Exogenous Shocks and Real Effects of Financial Constraints: Loan- and Firm-Level Evidence around Natural Disasters

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Abstract

This article studies how non-financial, exogenous shocks on a subset of borrowers constrain bank lending and affect real economic activities of non-shocked firms. I separate a loan supply effect from a loan demand effect by identifying borrower-level shocks with the occurrence of major U.S. natural disasters. Financially constrained banks reallocate post-disaster lending by restricting credit supply as well as increasing loan pricing to non-shocked firms but prioritizing the disaster firms with which they have strong pre-disaster relationships. I find one dollar of additional lending to disaster firms is associated with 11.5 cents of decline of the same bank's lending to non-shocked firms. Non-shocked firms' pre-disaster dependence on such banks for financing accounts for economically significant reductions of their total loan borrowing, investment, profitability, and sales-growth in the year following a natural disaster. Consistent with frictions deriving from asymmetric information, the real outcome losses are larger for financially constrained firms.

Keywords: Financial Constraints, Banking Frictions, Exogenous Shocks, Natural Disasters

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1 Introduction

Banks are a key part to the interaction between the real and financial sectors of an economy. Confronted with the repeated occurrence of financial crises, researchers have long focused on how financial shocks, such as the Great Recession, harm bank health and then influence real economic activities through lending (as illustrated in Panel A of Figure 1).[1] However, these common economic shocks have confounding effects that also directly affect the performance of the real economy; thus it is difficult to filter out the influence of the general economic climate.[2] My study addresses this issue by applying exogenous shocks to credit demand from a subset of borrowers (as illustrated in Panel B of Figure 1). I examine the extent to which those borrower-level exogenous shocks, coupled with the presence of financial frictions, lead to an exogenous contraction of banks' credit supply followed by reduced real economic activities on firms that are unaffected by the initial shocks.

This study exploits major natural disasters—hurricanes, tornadoes, earthquakes, floods, and so forth—to generate exogenous increases in credit demand in well defined geographic areas. I trace how these local excess credit needs lead to financial constraints on banks, affect those banks' lending to unaffected but "**connected firms**" (firms that are not located in the disaster areas but borrow from the same banks), and result in real losses in those connected firms. After natural disasters, banks increase lending to the firms exposed to the shocks ("**disaster firms**"), especially to ones with which banks have strong relationships. Meanwhile, banks restrict lending to connected firms and increase loan pricing if these firms do borrow, especially to ones with which banks have weak relationships. This contraction in lending is most pronounced for loans made by smaller banks or banks that are more geographically concentrated, as such banks are further subject to financial constraints when confronted with excess credit demand from disaster firms. Connected

[1] See, for example, Bernanke (1983), Kashyap, Lamont, and Stein (1994), Peek and Rosengren (1997, 2000), Khwaja and Mian (2008), Chava and Purnanandam (2011), Chodorow-Reich (2014), Bord, Ivashina, and Taliaferro (2017) for macro economic shocks.

[2] Several studies explore the effect of idiosyncratic bank supply shocks on borrowers; see Slovin, Sushka, and Polonchek (1993), Ashcraft (2005), and Amiti and Weinstein (2018).

firms that depend heavily on such banks for financing decrease their investment after disasters and subsequently suffer from drops in profitability and sales growth. These real spillovers are stronger at small firms or firms without publicly issued bonds. Combined, these results provide evidence that, through the lending channel, negative, non-financial local shocks impose significant output losses on the non-shocked real sector.

Two necessary conditions relate to frictions in lending for such a lending channel to work. First, banks are financially constrained. In theory, if there is no friction in the market and banks can easily raise funds to meet new credit demand, they would not need to restrict lending. However, in reality, the market is not frictionless, and banks bear cost to raise new funds. In short but big shocks, like natural disasters, the damage is large, and the need for excess credits emerges urgently. Though they need to meet these additional credit demands, not all banks can compensate for a liquidity shortfall through new financing—whether through interbank lending, new deposits, or securitization. Given financial constraints, banks reallocate lending by prioritizing disaster borrowers with which they have strong relationships and restricting credit supply to other firms. This reallocation decision resembles the discussion in the internal-capital markets literature about a constrained headquarter—given its resources are sparse—that moves funds toward the most deserving projects and away from less deserving ones (Stein, 1997).

The second condition is that, due to frictions deriving from asymmetric information, firms face significant costs in switching lenders (Hubbard, Kuttner, and Palia, 2002). If a connected firm can easily switch sources of financing when it faces a withdrawal of credit, the negative lending spillover caused by exogenous natural disasters will barely have real effects for the firm. However, information asymmetry can impede the ability of a firms, especially an informationally opaque one, to freely switch capital sources. As a result, the financial distress that disaster firms transmit to connected firms, through the common banks, is followed by reduced economic activities in connected firms.

In this study, I identify exogenous non-financial shocks with the occurrence of major natural disasters (hurricanes, tornadoes, earthquakes, floods, etc.) from 1994 to 2016, across different counties in the United States.[3] These exogenous events produce large disruptions for firms located in the disaster areas but do not directly disturb the real sector outside the disaster areas or the entire banking sector. To ensure that the shock stems from the demand side, I exclude bank-year observations for banks headquartered in a given year's disaster area from the test sample and control for each bank's allocation of deposits in disaster areas. Local credit demand increases in response to disasters, because disaster firms need to recover from disrupted production and rebuild damaged or destroyed physical capital. If support from the Federal Emergency Management Agency (FEMA) and insurance companies is not sufficient for disaster reconstruction, affected firms increase borrowing from banks.[4] In the first part of my analyses, I document that bank lending to disaster firms increases during the months following disasters, and that the growth of lending concentrates among banks' strong-relationship borrowers.

Armed with the above shocks, I test the subsequent lending and real effects elsewhere by focusing on the financing and performance of connected firms—the firms that banks lent to before the disaster but that are not directly affected by the disaster itself. My main analyses trace the complete events of connected firms: from loan origination to the final real consequences. Identification assumes that non-shocked firms are unaffected by natural disasters. To validate this assumption, I exclude firms whose headquarters are not in the disaster counties but in disaster states in a given year, as Dougal, Parsons, and Titman (2015) show that a firm's investment and growth are affected by local agglomeration economies. I also control for other economic channels through which a non-shocked firm can experience indirect exposure to natural disasters. One channel is that a non-local firm operates in disaster states. The other channel is, as Barrot and Sauvagnat (2016) document, at least one of a non-local firm's main suppliers is hit by a natural disaster, which

[3] 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 in mortgage lending, Dlugosz, Gam, Gopalan, and Skrastins (2018) for bank branches' ability to set deposit rates locally, etc.

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

imposes significant output losses on the customer. Moreover, the comprehensive dataset allows me to not only facilitate controls of lender- and borrower-characteristics but also 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.

Following a natural disaster, I find that bank lending to connected firms decreases during the months following disasters and the reduction of lending concentrates on banks' weak-relationship borrowers. As the test of capital movements from the disaster market to the connected market shows, every one dollar increase in bank lending to disaster firms is associated with an 11.5-cent fall, on average, in bank lending to connected firms. The fall is 25.6 cents if the connected firm is in a weak relationship with the bank. At the individual loan level—compared to loans of similar bank-firm pairs with unconnected firms—the loans of connected firms are significantly lower in dollar amount but higher in loan spreads, indicating that banks offer smaller loans to those firms while charging a higher interest rate. Negative spillovers in lending are most pronounced in loans made by small banks or geographically concentrated banks, which are more likely to experience credit constraints when confronted with excess demand shocks. At the firm level, one standard deviation in firms' ex-ante reliance on common lenders is associated with reductions of the total loan borrowing after a disaster by 0.65% of assets. Overall, these findings suggest that exogenous shocks constrain bank lending as well as disrupt the financing of connected firms.

My main tests also investigate how the negative lending spillover extends to the operations of connected borrowers. I examine how the reliance of non-shocked firms on common lenders affects those firms' investment and performance. Four quarters after a natural disaster, one standard deviation in firms' ex-ante reliance on common lenders is associated with reductions in investment by 0.35% of assets, in profitability by 0.36% of assets, and in sales growth by 1.29% of one-year lagged sales, respectively. A dynamic analysis shows that the maximum real disruptions occur three to four quarters after a natural disaster and dissipate six quarters after the shock. Further, I find that the real effect is much stronger for small firms, which are more informationally opaque, or bank-dependent firms, which have no access to the public bond market for financing. Note that the real effects are robust after I control for a firm's location, industry, size, and age in a given year as well other channels of indirect exposures to disasters, including the supply-demand link and local operations.

This study adds to the substantial banking literature on the lending- and real-effects of the shocks that affect loan supply. Bernanke (1983) introduces this strand of studies and shows a credit channel that translates bank shocks, such as the Great Depression, into real economic outcomes. This literature focuses on the consequences of **financial shocks** through the credit channel; for instance, the Japanese real estate bust influences bank lending or construction activity in U.S. markets (Peek and Rosengren, 1997, 2000) and affects investment or exports of Japanese firms (Gan, 2007; Amiti and Weinstein, 2011); the Russian sovereign default disrupts the performance of bank-dependent U.S. firms (Chava and Purnanandam, 2011); and the Great Recession causes contraction in bank lending (Ivashina and Scharfstein, 2010) and reduction in borrowers' employment (Chodorow-Reich, 2014).[5] **Idiosyncratic bank shocks** also generate reduced real economic activities on borrowers (Slovin, Sushka, and Polonchek, 1993; Amiti and Weinstein, 2018) or local areas (Ashcraft, 2005). The key contribution of this paper is to clearly separate a loan supply effect from a loan demand effect by tracing the effects of **exogenous, non-financial shocks** to a subset of borrowers. Related to banks' dominant role in the connection between the financial and real sectors of an economy, my findings imply that fluctuations in the supply of bank loans—even if caused by non-financial shocks—can still have significant consequences for real economic activities.

My work also relates to a growing body of research that studies how multi-market banks respond to local credit shocks by reallocating capital. Studies of housing markets show that,

[5] For more examples of the research on consequences of economic shocks through the credit channel, see De Haas and Van Horen (2012) and Schnabl (2012) for international shock transmission; see Kashyap, Stein, and Wilcox (1993), Kashyap and Stein (2000), and Jiménez, Ongena, Peydró, and Saurina (2014) for the transimission of monetary policies.

during housing price booms, banks increase mortgage lending to strong housing markets and decrease their commercial lending (Loutskina and Strahan, 2015; Chakraborty, Goldstein, and MacKinlay, 2018); in 2007 and 2008, banks operating in U.S. counties most affected by the decline in real estate prices reduced credit to unaffected counties (Bord, Ivashina, and Taliaferro, 2017). Both responses cause the cross-market transmission of housing shocks. My paper looks at a similar economic mechanism, applying a fully disaggregated approach with a novel strategy to identify exogenous non-financial shocks. Two recent papers find that mortgage lending in non-shocked areas is affected by banks' response to local non-financial shocks: one is recovering needs in natural disaster-shocked areas (Cortés and Strahan, 2017), and the other is a positive bank liquidity shock from shale booms (Gilje, Loutskina, and Strahan, 2016). Unlike these two studies of the mortgage market, my research focuses on the corporate loan market—an arena in which frictions make a more significant difference and real economic outcomes are more easily quantified. Echoing the literature, my findings underscore the importance of lending frictions and financial constraints in the transmission of credit shocks.

This article provides evidence that, as credit markets become integrated, non-financial shocks can transmit across borrowers via financial intermediaries, even though the borrowers might operate in seemingly unrelated businesses. Murfin (2012) also shows that the distress of a subset of borrowers affects loans to other borrowers through common banks: banks write tighter contracts after suffering payment defaults, even when defaulting borrowers are in different industries and regions from the current borrower. Murfin focuses on banks' lending decisions and attributes lender motivation in tightening contracts to updated beliefs about their own screening ability. Unlike in Murfin (2012), in this paper, it is financial constraints that force banks to restrict credit supply; besides, I focus not only on bank lending outcomes but also on real effects.

This article also adds to a broad study in financial economics that explores how firms are linked and thus affected by each other. A typical type of link is the supplier-customer relationship, 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 connections 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: sharing the same lenders. Further, 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 explains the identification strategy. Section 4 discusses the empirical methods and reports the results. Section 5 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, and 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.[6] Because DealScan coverage is sparse in earlier years

[6] 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").

(Schwert, 2017), I start the loan sample from 1989. My test requires five-year time window to construct relationship measures, so the test sample starts from 1994. Loans with either banks or borrowers based outside the United States are not included. 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. 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. Thus, a firm's "bank" or "lender" in this paper refers to the lead arranger on the loan.[7]

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 link of borrowers from Chava and Roberts (2008) and the link of lenders from Schwert (2017), both cover years to 2012. For years after 2012, I manually construct the similar borrower link and lender link. 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 a borrower's location, I firstly use the location information in DealScan (city, state). For these borrowers whose location is missing in DealScan, I cross-check the historic record of borrowers' headquarters information from Compact Disclosure, which provides location

[7] See Appendix B about more details of selection criteria of lead lenders.

information (city, state) on an annual basis over the period from 1988 to 2006.[8] 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.

2.1.3 Major Natural Disasters

I obtain information on each major natural disaster hitting the U.S. territory from the SHELDUS (Spatial Hazard Events and Loss Database for the United States) database maintained by Arizona State University. 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 28 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.

[8] Unlike Compact Disclosure, Compustat only reports the current state and county of firms' headquarters.

2.1.4 Other Datasets

To clearly trace the transmission of borrower-level shocks induced by local natural disasters, I control for other economic channels through which a non-shocked firm or a bank can experience indirect exposure to natural disasters. I obtain relevant information with the help of the following datasets.

A. Bank Branches and Deposits

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. These data allow me to 1) measure banks' direct exposure to natural disaster shocks using the pre-disaster share of deposits in disaster states, which is equal to the fraction of deposits in branches owned by each bank that are located in a disaster county; 2) measure banks' geographic concentration level in each year using the Herfindahl-Hirschman index (HHI) of banks' fractions of branches in each states.

B. Supplier-Customer Links

Regulation SFAS No. 131 requires firms to disclose certain financial information for any customer representing more than 10% of the total reported sales. The supplier-customer links applied in this study is based on information in the Compustat Segment files, which provides the names of a certain firm's principal customers and associated sales.[9] I connect these links to Compustat and Compact Disclosure to get the location information of each firm's suppliers.

[9] The data are from Jean-Noel Barrot's website: http://mitmgmtfaculty.mit.edu/jnbarrot/.

C. Geographic Dispersion of Borrowers' Business Operations

Firms report their operation details and properties information in their annual 10K reports. I count the occurrence of state names in sections of "Item 1: Business," "Item 2: Properties," "Item 6: Consolidated Financial Data," and "Item 7: Managements Discussion and Analysis." Following Garcia and Norli (2012), I measure non-local firms' main operations in different states using the number of different states mentioned in these four sections.

2.2 Measures of Relationships

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 lending relationship. Every time when a new loan is originated between firm i and bank j in the month t, I review the lending record over the past five years between the borrower and the bank, and capture the *size* and *frequency* of the bank-borrower pair's past lending: $Lending\ Size_{i,j,t} = \frac{\text{\$ Amount of loans to borrower } i \text{ by bank } j}{\text{Total \$ amount of loans by bank } j}$, $Lending\ Freq_{i,j,t} = \frac{\text{Number of loans to borrower } i \text{ by bank } j}{\text{Total number of loans by bank } j}$. The two measures range from 0 to 1, representing how big in loan size and in frequency a given bank j lend to a borrower i comparing with j's lending to its other borrowers.

Given that the establishment of strong bank-borrower relationships can generate significant benefits for both the borrower and the bank, the *size* and *frequency* of the past lending would be positively correlated with the existence of a strong relationship: a given bank lends in larger loan size and higher frequency to relationship borrowers. Thus, I construct the relationship strength dummies: $Strong\text{-}Relation$ and $Weak\text{-}Relation$. A borrower-bank pair (i, j) is considered to have a **strong** relationship in the month t if $Lending\ Size_{i,j,t}$ is **above** the median for that bank i in the past five years; otherwise a weak relationship. The similar dummy variables $Strong\text{-}Relation^{freq}$ and $Weak\text{-}Relation^{freq}$ are constructed following the same definition for $Lending\ Freq_{i,j,t}$. These bank-based relationship strength variables represent how important a borrower is for a given bank comparing with its other borrowers.

2.3 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 to non-shocked firms 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. Though all the banks are lead arrangers in the syndicated loan market, the bank market equity ratio exhibits substantial variation with a mean of 11.55% and a standard deviation of 7.33%. 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 geographic 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 borrower in the sample has \$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. In 47% of firm-quarter observations, the borrower does not have a long-term rating from S&P. The average ratio of the count of disaster states to the count of all states in a given firm's most recent 10-K report before a natural disaster hit is 2.6%, and the probability that (at least) one of a given non-shocked firm's main supplier is hit by a natural disaster is 5.7%.

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 Identification Strategy

3.1 Classify Borrowers

The prerequisite of studying the propagation of shocks in borrower-bank 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 headquartered in a county that is hit by the natural disaster; banks 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 headquartered in a state that is hit by the natural disaster is a non-shocked firm.[10] If a non-shocked firm also borrows from disaster lending banks in

[10] Identification assumes that non-shocked firms are unaffected by natural disasters. To validate this assumption, I exclude firms whose headquarters are not in the disaster counties but in disaster states in a given year, as Dougal,

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.

3.2 Natural disasters as Negative Demand Shocks

To validate the basic premise of the spillovers of the exogenous shocks, I first examine how natural disasters immediately affect banks' following lending to disaster firms.

I focus on the six-month period before and after a natural disaster hit, and compute the period-by-period growth in supply of loans by estimating the growth in the amount of loans for a given period as compared to the previous six-month period. As shown in Panel A of Figure 3, averagely there is a remarkable increase (12.86%) in the amount of loans issued to disaster firms after a natural disaster hit compared to the pre-disaster period. The increase in the insurance of new loans is concentrated in the subsamples of loans to strong-relations firms (16.93% and 18.03%), namely the ones that a bank lent in larger size ratio or higher frequency during the prior five years. As a comparison, the subsamples of weak-relations firms suffer dramatic decline in the issuance of new loans (-34.33% and -34.90%).

I also go a step further to test the change of lending to disaster firms at the loan level. To do so, I regress the amount or the all-in-drawn spread on a dummy of disaster loans in loan-level cross-sectional regressions (see Appendix C and Table A.1). The results show that, at the individual loan level, the amount of loans to disaster firms is significantly higher than other loans, especially if a disaster firm is in a strong pre-disaster relationship with the lender; however, banks do not charge significantly higher interest rate (all-in-drawn spread) to disaster firms. Thus, the increase in bank lending to some but not all disaster firms is less likely to be associated with seeking for profits but more likely to reflect banks' function of securing its important customers that suffer losses in

Parsons, and Titman (2015) show that a firm's investment and growth is affected by local agglomeration economies.

natural disasters—similar to the function of insurance companies.

3.3 Exposure to Natural Disasters through Disaster Firms

Natural disasters create exogenous shocks on disaster firms. At the core of my analysis is the extent to which banks and connected-firms are also exposed to these shocks through the borrower-lender network. I use the lending strength measures in Section 2.2 to construct indirect-exposure variables.

3.3.1 Banks' Pre-Disaster Exposure to Disaster Firms

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

$$\textit{Bank-Disaster-Exposure}_{j,d} = \sum_{i \in I^d} \textit{Lending Size}_{i,j,dt},$$
$$\textit{Bank-Disaster-Exposure}^{freq}_{j,d} = \sum_{i \in I^d} \textit{Lending Freq}_{i,j,dt};$$

otherwise

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

$\textit{Lending Size}_{i,j,dt}$ and $\textit{Lending Freq}_{i,j,dt}$ are the lending size and frequency of bank j to a disaster firm in I^d. *Bank-Disaster-Exposure* is 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.

3.3.2 Connected Firms' Pre-Disaster Exposure to Disaster Firms

Similarly, I construct a measure of connected firm i's indirect exposure to a natural disaster d in the month t through their common lenders with disaster firms: $Firm\text{-}Disaster\text{-}Exposure_{i,t}$. Every time when a new loan is originated between firm i and bank j in the month t, I review the lending record over the past five years between the borrower and the bank, and capture the borrower's reliance on the bank: $Reliance_{i,j,t} = \frac{\text{\$ Amount of loans to borrower } i \text{ by bank } j}{\text{Total \$ amount of loans by borrower } i}$, or $Reliance^{freq}_{i,j,t} = \frac{\text{Number of loans to borrower } i \text{ by bank } j}{\text{Total number of loans by borrower } i}$. Firms' indirect exposure to disasters through banks is constructed in this way:

$$\begin{aligned} &Firm\text{-}Disaster\text{-}Exposure_{i,d} \\ &\quad = \sum_j Reliance_{i,j,dt} \times \frac{Bank\text{-}Disaster\text{-}Exposure_{j,d}}{N_{j,d}}, \\ &Firm\text{-}Disaster\text{-}Exposure^{freq}_{i,d} \\ &\quad = \sum_j Reliance^{freq}_{i,j,dt} \times \frac{Bank\text{-}Disaster\text{-}Exposure^{freq}_{j,d}}{N_{j,d}}. \end{aligned}$$

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.

3.4 Other Identification Concerns

There are a few other identification concerns that I address in my empirical approach.

The first concern is that *Bank-Disaster-Exposure*$_{j,d}$ is also likely to be correlated with banks' exposure to natural disasters through other channels. To ensure that *Bank-Disaster-Exposure*$_{j,d}$ captures shocks that are stemming from the demand side, I exclude bank-year observations for banks headquartered in a given year's disaster area from the test sample. Banks that lend to disasters in large size ratio or high frequency are also like to have larger proportion of deposit business there, so banks with higher *Bank-Disaster-Exposure*$_{j,d}$ also suffer larger loss in deposits from natural disasters hits. To mitigate this disturbance, I also control for each bank's pre-disaster reliance in deposits from disaster areas. Moreover, a further test directly tests the effect of each bank's additional lending in disaster areas on its lending change in connected firms. The reduction of banks' deposits in disaster states can barely affect this mechanism.

The other concern is that non-shocked firms are likely to be affected by natural disasters through other channels. For example, non-shocked firms may have a large share of business operating in disaster states or have important suppliers that suffer from the natural disaster hit. These economic channels may affect non-shocked firms' performance, and then the change in bank lending to these firms and the reductions in their real economic activities are not necessarily driven by the shocks transmitted through the lending channel. I address these concerns in a few ways. First, my control variables include firms' economic links with disaster states through customer-suppler connections and through firms' business operations. Further, in the tests of lending outcome at the bank-firm level or loan level, I use firm-time fixed effects to remove any factors specific to a firm at a given point in time. That way I can compare how the same non-shocked firm's loans from a disaster lending bank change, relative to another bank that does not lend to disaster firms.

4 Methods and Results

My main tests of spillover effects include two parts. First, as part of the shock transmission, the spillovers will be reflected in the lending to connected firms. I trace capital flows from connected firms to disaster firms after natural disasters, and I also examine how the amount and the pricing of connected firms' loans change comparing with unconnected firms' loans. Second, the negative loan change would trigger further influence on connected firms' real outcomes. I focus on natural disasters' influence on non-shocked firms' succeeding investment, profitability and sales growth.

4.1 Lending Spillovers on Connected Firms

In this section, I explore the lending spillovers on non-shocked but connected firms caused by natural disasters. As shown in Panel B of Figure 3, there is a remarkable decrease (-7.21%) in the amount of loans issued by disaster lending banks to disaster firms after a natural disaster hit, and the decrease comes from the subsamples of loans to weak-relations firms (-24.93% and -24.31%), namely the ones that a bank lent in smaller size ratio or lower frequency during the prior five years. As a comparison, Panel C shows there is no significant change in the growth of new loans to unconnected firms after a natural disaster hit. Figure 4 shows the change of loan growth at the individual bank-level again indicate the change of an average bank's lending pattern around natural disasters. Combined with the analyses of Panel A in section 3.2, the change of growth in bank loans to different firms around natural disaster provide some preliminary evidence that banks fulfill the excess credit needs in disaster areas by cutting down lending to non-shocked areas: when banks increase lending to disaster firms that are their important customers, they also cut lending to connected firms that are not their important customers.[11]

[11] My test focuses on relationship loans, which are not transaction loans, namely the first loan made between a bank and a firm. Figure A.1 shows the growth in transaction loans, which display the same pattern of loans to weak-relationship borrowers.

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

As a direct test of the spillover effect on lending to connected firms from banks with disaster lending, I firstly examine capital movements from the disaster market to the connected market. When being faced with rapid increases in credit demand from the disaster areas, if the market is frictionless—as assumed in many theoretical works in finance studies, banks can easily get new money from somewhere else—either through internal financing or through external channels like interbank lending. If there are frictions in the real market, financial constraints will cause contraction in credit supply to some extent, and banks have to cut loans from some the non-shocked areas to fulfill the disaster firms' needs.

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- and 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, the decremental lending to each non-shocked firm i from each of its lenders j surrounding the disaster d is

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

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. This sample include all the firm-bank-disaster triplets where the firm is a non-shocked 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:

$$\begin{aligned}\frac{\Delta Lending_{i,j,d}}{Total\text{-}Lending_{j,d}} =&\beta_1 \frac{Disaster\text{-}Lending_{j,d}}{Total\text{-}Lending_{j,d}} + \beta_2 Weak\text{-}Relation_{i,j,d} \\ &+ \beta_3 \frac{Disaster\text{-}lending_{j,d}}{Total\text{-}Lending_{j,d}} \times Weak\text{-}Relation_{i,j,d} \\ &+ \beta_4 Control_{j,d} + \alpha_{i,d} + \gamma_j + \eta_s + \varepsilon_{i,j,d},\end{aligned} \tag{1}$$

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 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.

In all regressions, I control for bank size, bank equity ratio, bank deposit ratio, and the fraction of a bank's deposits from natural disaster states, so that the βs are not driven by differences in the condition of banks, especially the reduction of deposits caused by natural disasters. I focuses on borrowers being public firms, which can be matched with Compustat and allow for the control of borrowers' industries. All the control variables measured in the most recent year before the disaster occurs.

Finally, I include firm-disaster fixed effects $\alpha_{i,d}$ to remove factors that affect lending to a given firm after a given disaster. I also sweep out bank fixed effects γ_j and state fixed effects η_s that affect lending to a given state. 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 in one pair is a disaster lending bank and thus has nonzero *Disaster-Lending*, while the bank in the other pair is not. I cluster by bank and firm in building standard errors.

[Insert Table 3 about here]

Table 3 reports the regression estimates. Columns (1) and (2) 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- and firm-characteristics, 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.[12] This provides the most direct evidence of lending effects of market frictions in this empirical setting. Theoretically, If the market is fully frictionless, through internal or external financing, banks can fully absorb the credit demand shock induced by natural disasters, and the estimate of β_1 should be zero; if the market if full of frictions, banks need to entirely depend on reducing lending elsewhere to provide additional credit to disaster states, then the estimate of β_1 should be 1. The estimate 11.5 cents give an empirical estimation of the value of frictions in the lending market.

Columns (3) to (6) include weak relationship measures. The *Weak-Relation* $\times$ *Disaster-Lending* interaction terms obtain negative and significant coefficients. This shows that, for per dollar of lending increase to disaster firms, lending to per connected and weak-relationship firm falls by 25.6 (21.8 if measured by frequency-based relationship measure) cents more, compared with other 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 25.6 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 10% of the median amount in the loan sample.

[12] When including borrowers being private firms, the estimate of the reductions increases to 33.5 cents, see Appendix A.2.

These results suggest, being faced with urgent needs for credit from large natural disaster, banks seem to raise some additional funds, because they do not entirely cut down non-disaster loans; but they are not able to fully compensate the money shortfall through new financing, so they reduce the non-disaster lending to the extent of nearly cents per dollar of extra disaster lending, the reduction raise to nearly 26 cents when non-shocked borrowers are in weak-relationships with those banks.

One concern is that heterogeneity of disasters (e.g., severity, predictability) might affect the estimates above. Firstly, for disasters like hurricanes which occur routinely and are easier to predict, banks or firms plausibly might hold back cash buffers—although this should go against with my results. Secondly, the findings above may be driven solely by one or two big shocks, such as Katrina. I conduct two sub-sample tests, one excludes all hurricanes, the other excludes Hurricane Katrina. The estimates of capital movement do not change fundamentally, although vary in magnitude. The results are reported in the Appendix (see Table A.4).

4.1.2 The loan-level evidence

To further test the lending spillovers, I analyze how the natural disaster affect individual loans lent to non-shocked firms. I build a dataset at the loan level including all the firm-bank-month triplets in which the bank at least lent once to the firm in the prior five calendar years. Given the existence of lending history, these firms are assumed to be the relevant lending markets for each bank to start a new loan. The sample does not include disaster loans—loans lent to disaster firms within 12 months after the corresponding natural disaster, because the aim here to test how the shock affects lending in non-shocked markets.

I report the regression as follows (firm i, bank j, loan k, month t, year y, and state s):

$$\begin{aligned} \textit{Loan Lending}_k = & \beta_1 \textit{Bank-Disaster-Exposure}_{j,t} + \beta_2 \textit{Weak-Relation}_{i,j,t} \\ & + \beta_3 \textit{Bank-Disaster-Exposure}_{j,t} \times \textit{Weak-Relation}_{i,j,t} \\ & + \beta_4 \textit{Control}_{j,t} + \alpha_{i,y} + \gamma_j + \mu_t +, \eta_s + \varepsilon_{i,j,t}. \end{aligned} \tag{2}$$

The dependent variable is $\textit{Loan Amount}_k$—the log of each loan's amount in dollar value of 2016, or $\textit{Loan Spread}_k$—the all-in-drawn spread in basis points. $\textit{Bank-Disaster-Loan}_{j,t}$ 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. $\textit{Weak-Relation}_{i,j,t}$ is the lender-based weak relationship variable introduced in the section 2.2, measured either in lending size or in lending frequency. The $\textit{Control}_{j,t}$ contains the same bank-specific variables in Eq.(1). To ensure the relationship strength variable and the control variables are ex-ante thus not affected by a natural disaster shock, for 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 ($\textit{Weak-Relation}_{i,j,dt}$), and the control variables from the most recent quarter before the disaster occurs.

I include loan-type fixed effects to control loan attributes, firm-year effects $\alpha_{i,y}$ to remove factors that affect lending to a given firm in a given year, 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 η_s that affect lending to a given state. Conceptually, my analysis compares the 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 4 about here]

Table 4 reports estimates of the regressions in Eq.(2). Column (1) and Column (4) show a statistically significant negative relation between banks' ex-ante exposure to natural disasters and the dollar amount of an individual loan. Based on the estimates in Column (1) and Column (3), one standard deviation increase in *Bank-Disaster-Exposure* (*Bank-Disaster-Exposure*^{freq}) is associated with a reduction of loan amount by 10.95% (11.66%).[13]

Column (2) and (4) decompose the above negative effect by introducing the weak relationship measure and its interaction with the bank-level disaster exposure measure, which allows 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 the coefficient 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, one standard deviation increase in *Bank-Disaster-Exposure* (*Bank-Disaster-Exposure*^{freq}) is associated with a reduction of loan amount to weak-relationship and connected firms by 24.35% (19.35%). In contrast, the marginal effect of banks' exposure to disasters is not significantly negative on non-weak-relationship firms. These results show that the restriction of lending to non-shocked firms is concentrated on the ones which are in weak relationships with disaster lending banks.

The rest columns test whether the loan pricing of connected firms is abnormally high in the months following natural disasters. Column (5) and Column (7) show a statistically significant positive relation between banks' ex-ante exposure to natural disasters and the spread of individual loans. For one standard deviation increase in *Bank-Disaster-Exposure* (*Bank-Disaster-Exposure*^{freq}), the post-disaster all-in-drawn spread of per non-shocked connected loan increase by 30.3 basis points (26.83 basis points). Similarly, Column (6) and (8) decompose the positive effect by introducing the weak relationship measure and its interaction with the bank-

[13] When I use loan amount in million dollars as the dependent variable, the corresponding reduction is \$21.05 million (\$19.80 million), which is economically equivalent to 9.01% (8.48%) of the sample median.

level disaster exposure measure. 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, a median disaster-lending bank increases its post-disaster loan price on weak-relationship and connected firms 13.86 basis points (testing with size-based *Bank-Disaster-Exposure* and *Weak-Relation*) or 10.87 basis points (testing with frequency-based *Bank-Disaster-Exposure* and *Weak-Relation*) more. In contrast, the marginal effect of banks' exposure to disasters is not significantly positive on non-weak-relationship firms. These results show that, compared to strong-relationship firms, disaster lending banks increase post-disaster loan pricing sharply in non-shocked weak-relationship firms.

The main loan sample contains borrowers that are public firms only. In Table A.3, I report the results of similar tests including loans to private firms. The magnitude of spillover effects on individual loans—decreasing dollar amount and increasing loan pricing—is larger when loans to private firms are considered.

4.1.3 Financially constrained banks

The above impact of natural disaster shocks on non-shocked but connected firms through the borrower-lender networks should be stronger when the banks are more likely to suffer financial constraints. In this section, I introduce variables for bank-level financial constrains and their interaction with bank disaster lending variables to the similar lending tests in the previous sections.

The first dimension of constraints is bank size. Every year, I group all banks in my test sample into quintiles in an ascending order based on bank assets in the previous year. Q^i are quintiles based on bank assets in an ascending order.

[Insert Table 5 about here]

The models in Table 5 compare lending spillover effects among banks in different size groups. The models allow the magnitude of capital flows or loan-level lending change to vary across bank size. The table shows that the lending spillover effects documented in previous sections are concentrated on banks in the two smallest quintiles. For example, compared with Q3, the reference group, Column (1) shows banks in Q1 reduce the non-disaster lending for per dollar of extra disaster lending by 33.92 cents more, and banks in Q2 reduce by 24.22 cents more; in contrast, there is no significant difference from Q3 when banks are in Q4 or Q5. Similarly, the loan-level tests in Column (2) and (3) shows the loans to connected firms with smaller amount or higher spread are concentrated on loans made by banks in Q1 and Q2.

Banks' geographic layout is the other dimension for bank financial constrains. The dummy $Regional\ Bank^{branches}$ (or $Regional\ Bank^{deposits}$) equals one if the Herfindahl-Hirschman index of a bank's numbers of branches (amounts of deposits) across all the states is above the sample median.

[Insert Table 6 about here]

As shown in Table 6, *RegionalBanks* account for the lending spillovers on connected firms. Overall, the baseline results are accounted for by banks that are smaller or geographically more concentrated. An example of such a bank is Bank Synovus, a regional bank headquartered in Georgia and operating across five southern states, including Georgia, Alabama, Tennessee, South Carolina, and Florida. Unlike nationwide mega banks such as Bank of America or Citi Bank, Bank Synovus is less robust and more likely to be influenced by a natural-disaster-induced demand shock from one of these five states—for example, Hurricane Irma destroyed Florida in the fall of 2017. Such regional, multi-market banks are the main conduits in the transmission of shocks from disaster firms to non-shocked but connected firms.

4.2 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.

If the market is frictionless, connected firms can easily substitute other sources of financing when they face a withdrawal of credit, there will barely be real effects for these firms. If there is frictions in the market, the more a non-disaster firm depends on banks with disaster-lending for financing, the harder this firm is able to freely switch to new lender, and the firm suffer financial constraints followed by reduced economic activities. For example, for two Georgia firms get loans cut down by Bank Synovus after hurricane Irma, the one that treats Synovus as its main lender will suffer more real losses.

I apply the variable of pre-disaster exposure to disaster firms in section 3.3.2. I also construct a similar measure based on the changes of banks' disaster lending, which I call $\widehat{Firm\text{-}Disaster\text{-}Exposure}_{i,d}$, 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

$$\widehat{Firm\text{-}Disaster\text{-}Exposure}_{i,d} = \sum_j Borrowing\ Size_{i,j,dt} \times \frac{Disaster\text{-}Lending_{j,d}}{Asset_{i,dt}},$$
$$\widehat{Firm\text{-}Disaster\text{-}Exposure}^{freq}_{i,d} = \sum_j Borrowing\ Freq_{i,j,dt} \times \frac{Disaster\text{-}Lending_{j,d}}{Asset_{i,dt}}.$$

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 hits, 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.

4.2.1 Firm-level total loan borrowing

To test the real consequences on connected firms, I firstly examine the relation between the change of a firm's total loan borrowing around natural disasters and its indirect exposure to natural disasters. High *Firm-Disaster-Exposure* implies a firm has high reliance on banks that have high weight in disaster areas. Hypothetically, due to lending friction, it will be difficult for such firm to quickly switch to other banks, thus its total loan borrowing amount will decrease more after disasters.

For each non-shocked firm in each disaster d, I calculate its total change of loan borrowing—$\Delta Borrowing_{i,d}$— between two periods: 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. Then I conduct the following test at the firm-disaster level:

$$\Delta Borrowing_{i,d} = \beta_1 Firm\text{-}Disaster\text{-}Exposure_{i,d} + \beta_2 Control_{i,j,d} + \alpha_i + \varepsilon_{i,d},$$

The matrix $Control_{i,j,d}$ contains Size-, Age-, ROA-tercile$\times$Year dummies, as well as two variables about the weight of a firm's business and establishment operated in disaster areas, and the weight of its suppliers are affected by disasters.

[Insert Table 7 about here]

As shown in Table 7, across Column (1) to (6) the estimates of β_1 are significantly negative. The results indicate that when a non-shocked firm has high exposure to disaster areas through the common banks, its total loan borrowing decreases after disaster hits. Take Column (3) as an example, when everything else equal, one standard deviation in *Firm-Disaster-Exposure* account for 49.95 million decrease in total loan lending to a non-shocked firm, which equals to 4.45% of the sample median firm asset.

4.2.2 Post-disaster economic activities

The main 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:

$$Real\ Outcome_{i,q} = \alpha_i + \gamma_q + \beta Firm\text{-}Disaster\text{-}Exposure_{i,q-4} + \varepsilon_{i,q}, \tag{3}$$

$Real\ Outcome_{i,q}$ 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-Disaster-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.[14] 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. Like the tests in Section 4.2.1, I take care of possible economic links that may connect firms to the natural disaster areas. Two variables are added, one is the weight of a firm's business and establishment operated in disaster areas, and the other is the weight of its suppliers are affected by disasters. In all regressions, standard errors are clustered at the firm level.

[Insert Table 8 about here]

The baseline results are presented in Panel A and Panel B of Table 8. 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

[14] To test if *Firm-Disaster-Exposure* also affects firm-level loan financing, in Table 7, I conduct a similar test with non-shocked firms' $\Delta Lending$ as the dependent variable. The test ueses panel data at the firm-disaster level.

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. 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% of assets, for an average connected firm four quarters after a natural disaster hits. Relative an average *Investment* of 2.93% of assets in the sample, the estimate translates into a relative decrease in capital expenditures of 12% . Similarly, Column (6) indicates a loss in profitability of 0.37%of assets; and Column (9) indicates a reduction in sales-growth rate of 1.33%. 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 $\widehat{Firm\text{-}Disaster\text{-}Exposure}$, which is based on the change of overlapped banks' lending to disaster areas, as the regressor. As shown in Table 8, the coefficient estimates of $\widehat{Firm\text{-}Disaster\text{-}Exposure}$ 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 $\widehat{Firm\text{-}Disaster\text{-}Exposure}$ 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%, for an average connected firm four quarters after a natural disaster hits. Similarly, a loss in profitability of 0.41%of assets is estimated from Column (6), and a reduction in sales-growth of rate of 1.27%is estimated in Column (9). These estimations are quite close to the one indicated in Panel A and are also economically large, compared with the sample means listed above.

I also estimate the length of the real effects. I illustrate the results in Figure 5, which compares the effect of *Firm-Disaster-Exposure* on investment, profitability, and sales growth at different quarters surrounding a major natural disaster for non-shocked firms. The graph highlights that the disruption in profitability and sales growth follows the reduction in investment. The reduction in investment peaks in the third quarter after a natural disaster and reverts back to the pre-disaster level in the sixth quarter; the peak and full reversion of the disruption in profitability both come with one-quarter lag; sales growth keeps slowing down until the sixth quarter.

4.2.3 Financially constrained firms

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 9 about here]

As the table shows, the real effect is much stronger for small firms or bank dependent firms. Hence, the results suggest that if financial constraints prevent firms from being able to raise capital from sources other than their constrained banks, those firms will suffer more real losses from the transmission of the natural disaster shocks from the banking channel.

5 Conclusion

In this paper, I examine how exogenous non-financial shocks, coupled with the presence of financing frictions, can contract bank lending as well as disrupt the financing and real economic activities of non-shocked borrowers. I test the transmission of borrower-level shocks via borrower-lender networks. Relying on the exogenous occurrence of natural disasters in the United States over 20 years, I identify firm-level exogenous shocks and trace their influence via banks with disaster lending. Disaster-affected borrowers in strong relationships with these banks are found to receive more loans after the disaster. As a consequence of a subsequent spillover effect, their connected peers that are not affected by the natural disaster suffer substantial loan declines and real outcome losses. The lending spillovers are stronger when banks tilt toward being financially constrained. My estimates are economically large and highlight banks' dominant role as the connection between the Wall Street and the Main Street. My tests also quantify the empirical effect of market frictions, which result in financial constraints for both banks and firms. The findings imply the importance of credit markets in connecting firms, even if the involved firms do not have more transparent connections.

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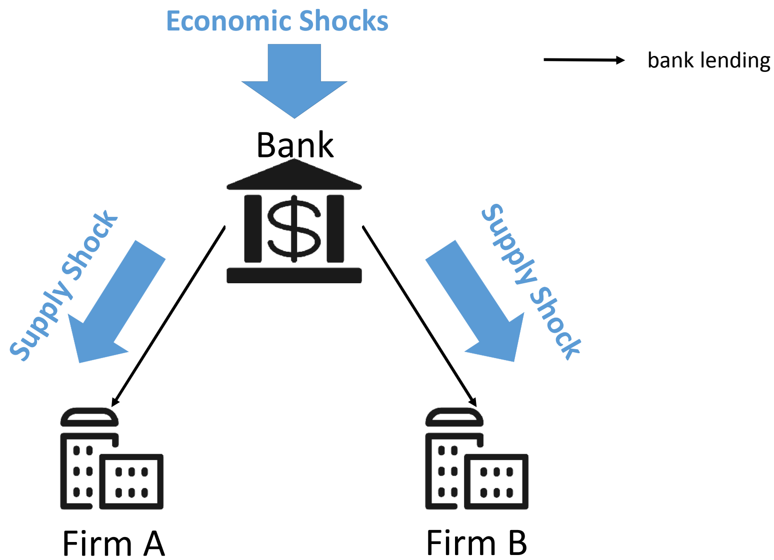
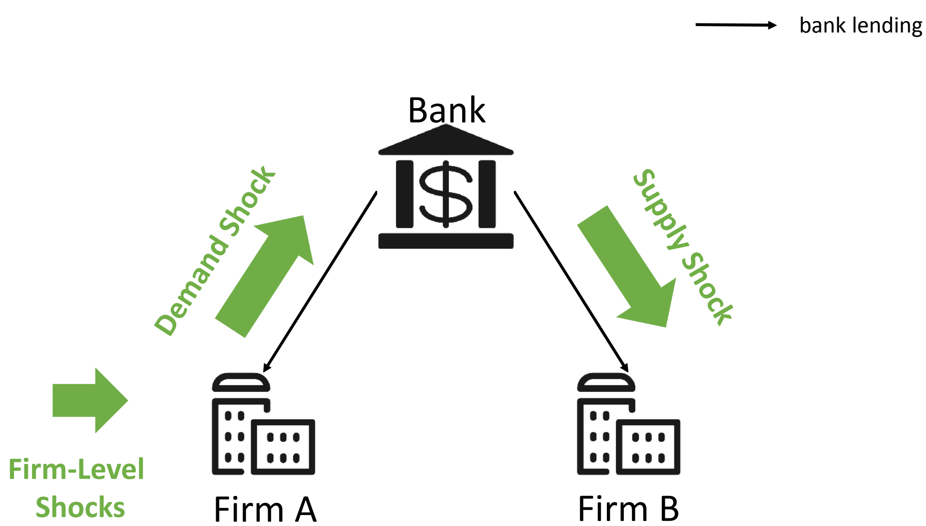


Panel A: The transmission of bank shocks



Panel B: The transmission of borrower shocks

Figure 1: Credit shocks transmission through lender-borrower networks
This figure illustrates two different paths of the transmission of credit shocks through bank-borrower networks. Panel A is for shocks originated from economic shocks which directly affect banks. Panel B is for shocks originated from exogenous shocks which only affect a group of borrowers.

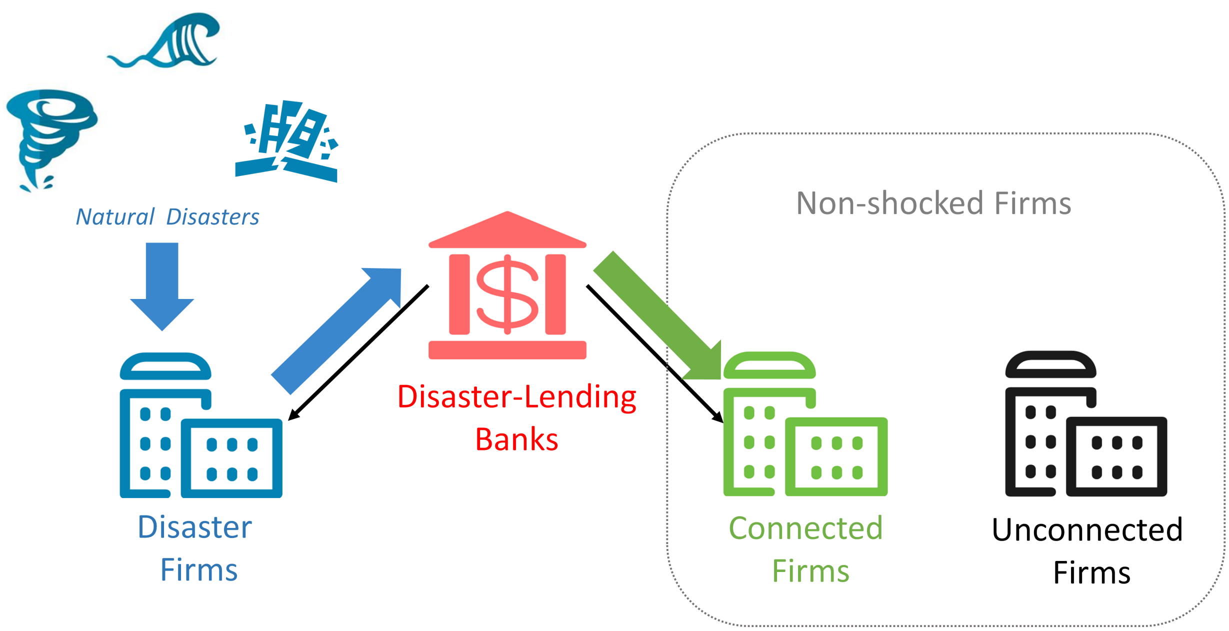
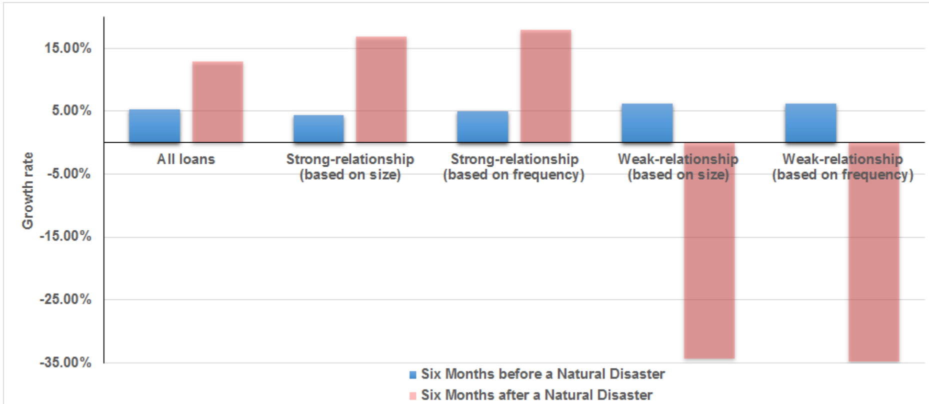
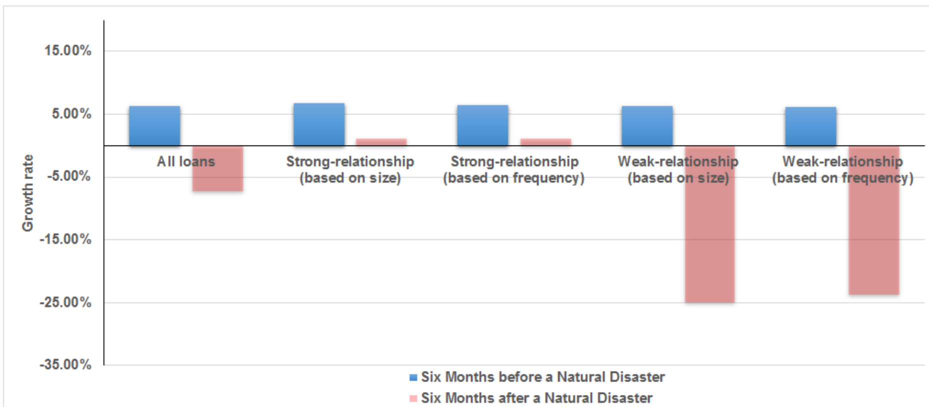


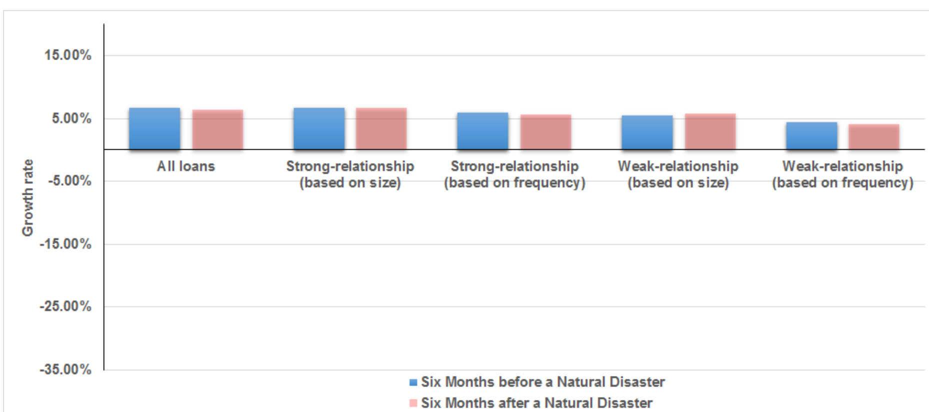
Figure 2: Borrowers and lenders when regional natural disasters hit
This figure illustrates the identification of different borrowers right after a natural disaster hit. Firms headquartered in the disaster county are flagged as "disaster firms"; banks that once lent to these firms in the past five years are "disaster lending banks"; other firms headquartered outside the disaster states are "non-shocked firms". If a non-shocked firm also borrows from disaster lending banks in the past five years, it is flagged as a "connected firm"; otherwise it is an "unconnected firm". I leave these flags on for 12 months after a disaster hit.



Panel A: Disaster firms



Panel B: Connected firms



Panel C: Unconnected firms

Figure 3: Growth in loans
The figures plot the average growth rates in the total amount of loans around the 28 natural disasters. I apply data for loans made during six months before a natural disaster and six months after. The period-to-period growth rate is calculated by comparing to previous six months. Given a natural disaster, panel A covers all loans made to the corresponding disaster firms, panel B covers loans made by disaster lending banks to the connected firms, panel C covers all loans made to the unconnected firms.

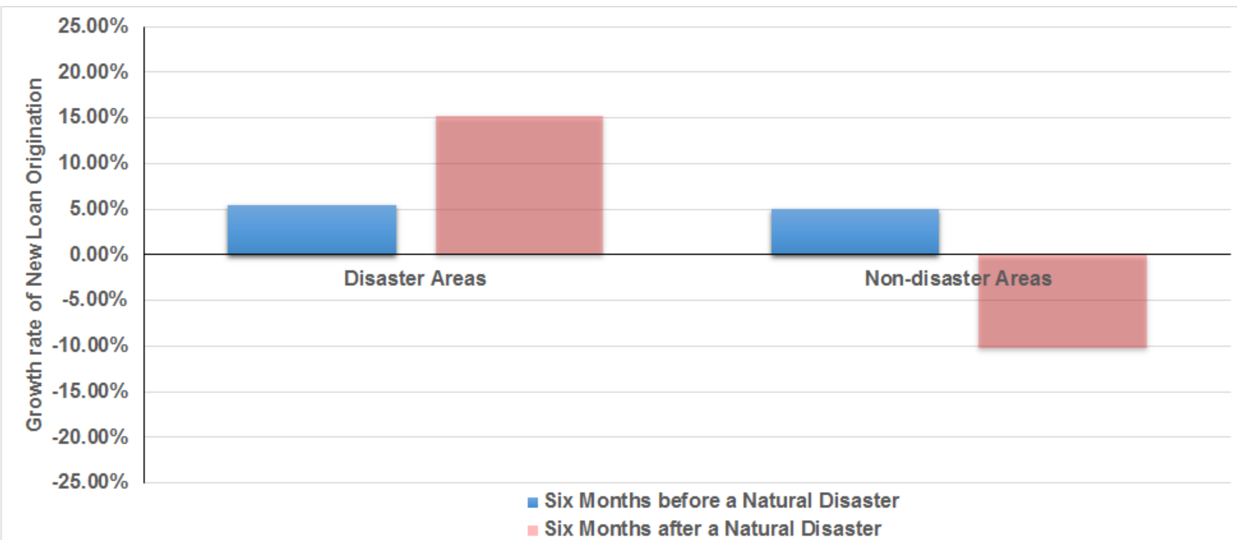


Figure 4: Bank-level lending change

The figure plots the average growth rates in the total loan lending of each bank around the 28 natural disasters. I apply data for bank lending six months before a natural disaster and six months after. The period-to-period growth rate is calculated by comparing to previous six months.

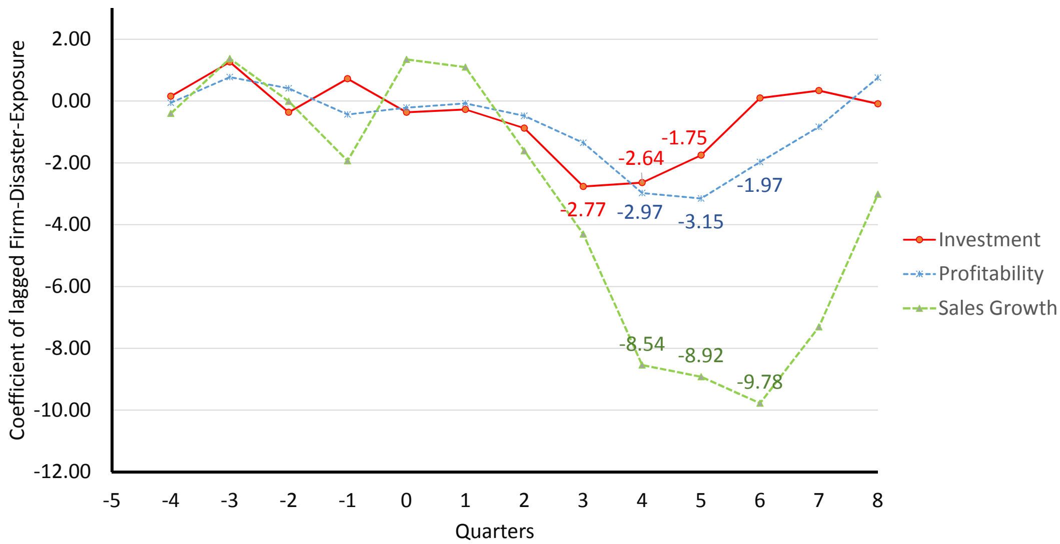


Figure 5: The real effects of natural disaster strikes on non-shocked firms through bank lending
This figure presents estimates of the real effects of natural disaster strikes on non-shocked firms through bank lending in the year before and the two years after a major natural disaster. The lines connect estimated coefficients of the following regression:

$$Real\ Outcome_{i,q} = \alpha_i + \gamma_q + \sum_{k=-4}^{k=8} \beta^k \times Firm\text{-}Disaster\text{-}Exposure_{i,q-k} + \varepsilon_{i,q}$$

t-statistics are based on clustered standard errors by firm. The marked estimates are the ones with at the 10% level.

Table 1: Major Natural Disasters from 1994-2016

This table describes the 28 natural disasters included in the sample. The sample period is from January 1994 to December 2016.

Disaster	Date	Affected Counties	Damage ($ Billion)
Northridge earthquake	Jan-94	1	32.98
Hurricane Alberto	Jul-94	87	1.03
Hurricane Opal	Oct-95	207	5.44
Blizzard	Jan-96	368	1.15
Hurricane Fran	Sep-96	157	6.23
Ice storm Janu	Jan-98	42	1.54
Hurricane Bonnie	Aug-98	37	1.51
Hurricane Georges	Sep-98	102	2.10
Hurricane Floyd	Sep-99	297	8.13
Hurricane Allison	Jun-01	164	7.18
Hurricane Isabel	Sep-03	221	1.17
Southern California wildfires	Oct-03	6	2.45
Hurricane Charley	Aug-04	81	10.67
Hurricane Frances, Ivan, Jean	Sep-04	584	13.89
Hurricane Dennis	Jul-05	180	2.24
Hurricane Katrina	Aug-05	280	95.36
Hurricane Rita	Sep-05	99	5.60
Hurricane Wilma	Oct-05	24	13.06
Midwest floods	Jun-08	216	13.22
Hurricane Gust, Ikeav	Sep-08	248	4.09
Blizzard, Groundhog Day	Feb-11	232	1.10
Hurricane Irene	Aug-11	193	2.14
Hurricane Isaac	Aug-12	96	3.69
Hurricane Sandy	Oct-12	280	26.76
Colorado Flooding	Sep-13	8	1.51
Tornadoes and Flooding	Apr-14	268	1.55
Flood	Oct-15	162	1.75
Hurricane Matthew	Sep-16	170	13.09

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.Variables follow the definition in Appendix A

	Obs.	Mean	*SD*	p25	p50	p75
Panel A: Loan lending						
Loan Variables						
Amount ($MM)	25971	587.117	956.785	84.522	233.544	639.907
Maturity (Years)	23311	3.947	2.033	2.667	4.333	5.000
Credit Spread (bps)	23788	212.765	146.122	100	185	300
Revolving Loan	25971	0.634	0.435	0.119	1.000	1.000
Term Loan	25971	0.302	0.409	0.000	0.000	0.750
Participant Count	25971	10.280	16.882	2	5	12
Strong-Relation	25971	0.298	0.457	0.000	0.000	1.000
Strong-Relation^{freq}	25971	0.365	0.482	0.000	0.000	1.000
Bank Variables						
Bank Assets ($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
Market Equity (%)	1676	11.550	7.327	6.924	11.396	15.886
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
Bank-Disaster-Exposure(%)	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

Table 2: Continuted

	Obs.	Mean	*SD*	p25	p50	p75
Panel A: Loan lending						
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	23763	0.158	0.154	0.040	0.100	0.233
%Disaster-Operations	23763	2.578	11.021	0.000	0.000	0.000
Hits-Supplier	23763	0.057	0.231	0.000	0.000	0.000
Firm-Disaster-Exposure^{freq}	23763	0.142	0.126	0.047	0.097	0.208
$\widehat{\text{Firm-Disaster-Exposure}}$	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	10.269	40.867	-5.624	7.075	18.000

Table 3: Trace out capital flows

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 includes all firm-bank-disaster triplets with non-shocked firms.t-statistics based on two-way clustered standard errors by firm and bank are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ Lending					
Disaster-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			-0.470	-0.376		
			(-0.833)	(-0.758)		
Disaster-Lending			-0.243***	-0.256***		
×Weak Relation			(-6.742)	(-6.670)		
Weak Relation^{freq}					-0.557	-0.581
					(-1.004)	(-1.005)
Disaster-Lending					-0.273***	-0.218***
×Weak Relation^{freq}					(-4.570)	(-4.197)
Bank Size		1.709***		1.766***		1.692***
		(4.042)		(4.068)		(3.984)
%Disaster-Deposits		-1.609**		-1.519**		-1.752**
		(-2.349)		(-2.222)		(-2.438)
Deposits/Assets (%)		-0.752		-0.571		-0.741
		(-0.319)		(-0.243)		(-0.321)
Bank Equity Ratio (%)		1.192		1.182		1.489
		(0.644)		(0.648)		(0.844)
Fixed Effects	Borrower×Disaster, Bank, State					
Observations	17273	17273	17273	17273	17273	17273
Adjusted R^2	0.419	0.547	0.593	0.644	0.591	0.638

Table 4: The effect of natural disasters on non-shocked firms: loan-level evidence

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. The dependent variable in Columns (1) to (4) is *Loan Amount*$_k$—the log of each loan's amount in dollar value of 2016; the dependent variable in Columns (5) to (8) is *Loan Spread*$_k$—each loan's all-in-drawn spread in basis points. *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. *Weak-Relation*$_{i,j,t}$ is the lender-based weak relationship variable measured either in lending size or in lending frequency. t-statistics based on two-way clustered standard errors by firm and bank are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Loan Amount				Loan Spread			
Bank-Disaster-Exposure	-0.116**	-0.052			1.667*	1.190		
	(-2.334)	(-1.593)			(1.911)	(1.004)		
Weak Relation		-0.291***				15.265*		
		(-7.245)				(1.831)		
Bank-Disaster-Exposure ×Weak Relation		-0.279***				2.902**		
		(-3.426)				(2.308)		
Bank-Disaster-Exposure^{freq}			-0.124**	-0.069			1.476*	1.154
			(-2.442)	(-1.484)			(1.731)	(1.628)
Weak Relation^{freq}				-0.225**				12.535*
				(-2.387)				(1.762)
Bank-Disaster-Exposure^{freq} ×Weak Relation^{freq}				-0.215**				2.276***
				(-2.405)				(2.766)
Bank Size	0.841***	0.688**	0.813**	0.664**	4.569	4.152	4.438	5.576
	(2.994)	(2.179)	(2.505)	(2.286)	(1.506)	(1.636)	(1.502)	(1.638)
%Disaster-Deposits	-0.126	-0.151	-0.145	-0.108	-1.863	-1.551	-1.746	-1.285
	(-0.184)	(-0.090)	(-0.115)	(-0.198)	(-0.139)	(-0.122)	(-0.186)	(-0.155)
Deposits/Assets (%)	0.312	0.347	0.335	0.379	0.191	0.085	0.201	-0.220
	(0.629)	(0.657)	(0.634)	(0.653)	(0.043)	(0.019)	(0.046)	(-0.051)
Bank Equity Ratio (%)	0.568**	0.604*	0.398**	0.586**	1.969	2.264	1.942	2.305
	(2.096)	(1.803)	(2.066)	(2.103)	(0.544)	(0.643)	(0.536)	(0.628)
Fixed Effects	Loan Type, Month, Borrower×Year, Bank, State							
Observations	21748	21748	21748	21748	20048	20048	20048	20048
Adjusted R^2	0.754	0.824	0.720	0.820	0.781	0.870	0.742	0.859

Table 5: Financially constrained banks: bank size

Q^i are quintiles based on annual bank assets in an ascending order. The dependent variable is $\Delta Lending$ in Column (1), $Loan\ Amount_k$ in Column (2), and $Loan\ Spread_k$ in Column (3). The sample and variables in Column (1) are the same with the ones in Table 3, the sample and variables in Columns (2) and (3) are the same with the ones in Table 4. t-statistics based on two-way clustered standard errors by firm and bank are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1) Δ Lending	(2) Loan Amount	(3) Loan Spread
Disaster-Lending	-8.011*		
	(-1.834)		
Bank-Disaster-Exposure		-0.099*	1.406
		(-1.733)	(1.013)
Disaster-Lending×Q1	-33.918***		
	(-3.201)		
Disaster-Lending×Q2	-24.221***		
	(-2.875)		
Disaster-Lending×Q4	-6.161		
	(-0.076)		
Disaster-Lending×Q5	0.106		
	(0.441)		
Bank-Disaster-Exposure×Q1		-0.526***	3.406***
		(3.265)	(2.752)
Bank-Disaster-Exposure×Q2		-0.240**	2.771**
		(-2.008)	(2.528)
Bank-Disaster-Exposure×Q4		0.089	0.315
		(0.929)	(0.888)
Bank-Disaster-Exposure×Q5		0.066	0.472
		(0.542)	(0.973)
Q1	-4.231**	-0.201*	-1.406
	(-2.222)	(-1.793)	(-1.052)
Q2	-1.949*	-0.111	2.447*
	(-1.693)	(-1.306)	(1.756)
Q4	-6.427	0.076	0.021
	(-1.106)	(1.252)	(1.024)
Q5	-0.092	0.021	0.172
	(-0.397)	(0.814)	(0.870)
Loan Type	–	Y	Y
Month	–	Y	Y
Fixed Effects		Borrower × Year, State	
Control Variables		Yes	
Observations	17273	21748	20048
Adjusted R^2	0.537	0.639	0.725

Table 6: Financially constrained banks: geographic layout

Regional Bank^{branches} is one if the Herfindahl-Hirschman index of a bank's numbers of branches across all states is above the sample median, *Regional Bank*^{deposits} is one if the Herfindahl-Hirschman index of a bank's deposits across all states is above the sample median. The dependent variable is Δ*Lending* in Columns (1) and (2), *Loan Amount*$_k$ in Columns (3) and (4), and *Loan Spread*$_k$ in Columns (5) and (6). The sample and variables in Columns (1) and (2) are the same with the ones in Table 3, the sample and variables in Columns (2) to (6) are the same with the ones in Table 4. t-statistics based on two-way clustered standard errors by firm and bank are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ Lending		Loan Amount		Loan Spread	
Disaster-Lending	-9.861*	-8.344*				
	(-1.733)	(-1.709)				
Bank-Disaster-Exposure			-0.083*	-0.081	1.052	1.511
			(-1.709)	(-1.532)	(1.009)	(1.014)
Disaster-Lending	-36.129 ***					
×Regional Bank^{branches}	(-2.845)					
Bank-Disaster-Exposure			-0.582***		3.458***	
×Regional Bank^{branches}			(-2.800)		(2.905)	
Regional Bank^{branches}	-2.017		-0.169**		-13.754	
	(-1.123)		(-2.454)		(-1.483)	
Disaster-Lending		-26.989**				
×Regional Bank^{deposits}		(-2.018)				
Bank-Disaster-Exposure				-0.577***		3.466***
×Regional Bank^{deposits}				(-4.802)		(2.910)
Regional Bank^{deposits}		-1.114		-0.145**		-21.250
		(-1.167)		(-2.237)		(-1.477)
Loan Type	–	–	Y	Y	Y	Y
Month	–	–	Y	Y	Y	Y
Fixed Effects	Borrower×Year, State					
Control Variables	Yes					
Observations	17273	17273	21748	21748	20048	20048
Adjusted R^2	0.636	0.622	0.779	0.776	0.798	0.795

Table 7: Firm-level evidence: the total change to loan borrowing

This table reports regressions of Δ*Borrowing*, the total change of loan borrowing of each non-shocked firm surrounding natural disasters, on *Firm-Disaster-Exposure*, the firm-level average of bank's disaster exposures, weighted by a firm's reliance on the bank. t-statistics based on two-way clustered standard errors by firm and bank are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ Borrowing					
Firm-Disaster-Exposure	-3.127**	-3.023**	-2.298***			
	(-2.643)	(-2.555)	(-2.639)			
Firm-Disaster-Exposure^{freq}				-1.593**	-1.475***	-1.250***
				(-1.995)	(-2.663)	(-2.915)
Observations	8818	8818	8818	8818	8818	8818
Adjusted R^2	0.507	0.607	0.667	0.553	0.626	0.657
State$\times$Year FE	N	Y	Y	N	Y	Y
Disaster Operations & Suppliers	N	N	Y	N	N	Y
Fixed Effects	Borrower, Industry $\times$ Year					
Control Variables	Size-, Age-, ROA-tercile$\times$Year					

Table 8: The effect of natural 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. $Real\ Outcome_{i,q}$ is measured by $Investment_{i,q}$ (quarterly investments scaled by lagged assets) in Columns (1) to (3), by $Profitability_{i,q}$ (quarterly operating income to total asset ratio) in Columns (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 Columns (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. 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 parentheses. *, **, 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)
Panel A: Firm disaster exposure									
Firm-Disaster-Exposure	-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: Firm disaster exposure through disaster lending									
Firm-Dis$\widehat{\text{aster-}}$Exposure	-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
Year-quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Disaster Operations & Suppliers	N	Y	Y	N	Y	Y	N	Y	Y
Size-, Age-, ROA-tercile$\times$Year FE	N	N	Y	N	N	Y	N	N	Y
State$\times$Year FE	N	Y	Y	N	Y	Y	N	Y	Y
Industry$\times$Year FE	N	Y	Y	N	Y	Y	N	Y	Y

Table 9: Financially constrained 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. 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 8. t-statistics based on clustered standard errors by firm are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Investment (%)		Profitability (%)		Sales Growth (%)	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Firm size						
Firm-Disaster-Exposure	-0.810*		-2.268*		-8.949**	
	(-1.651)		(-1.798)		(-2.514)	
Firm-Disaster-Exposure $\times$ Small-Firm	-3.145**		-10.145**		-11.851***	
	(-2.213)		(-2.188)		(-3.060)	
$\widehat{\text{Firm-Disaster-Exposure}}$		-1.201**		-2.995*		-9.851*
		(-2.299)		(-1.779)		(-1.721)
$\widehat{\text{Firm-Disaster-Exposure}}$ $\times$ Small-Firm		-4.293***		-7.269**		-13.267***
		(-2.666)		(-2.326)		(2.770)
Small-Firm	1.799***	1.851***	0.037**	0.037**	28.647***	29.045***
	(8.802)	(8.894)	(2.018)	(2.004)	(16.486)	(16.306)
Fixed effects: Year-quarter, Size-, Age-, ROA-tercile $\times$ Year, State $\times$ Year, Industry $\times$ Year, Disaster Operations & Suppliers						
Observations	172239	172239	161985	161985	170744	170744
Adjusted R^2	0.233	0.282	0.428	0.425	0.241	0.240
Panel B: Dependence on banks						
Firm-Disaster-Exposure	-1.153		-2.577		-7.414	
	(-0.541)		(-0.988)		(-0.951)	
Firm-Disaster-Exposure $\times$ Bank-Dependent	-3.957***		-8.842***		-16.789***	
	(-2.917)		(-3.267)		(-3.099)	
$\widehat{\text{Firm-Disaster-Exposure}}$		-2.075		-2.254		-8.387
		(-0.839)		(-1.541)		(-1.217)
$\widehat{\text{Firm-Disaster-Exposure}}$ $\times$ Bank-Dependent		-5.079**		-8.602***		-18.575***
		(-2.274)		(-3.161)		(-2.957)
Bank-Dependent	-0.609***	-0.600***	-0.606***	0.127***	-10.542***	-10.876***
	(-2.673)	(-2.580)	(-2.654)	(5.518)	(-6.118)	(-6.312)
Fixed effects: Year-quarter, Size-, Age-, ROA-tercile $\times$ Year, State $\times$ Year, Industry $\times$ Year, Disaster Operations & Suppliers						
Observations	172239	172239	161985	161985	170744	170744
Adjusted R^2	0.241	0.281	0.529	0.537	0.247	0.246

Appendix

A Variable Definitions

Loan Variables	
Loan Amount	The log of each loan's amount in 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	
$Disaster\text{-}Firm_{i,t}$	A firm-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 $dt < t \leq dt + 12$.
$Strong\text{-}Relation_{i,j,t}$	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
$Weak\text{-}Relation_{i,j,t}$	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: $Lending\ Freq_{i,j,t} = \frac{\text{Number of loans to borrower } i \text{ by bank } j}{\text{Total number of loans by lender } j}$
$Reliance_{i,j,t}$	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: $Borrowing\ Size_{i,j,t} = \frac{\text{\$ Amount of loans to borrower } i \text{ by bank } j}{\text{Total \$ amount of loans by borrower } i}$
$Reliance^{freq}_{i,j,t}$	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
$Market\ Equity_{j,y}$	The ratio of a bank j's market capitalization to its book assets minus its book equity plus the market capitalization
$Bank\text{-}Disaster\text{-}Exposure_{j,d}$	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 $Bank\text{-}Disaster\text{-}Exposure_{j,d} = \sum_{i \in I^d} Lending\ Size_{i,j,dt}$, 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 $Firm\text{-}Disaster\text{-}Exposure_{i,d} = \sum_j Borrowing\ Size_{i,j,dt} \times \frac{Bank\text{-}Disaster\text{-}Exposure_{j,d}}{N_{j,d}}$, 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 $Firm\text{-}Disa\widehat{ster\text{-}E}xposure_{i,d} = \sum_j Borrowing\ Size_{i,j,dt} \times \frac{Disaster\text{-}Lending_{j,d}}{Asset_{i,dt}}$, the frequency-based $Firm\text{-}Disa\widehat{ster\text{-}Exposure}^{freq}_{i,d} = \sum_j Borrowing\ Freq_{i,j,dt} \times \frac{Disaster\text{-}Lending_{j,d}}{Asset_{i,dt}}$. $N_{j,d}$ 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.
$\%Disaster\text{-}Operations_{i,t}$	A measure for the level of a non-shocked firms operating in disaster states. It is a ratio of the count of disaster states to the count of all states in a given firm's most recent 10-K report before a natural disaster hit.
$Hits\text{-}Supplier_{i,t}$	A dummy variable that takes the value of one for firms with at least one supplier hit by natural disasters during $(t-12)$ to t

B Lead Lenders in Syndicated Loans

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

C Loan-level Tests of Disaster Firms

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, loan k, bank j, month t, year y, and state s):

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

The dependent variable $Loan\ Amount_k$ is each loan's dollar amount in million dollar value of 2016. $Disaster\text{-}Firm_{i,t}$ 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 2.2, measured either in lending size or in lending frequency. The matrix $Control_{i,j,t}$ 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. My main test sample focuses on borrowers being public firms, which can be matched with Compustat and allow for the control of borrower characteristics—including size, return of asset, years since IPO—to mitigate the impact of omitted factors that are correlated with the borrower quality. Finally, I include loan-type fixed effects to control for 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×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 A.1 about here]

Table A.1 reports the regression estimates. The coefficient on the disaster loan indicator in Columns (1) and (2) is positive, indicating that banks lending increases to a firm increases within 12 months after the firm is hit by natural disaster. Column (1) implies that the amount of an average disaster loan is about $28.7 million higher. In Column (2), 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 $82.14 million ($73.71 million) per loan. Given the median loan amount is $302.19 million of this test sample, the above increases are economically high.

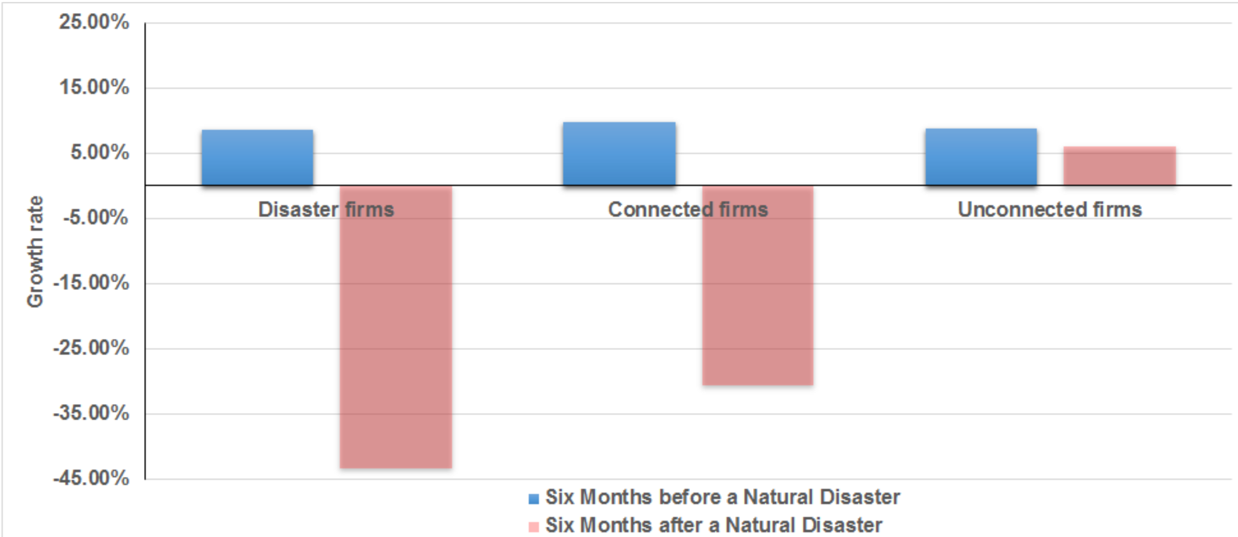


Figure A.1: Growth in transaction loans

The figure plots the average growth rates in the total amount of transaction loans around the 28 natural disasters. A transaction loan is a new loan made to a firm which the bank never lent to during the previous five years. I apply data for loans made during six months before a natural disaster and six months after. The period-to-period growth rate is calculated by comparing to previous six months.

Table A.1: The effect of natural disasters on loans of disaster firms

This table examines how natural disasters affect lending 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. The dependent variable is either *Loan Amount*$_k$, each loan's dollar amount in million dollar value of 2016, or *Loan Spread*$_k$, each loan's all-in-drawn spread in basis points. *Disaster-Firm*$_{i,t}$ 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-Relation*$_{i,j,t}$ is the lender-based strong relationship variable measured either in lending size or in lending frequency. Control variables include bank size, ratio of bank branches hit by a natural disaster, borrower size, profitability, years since IPO, and loan type dummies. t-statistics based on two-way clustered standard errors by firm and bank are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Loan Amount in Millons			Loan Spread		
Disaster-Firm	28.708*	18.483	18.371	8.473	8.592	8.785*
	(1.820)	(1.194)	(1.403)	(1.632)	(1.643)	(1.666)
Strong-Relation		54.205***			-4.799***	
		(3.019)			(-2.633)	
Strong-Relation×Disaster-Firm		82.147**			3.616	
		(3.087)			(1.487)	
Strong-Relation^{freq}			46.852***			-5.305***
			(3.350)			(-3.228)
Strong-Relation^{freq}×Disaster-Firm			73.712***			3.625*
			(3.443)			(1.670)
Observations	17185	17185	17185	14956	14956	14956
Adjusted R^2	0.715	0.747	0.746	0.788	0.836	0.805
Fixed Effects	Loan Type, Month, Borrower, Bank×Year					
Controls	Yes					

Table A.2: Trace out capital flows: including private 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 $Total\text{-}Lending$ as a normalization that will help reduce heteroskedasticity. The data are measured at the firm-bank-disaster level. The sample includes all firm-bank-disaster triplets with non-shocked firms.t-statistics based on two-way clustered standard errors by firm and bank are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
			Δ Lending			
Disaster-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			-0.435***	-0.466***		
$\times$Weak Relation^{size}			(-4.242)	(-4.207)		
Weak Relation^{freq}					-0.447	-0.411
					(-1.175)	(-1.151)
Disaster-Lending					-0.355***	-0.368***
$\times$Weak Relation^{freq}					(3.650)	(-3.440)
Bank Size		1.371***		1.424***		1.371***
		(5.247)		(5.182)		(5.216)
%Disaster-branches		-1.303**		-1.171**		-1.297**
		(-2.408)		(-2.219)		(-2.373)
Deposits/Assets (%)		-0.608		-0.597		-0.551
		(-0.256)		(-0.248)		(-0.232)
Bank Equity Ratio (%)		3.195		3.911		3.743
		(1.492)		(1.557)		(1.538)
Fixed Effects			Borrower$\times$Year, Bank, State			
Observations	29086	29086	29086	29086	29086	29086
Adjusted R^2	0.456	0.608	0.510	0.674	0.457	0.633

Table A.3: The effect of natural disasters on non-shocked firms: loan-level evidence, including private firms

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. The dependent variable in Columns (1) to (4) is *Loan Amount*$_k$—the log of each loan's amount in dollar value of 2016; the dependent variable in Columns (5) to (8) is *Loan Spread*$_k$—each loan's all-in-drawn spread in basis points. $\textit{Bank-Disaster-Loan}_{j,t}$ 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. $\textit{Weak-Relation}_{i,j,t}$ is the lender-based weak relationship variable measured either in lending size or in lending frequency. t-statistics based on two-way clustered standard errors by firm and bank are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Loan Amount				Loan Spread			
Bank-Disaster-Exposure	-0.147*	-0.075			3.236*	2.121		
	(-1.758)	(-0.991)			(1.858)	(1.028)		
Weak Relation		-0.400***				11.950*		
		(-4.501)				(1.857)		
Bank-Disaster-Exposure		-0.373***				4.150**		
×Weak Relation		(-3.594)				(2.387)		
Bank-Disaster-Exposure^{freq}			-0.182**	-0.075			2.557*	2.487
			(-2.205)	(-0.457)			(1.708)	(1.241)
Weak Relation^{freq}				-0.228***				11.545*
				(-2.850)				(1.947)
Bank-Disaster-Exposure^{freq}				-0.312**				4.774**
×Weak Relation^{freq}				(-2.395)				(2.550)
Bank Size	0.880***	0.928***	0.878***	0.779***	3.397	7.298	3.357	5.471
	(2.713)	(2.585)	(2.717)	(2.623)	(0.604)	(0.814)	(0.703)	(0.769)
%Disaster-Deposits	-0.013	-0.165	-0.129	-0.189	-1.860	-1.255	-1.435	-1.878
	(-0.106)	(-0.161)	(-0.142)	(-0.153)	(-0.128)	(-0.187)	(-0.161)	(-0.144)
Deposits/Assets (%)	0.609	0.900	0.607	0.534	-2.561	-2.437	-2.563	-2.578
	(0.236)	(0.356)	(0.235)	(0.204)	(-0.662)	(-0.641)	(-0.662)	(-0.681)
Bank Equity Ratio (%)	0.488	0.498	0.490	0.447	1.681***	1.814***	1.561***	1.868***
	(1.582)	(1.533)	(1.583)	(1.626)	(3.015)	(3.100)	(3.016)	(3.053)
Fixed Effects	Loan Type, Month, Borrower×Year, Bank, State							
Observations	35322	35322	35322	35322	31727	31727	31727	31727
Adjusted R^2	0.682	0.784	0.678	0.781	0.661	0.712	0.653	0.702

Table A.4: Trace out capital flows: exclude Hurricanes or Katrina

This table reports regressions same with Table 3, while Columns (1) to (3) are for the firm-bank-disaster sample excluding Hurricanes, and Columns (4) to (6) are for the firm-bank-disaster sample excluding Katrina. t-statistics based on two-way clustered standard errors by firm and bank are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ Lending					
	Exclude Hurricanes			Exclude Katrina		
Disaster-Lending	-0.272**	-0.111	-0.122	-0.106**	-0.134*	-0.105
	(-2.324)	(-1.483)	(-1.606)	(-2.333)	(-1.509)	(-1.532)
Weak Relation		-0.583			-0.778	
		(-0.762)			(-0.469)	
Bank-Disaster-Exposure		-0.314***			-0.253***	
$\times$Weak Relation		(-4.384)			(-4.490)	
Weak Relation^{freq}			-0.495			-0.367
			(-1.052)			(-1.234)
Bank-Disaster-Exposure^{freq}			-0.380***			-0.196***
$\times$Weak Relation^{freq}			(-4.253)			(3.022)
Bank Size	1.831**	1.219***	1.066**	1.126**	1.152**	1.150**
	(2.343)	(2.928)	(2.471)	(2.205)	(2.202)	(2.088)
	(-2.171)	(-2.220)	(-2.158)	(-2.302)	(-2.311)	(-2.134)
Deposits/Assets (%)	-0.024	-0.032	-0.041	-0.034	-0.038	-0.030
	(-0.119)	(-0.115)	(-0.147)	(-0.183)	(-0.188)	(-0.170)
Bank Equity Ratio (%)	1.044	1.779	1.583	1.834	1.938	1.130
	(0.713)	(0.836)	(0.762)	(0.683)	(0.888)	(0.717)
Fixed Effects	Borrower$\times$Year, Bank, State					
Observations	5552	5552	5552	14656	14656	14656
Adjusted R^2	0.531	0.625	0.672	0.585	0.628	0.686