during the five-year window preceding the month t
$Lending\ Size_{i,j,t}$	Ratio of the dollar value of loans contracted by a firm i with the lending bank j to the total dollar value of loans lent by the bank during the five-year window preceding the month t: $Lending\ Size_{i,j,t} = \frac{\text{\$ Amount of loans to borrower } i \text{ by bank } j}{\text{Total \$ amount of loans by lender } j}$
$Lending\ Freq_{i,j,t}$	Ratio of the number of loans contracted by a firm i with the lending bank j to the total number of loans lent by the bank during the five-year window preceding the month t: $Lending\ Freq_{i,j,t} = \frac{\text{Number of loans to borrower } i \text{ by bank } j}{\text{Total number of loans by lender } j}$

$Borrowing\ Size_{i,j,t}$	Ratio of the dollar value of loans contracted by a firm i with the lending bank j to the total dollar value of loans contracted by the firm during the five-year window preceding the month t: $Borrowing\ Size_{i,j,t} = \frac{\text{\$ Amount of loans to borrower } i \text{ by bank } j}{\text{Total \$ amount of loans by borrower } i}$
$Borrowing\ Freq_{i,j,t}$	Ratio of the number of loans contracted by a firm i with the lending bank j to the total number of loans contracted by the firm during the five-year window preceding the month t: $Borrowing\ Freq_{i,j,t} = \frac{\text{Number of loans to borrower } i \text{ by bank } j}{\text{Total number of loans by borrower } i}$
$\Delta Lending_{i,j,d}$	The change of bank j's lending to firm i between one-to-12-month before and after a natural disaster d hit in the month dt: $\Delta Lending_{i,j,d} = \sum_{t=dt-12}^{dt-1} Loan\ Amount_{i,j,t} - \sum_{t=dt+1}^{dt+12} Loan\ Amount_{i,j,t}$
Bank Variables	
$Bank\ Size_{j,y}$	The log value of a bank j's annual total asset in million dollar
$Bank\text{-}Disaster\text{-}Exposure_{j,d}$	The bank j's exposure to a natural disaster d through ex-ante loan lending. Firm i is hit by a natural disaster d in the month dt, the size-based $Bank\text{-}Disaster\text{-}Exposure_{j,d}^{size} = \sum_{i \in I^d} Lending\ Size_{i,j,dt}$, and the frequency-based $Bank\text{-}Disaster\text{-}Exposure_{j,d}^{freq} = \sum_{i \in I^d} Lending\ Freq_{i,j,dt}$.
$\Delta Lending\text{-}in\text{-}disaster\text{-}states_{j,d}$	The change of bank j's lending to disaster firms i between the post- and pre-disaster period of a natural disaster d which hit in the month dt: $\Delta Lending\text{-}in\text{-}disaster\text{-}states_{j,d} = \sum_{i \in I^d} \sum_{t=dt-12}^{dt-1} Loan\ Amount_{di,j,t} - \sum_{i \in I^d} \sum_{t=dt+1}^{dt+12} Loan\ Amount_{di,j,t}$
$Disaster\text{-}Lending_{j,d}$	$Disaster\text{-}Lending_{j,d} = \frac{\Delta Lending\text{-}in\text{-}disaster\text{-}states_{j,d}}{N_{j,d}}$. $N_{j,d}$ equals the number of non-shocked firms connected to bank j in disaster d. I parcel out $\Delta Lending\text{-}in\text{-}disaster\text{-}states_{j,d}$ equally across each of the connected firms.
$HHI_{j,y}^{deposits}$	the Herfindahl-Hirschman index based on bank j's annual deposits in dollars in each state s: $HHI_{j,y}^{deposits} = \sum_s (\frac{Deposit_{j,y,s}/Total\ Deposit_{j,y}}{N})^2$, where N is the total number of states.
$HHI_{j,y}^{branches}$	the Herfindahl-Hirschman index based on bank j's branch numbers in each state s: $HHI_{j,y}^{branches} = \sum_s (\frac{Branches_{j,y,s}/Total\ Branches_{j,y}}{N})^2$, where N is the total number of states.
$\%Disaster\text{-}deposits_{j,y}$	The ratio of a bank j's annual deposits in disaster areas over its total deposits
$\%Disaster\text{-}branches$	The ratio of a bank's branch number in disaster areas over its total branch number
Firm Variables	
$Investment_{i,q}$	Firm i's capital expenditure in the quarter q scaled by its lagged asset in the quarter $(q-4)$: $Investment_{i,q} = \frac{CAPX_{i,q}}{AT_{i,q-4}}$
$Profitability_{i,q}$	Firm i's operating income in the quarter q scaled by its lagged asset in the quarter $q-4$: $Profitability_{i,q} = \frac{OIBDP_{i,q}}{AT_{i,q-4}}$
$\Delta Sales_{i,q,q-4}$	Firm i's sales growth between the quarter q and the same quarter in the previous year $q-4$:

	$\Delta Sales_{i,q,q-4} = \frac{(Sales_{i,q} - Sales_{i,q-4})}{Sales_{i,q-4}}$
$Firm\ Size_{j,y}$	The log value of a firm i's annual total asset in million dollar
$Firm\text{-}Disaster\text{-}Exposure_{i,d}$	The non-disaster firm i's exposure to natural disasters in the month t through their common lenders with disaster firms A natural disaster d occurs in the month dt, the size-based $Firm\text{-}Disaster\text{-}Exposure^{size}_{i,d} = \sum_j Borrowing\ Size_{i,j,dt} \times \frac{Bank\text{-}Disaster\text{-}Exposure^{size}_{j,d}}{N_{j,d}}$, and frequency-based $Firm\text{-}Disaster\text{-}Exposure^{freq}_{i,d} = \sum_j Borrowing\ Freq_{i,j,dt} \times \frac{Bank\text{-}Disaster\text{-}Exposure^{freq}_{j,d}}{N_{j,d}}$. $N_{j,d}$ is the total number of bank j's non-shocked but connected firms when the disaster d occurs.
$Firm\text{-}Disa\widehat{ster\text{-}E}xposuree_{i,d}$	The non-disaster firm i's exposure to a natural disaster d through their common lenders A natural disaster d occurs in the month dt, the size-based $Firm\text{-}Disa\widehat{ster\text{-}E}xposure^{size}_{i,d} = \sum_j Borrowing\ Size_{i,j,dt} \times \frac{Disaster\text{-}Lending_{j,d}}{Asset_{i,dt}}$, the frequency-based $Firm\text{-}Disa\widehat{ster\text{-}E}xposure^{freq}_{i,d} = \sum_j Borrowing\ Freq_{i,j,dt} \times \frac{Disaster\text{-}Lending_{j,d}}{Asset_{i,dt}}$. $N_{j,d}$ is the total number of bank j's non-shocked but connected firms when the disaster d occurs.
$Bank\text{-}Dependent_{i,t}$	A proxy for bank dependence of the firm. It is a dummy variable that takes the value of one for firms with a S&P long-term credit rating, and zero for firms without the credit rating.

Table A.1: The effect of natuaral disasters on loan amounts: exlude financial crises periods
This table reports the results of the similar tests to Table 4, with the exclusion of bank crisis periods of 1998-2001 and 2008-2009.

			Strong-Relation(size)		Strong-Relation(freq)	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: all borrowers						
Disaster-Loan	43.284**	31.042*	23.139	35.440	22.094	24.888*
	(2.074)	(1.735)	(1.402)	(1.599)	(1.383)	(1.748)
Strong-Relation			46.809*	57.301***	34.477	41.580**
			(1.672)	(2.803)	(1.689)	(2.032)
Disaster-Loan× Strong-Relation			82.873**	83.191*	58.557*	75.646***
			(2.262)	(1.901)	(1.788)	(2.689)
Bank Size		10.329*		9.989*		10.990*
		(1.741)		(1.699)		(1.840)
%Disaster-branches		-1.090		-1.811		-1.923
		(-0.225)		(-0.268)		(-0.166)
Month FEs	Y	Y	Y	Y	Y	Y
Borrower FEs	Y	Y	Y	Y	Y	Y
Bank×Year FEs	Y	Y	Y	Y	Y	Y
State FEs	Y	Y	Y	Y	Y	Y
Loan Type FEs	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y
Observations	19249	19249	19249	19249	19249	19249
Adjusted R^2	0.512	0.526	0.553	0.558	0.531	0.536
Panel B: public firms as borrowers						
Disaster-Loan	96.729***	38.834**	71.902	53.638	71.712	54.915
	(2.621)	(2.272)	(1.462)	(1.360)	(1.455)	(1.364)
Strong-Relation			28.293**	75.548*	3.302**	45.157*
			(2.134)	(1.702)	(2.060)	(1.798)
Disaster-Loan × Strong-Relation			61.820*	132.095***	63.170*	88.542**
			(1.676)	(2.644)	(1.661)	(2.229)
Borrower Size	3.414***	3.298***	3.776***	3.949***	3.015***	3.417***
	(4.565)	(3.734)	(4.671)	(3.824)	(4.650)	(3.755)
Borrower ROA	9.337***	6.762**	9.337***	6.745**	9.372***	6.710**
	(2.622)	(2.501)	(2.623)	(2.498)	(2.626)	(2.468)
Borrower Age	9.396	1.336	9.098	1.709	8.988	1.681
	(1.136)	(0.140)	(1.092)	(0.176)	(1.076)	(0.174)
Bank Size		8.317		7.964		9.612
		(0.690)		(0.658)		(0.766)
%Disaster-branches		-2.705		-2.075		-3.753
		(-0.165)		(-0.140)		(-0.145)
Month FEs	Y	Y	Y	Y	Y	Y
Borrower FEs	Y	Y	Y	Y	Y	Y
Bank×Year FEs	Y	Y	Y	Y	Y	Y
State FEs	Y	Y	Y	Y	Y	Y
Loan Type FEs	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y
Observations	14324	14324	14324	14324	14324	14324
Adjusted R^2	0.706	0.711	0.733	0.748	0.716	0.740

Table A.2: Loan amounts of disaster firms around natural disasters

			Strong-Relation(size)		*Strong-Relation(freq)*	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: 1986-2016						
Post	27.441	26.706	21.798	21.460	13.594	10.805
	(18.148)	(18.444)	(17.992)	(17.680)	(20.606)	(19.812)
Strong-Relation			79.488***	62.392***	60.059***	50.910***
			(25.487)	(19.941)	(22.202)	(16.012)
Post × *Strong-Relation*			64.034**	47.428**	32.150**	29.387*
			(26.365)	(19.967)	(14.016)	(16.303)
Bank Size		4.223		4.017		4.544
		(4.121)		(4.127)		(4.163)
Month FEs	Y	Y	Y	Y	Y	Y
Borrower FEs	Y	Y	Y	Y	Y	Y
Bank×Year FEs	Y	N	Y	N	Y	N
State FEs	Y	Y	Y	Y	Y	Y
Observations	4685	4609	4685	4609	4685	4609
Adjusted R^2	0.544	0.549	0.672	0.615	0.618	0.599
Panel B: excluding financial crises periods						
Post	33.157*	34.899*	24.326	24.673	17.027	13.347
	(19.724)	(21.118)	(19.390)	(19.858)	(21.883)	(22.083)
Strong-Relation			75.339***	79.072***	50.436**	56.552***
			(27.812)	(25.876)	(24.816)	(20.647)
Post ×*Strong-Relation*			51.007**	50.138**	37.432*	35.478**
			(24.686)	(21.743)	(22.552)	(17.842)
Bank Size		3.476		3.144		4.027
		(4.169)		(4.178)		(4.202)
Month FEs	Y	Y	Y	Y	Y	Y
Borrower FEs	Y	Y	Y	Y	Y	Y
Bank×Year FEs	Y	N	Y	N	Y	N
State FEs	Y	Y	Y	Y	Y	Y
Observations	3957	3682	3957	3682	3957	3682
Adjusted R^2	0.555	0.558	0.676	0.623	0.631	0.607

This table compares the loan amounts (in million dollar value of 2016) of disaster firms before and after each natural disaster.

$$Loan\ Amount_{i,j,t} = \alpha_i + \gamma_{j,y} + \mu_t + \eta_s + \beta_1 Post_t + \beta_2 Strong\text{-}Relation_{i,j,t} + \beta_3 Strong\text{-}Relation_{i,j,t} \times Post_t + \varepsilon_{i,j,t}.$$

The data are measured at the loan level, The sample includes loans of disaster firms during the two-year window with 12 months before and after natural disasters. *Post* is an indicate for the months after natural disasters. Other variables follow the definition in Appendix A. Standard errors are two-way clustered by firm and bank. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.