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Two Essays in Financial Intermediaries

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An abstract of
A dissertation submitted to the Faculty of the
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Abstract

Two Essays in Financial Intermediaries

By Ai He

This dissertation investigates the activities of financial intermediaries and financial institutions in the credit markets. In the first essay, I studies how 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. In the second essay, I explore the nature and impacts of relationship lending in shadow banks by analyzing a cross-holding relation (CHR) between financial firms who mutually hold each other's debt through their own affiliated money market funds (MMFs). Using novel security-level holdings data, I show that non-European financial firms increased their MMFs' portfolio weights on bilateral-connected European financial firms after Moody's downgrade review of European banks in mid-2011, a special period when MMFs generally reduced their exposure to European issuers to avoid further redemption. I provide evidence that this bias represents reciprocity between the bilateral-connected financial firms. In return, during the same period, the European financial firms accepted more unsecured than secure debt from their bilaterally-connected non-European partners through their affiliated MMFs. Issuer- or fund-characteristics do not explain the results. CHR is also found to affect MMFs after the 2013 Dodd-Frank stress test in the same pattern. A further test shows a spillover effect on issuers unconnected with MMFs due to MMFs' tilt to connected issuers.

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Dedication

To my beloved parents and grandpapa.

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Contents

List of Tables

List of Figures

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

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 (2014b), 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, 2014b).[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 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.

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 (Schwert, 2017), I start the loan sample from 1989. My test requires a five-year time window

[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").

to construct relationship measures, so the 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 borrower and lender links. 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, or 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 first use the location information in DealScan (city, state). For borrowers whose location is missing in DealScan, I cross-check the historic record of borrowers' headquarters information from Compact Disclosure, which provides location information (city, state) on an annual basis over the period from 1988 to 2006.[8] For the

[7] See Appendix B about more details of selection criteria of lead lenders.
[8] Unlike Compact Disclosure, Compustat only reports the current state and county of firms' headquarters.

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 United States 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. I also restrict the sample to major disasters, which account for total estimated damages above $1 billion in 2016 constant dollars and last less than 30 days.

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.

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; and 2) measure banks' geographic concentration level in each year, using the Herfindahl-Hirschman index (HHI) of banks' fractions of branches in each state.

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 are based on information in the Compustat Segment files, which provide 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.

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.

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

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 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 much and how often a given bank j lends to a borrower i compared 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 it has a weak relationship. Similar dummy variables, $Strong\text{-}Relation^{freq}$ and $Weak\text{-}Relation^{freq}$, are constructed for $Lending\ Freq_{i,j,t}$. These bank-based relationship strength variables represent how important a borrower is for a given bank compared 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.

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 months 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-third 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 a median of \$183 billion in assets. Though all the banks are lead arrangers in the syndicated loan market, their market equity ratios exhibit 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 and 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 and 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.

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 lent to these firms in the past five years (from month $t-60$ to $t-1$) are "disaster lending banks" and otherwise "non-disaster lending banks". A borrower not headquartered in a state hit by the natural disaster is a non-shocked firm.[10] If a non-shocked firm also borrows from disaster lending banks in the past five years, it is flagged as a "connected firm," because it is connected with the disaster firms through the historical common lenders; otherwise it is an "unconnected firm." I leave these flags on during the next 12 months and apply them on the bank-firm-loan sample and the firm-quarter sample.

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.

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

I focus on the six months period before and after a natural disaster 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 months period. As shown in Panel A of Figure 3, there is a remarkable increase (12.86%) in the amount of loans issued to disaster firms after a natural disaster hit. 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 amounts frequency during the prior five years. As a comparison, the subsamples of weak-relations firms suffer a 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 rates (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 important customers that suffer losses in 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 first 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

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

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, 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 that provides larger loans and does so more often 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: $\textit{Firm-Disaster-Exposure}_{i,t}$. 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: $\textit{Reliance}_{i,j,t} = \frac{\text{\$ Amount of loans to borrower } i \text{ by bank } j}{\text{Total \$ amount of loans by borrower } i}$, or $\textit{Reliance}^{freq}_{i,j,t} = \frac{\text{Number of loans to borrower } i \text{ by bank } j}{\text{Total number of loans by borrower } i}$. Firms' indirect exposure to disasters through banks is constructed in this way:

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

This is the average of *Bank-Disaster-Exposure* across banks that provide financing to firm i, weighted by the firm's borrowing size or frequency from these banks in past five years, 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 monthswindow 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 $\textit{Bank-Disaster-Exposure}_{j,d}$ is also likely to be correlated with banks' exposure to natural disasters through other channels. To ensure that $\textit{Bank-Disaster-Exposure}_{j,d}$ 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 amounts or great frequency are also likely to have more deposit business there, so banks with higher $\textit{Bank-Disaster-Exposure}_{j,d}$ also suffer a larger loss in deposits from natural disasters hits. To mitigate this disturbance, I also control for each bank's pre-disaster reliance on 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 compared 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]

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 first examine capital movements from the disaster market to the connected market. When 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 of the non-shocked areas to fulfill the disaster firms' needs.

[11] My test focuses on relationship loans, which are not transaction loans, namely the first loan made between a bank and a firm. Figure 6 shows the growth in transaction loans, which display the same pattern as loans to weak-relationship borrowers.

The incremental lending by each bank to 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 months after and before a natural disaster d. This sample includes 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 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 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. This 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 frequency, measured at the time of the disaster.

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 focus on borrowers being public firms, which can be matched with Compustat and allow for the control of borrowers' industries. All the control variables are 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.

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 the lending

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

effects of market frictions in this 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 must entirely depend on reducing lending elsewhere to provide additional credit to disaster states and then the estimate of β_1 should be 1. The estimate 11.5 cents gives an empirical estimation of the value of frictions in the lending market.

Columns (3) to (6) include weak relationship measures. The $\textit{Weak-Relation} \times \textit{Disaster-Lending}$ interaction terms obtain negative and significant coefficients. This shows that, per dollar of lending increase to disaster firms, lending to connected and weak-relationship firm falls by 25.6 (21.8 if measured by the 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 and the average number of loans a bank has with a connected firm is 1.17, the 25.6 cents connected-lending decrease to one dollar disaster lending increase means a reduction of $24.1 million in a connected loan, which is close to 10% of the median amount in the loan sample.

These results suggest, being faced with urgent needs for credit on account of a large natural disaster, banks raise additional funds, because they do not entirely cut non-disaster loans, but they cannot fully compensate for the money shortfall through new financing. So they reduce the non-disaster lending to the extent of nearly 12 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 affects 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 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):

$$\begin{aligned} Loan\ Lending_k =& \beta_1 Bank\text{-}Disaster\text{-}Exposure_{j,t} + \beta_2 Weak\text{-}Relation_{i,j,t} \\ &+ \beta_3 Bank\text{-}Disaster\text{-}Exposure_{j,t} \times Weak\text{-}Relation_{i,j,t} \\ &+ \beta_4 Control_{j,t} + \alpha_{i,y} + \gamma_j + \mu_t +, \eta_s + \varepsilon_{i,j,t}. \end{aligned} \tag{2}$$

The dependent variable is *Loan Amount*$_k$—the log of each loan's amount in dollar value of 2016, or *Loan Spread*$_k$—the all-in-drawn spread in basis points. $Bank\text{-}Disaster\text{-}Loan_{j,t}$ is a bank-month-level variable to measure 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 months window after a natural disaster, with the borrower being a connected firm regarding that disaster—*Bank-Disaster-Exposure* must be nonzero. $Weak\text{-}Relation_{i,j,t}$ is the lender-based weak relationship variable introduced in the section 2.2, measured either in lending size or frequency. The $Control_{j,t}$ 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 ($Weak\text{-}Relation_{i,j,dt}$), 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).

Table 4 reports estimates of the regressions in Eq.(2). Columns (1) and (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 Columns (1) and (3), a one standard deviation increase in *Bank-Disaster-Exposure* ($Bank\text{-}Disaster\text{-}Exposure^{freq}$) is associated with a reduction of loan amount by 10.95% (11.66%).[13]

Columns (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* ($Bank\text{-}Disaster\text{-}Exposure^{freq}$) 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 of the columns test whether the loan pricing of connected firms is abnormally high in

[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.

the months following natural disasters. Columns (5) and (7) show a statistically significant positive relation between banks' ex-ante exposure to natural disasters and the spread of individual loans. For a one standard deviation increase in *Bank-Disaster-Exposure* ($Bank\text{-}Disaster\text{-}Exposure^{freq}$), the post-disaster all-in-drawn spread of per non-shocked connected loan increases by 30.3 basis points (26.83 basis points). Similarly, Columns (6) and (8) decompose the positive effect by introducing the weak relationship measure and its interaction with the bank-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 by 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 28, 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 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.

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 among banks in the two smallest quintiles. For example, compared with Q3, the reference group, Column (1) shows banks in Q1 reduce 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 Columns (2) and (3) shows the loans to connected firms with smaller amounts or higher spreads are concentrated among 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 number of branches (amounts of deposits) across all the states is above the sample median.

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, and there will barely be real effects for these firms. If there are frictions in the market, the more a non-disaster firm depends on banks with disaster-lending for financing, the harder it is for this firm to freely switch to new lender, and the firm will suffer financial constraints followed by reduced economic activities. For example, for two Georgia firms that have their loans reduced 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 $\widehat{Firm\text{-}Disaster\text{-}Exposure}_{i,d}$, that provides a more intuitive measurement of 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×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.

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.

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 ensure that the estimates are not driven by heterogeneous trends among large or old firms, I also set lagged controls for size, age, and profitability by interacting year-quarter dummies with terciles of firms' assets, age, and ROA on one year 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.

[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 uses panel data at the firm-disaster level.

The baseline results are presented in Panels A and B of Table 8. A firm's indirect exposure to natural disasters is measured based on the overlapped banks' historical lending size. In Columns (2)–(3) and Columns (5)–(6), I include state by year fixed effects and 48 Fama-French industry fixed effects; In Column 3 and Column 6, I introduce controls for lagged size, age, and profitability. The coefficient estimates of *Firm-Disaster-Exposure* are negative at the statistical significance level of 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. Relative to 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 spillover effect that is caused by banks' disaster lending, in Panels C and D, I use $\textit{Firm-Dis}\widehat{\textit{aster-}}\textit{Exposure}$, which is based on the change of overlapped banks' lending to disaster areas, as the regressor. As shown in Table 8, the coefficient estimates of $\textit{Firm-Dis}\widehat{\textit{aster-}}\textit{Exposure}$ are negative at the statistical significance level of less than 5% across all the columns. Given that an average non-shocked firm has a size-based $\textit{Firm-Dis}\widehat{\textit{aster-}}\textit{Exposure}$ of 0.122 and a frequency-based one of 0.098, when everything else is 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 spillover tests with consideration of firm size or dependence on banks. A firm is defined as small if its one-year lagged total assets are smaller than the cross-sectional sample median. I use the absence of public debt rating as the proxy for bank dependence.

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 raising 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.

Second Essay: Reciprocity in Shadow Bank Lending: Evidence from the Cross-Holding Relation in Money Market Funds

"You scratch my back, and I will scratch yours."

—English idiom

1 Introduction

As a key source of wholesale funding in short-term credit markets, money market mutual funds (MMFs) are important intermediaries in the shadow banking system. As of June 2015, assets under the management (AUMs) of MMFs in the United States reached $2.96 trillion.[15] Many financial conglomerates issue money market instruments at the same time that they sponsor MMFs. During 2010–2015, 163 banks issued different financial securities held by U.S. MMFs; more than twenty of these banks had affiliated MMFs. Engaged in both borrowing and lending activities in this shadow banking context, banks borrow from other MMFs, on the one hand, while their affiliated MMFs lend to other banks, on the other. This novel feature of serving dual roles enables two financial conglomerates to mutually lend to each other through their affiliated MMFs, hence, establishing a cross-holding relation (CHR).

When two financial conglomerates are bilaterally-connected in a CHR, a potential *reciprocity* naturally arises. Although MMF lending is market-based and, in theory, should be fully arm's length, this potential reciprocity may bias MMF portfolio holdings toward bilaterally-connected issuers. This paper examines the extent to which the *reciprocal* CHR affects shadow bank lending through MMFs, especially during financial crises in which some banks experience trouble in borrowing.

To understand why a CHR can have a broader influence in the MMF market, it is important to note that dual-role banks bear heavy weight on both the issuer side and the fund side; that the financial securities they issued account for more than 30% of holdings in MMFs' overall portfolios; and that their affiliated MMFs manage more than 46% of the total AUMs of all MMFs.

[15] Data source: The report "Money Market Fund Statistics" by the Division of Investment Management of the U.S. Securities and Exchange Commission in June, 2015.

Analyzing the effect of a cross-holding relation on MMFs' lending poses a significant empirical challenge with regard to endogeneity. MMFs' higher exposure to their bilaterally-connected issuers may also be endogenously associated with these issuers' good creditworthiness. Following Chernenko and Sunderam (2014), this study uses the summer of 2011 as timeframe to address this issue. Securities held by MMFs are supposed to be credit-worthy financial instruments with high liquidity; however, in mid-2011, after Moody's put several European banks under downgrade review as fears about European sovereign debt problems mounted, investors suddenly lost faith in the creditworthiness of European banks, and MMFs with high exposure to these banks suffered large outflows. This shock presents an ideal laboratory environment for my study. During this short, special period, money market instruments issued by European banks were generally viewed as risky; hence, differences in MMFs' portfolio weights of different European banks should be independent of these banks' creditworthiness. The endogeneity issue may be still of concern if issuers with different levels of creditworthiness were not equally affected by the Moody's downgrade review. The novel comprehensive MMF data allow me to mitigate this concern by controlling for time-varying variables and fixed effects on both the issuer side and the fund side.

The other concern is the agency problem between fund families and MMF managers when treating a bank and its affiliated MMFs as a unity. Although mutual funds are normally viewed as stand-alone entities, in the special context of MMFs, it is plausible to conduct a study at the firm-level, as other studies have recently done (e.g., Kacperczyk and Schnabl, 2013)), not only because MMF managers themselves are limited in terms of risk taking and asset selection, but also due to MMFs' dependence on voluntary sponsor support to maintain a stable NAV (Brady, Anadu, and Cooper, 2012; Parlatore, 2016). From a conglomerate's perspective, a financial firm combines affiliated MMFs and issuers, which respectively serve as channels in the short-term credit market to lend and borrow money, and these two channels jointly determine that financial firm's position in this particular market.[16]

[16]Other studies in different empirical settings also jointly consider financial institutions' different departments, see, for example, Ritter and Zhang (2007) of IPO underwriting and mutual fund investment, Massa and Rehman (2008) and Ivashina and Sun (2011) of corporate loan lending and mutual fund investment.

To explore the influence of a reciprocal CHR, I examine how this situation affected MMFs' lending to European banks during the European bank crisis in mid-2011. Prior to June 2011, U.S. MMFs were heavily exposed to European banks to reach for high yield. As shown in Figure 7, a particular U.S. financial conglomerate (e.g., J.P. Morgan)—whose affiliated MMFs lend to a European financial conglomerate (e.g., Deutsche Bank)—also borrows from MMFs that are sponsored by this European financial conglomerate; thus, a CHR is established between these two entities. My tests firstly show that: right after June 2011, U.S. financial conglomerates increased their MMFs' portfolio weights on European banks involved in a pre-existing CHR with them. This response is quite surprising given that MMFs had, in general, reduced their exposure to European banks since June 2011 to avoid further investor redemptions due to panic about the solvency of European banks that mounted during that special period. The second part of this paper digs deeper, finding that banks' increasing their MMFs' portfolio weights represents reciprocity behind a CHR: the bilateral connection provides an implicit guarantee when one side involved is in trouble. The third part of this article reveals that this change is also related to a negative lending spillover onto Non-European issuers, reflecting that this short-term credit market is not frictionless.[17]

My tests start by examining the change of MMFs' exposure to European banks around mid-2011. After June 2011, an average MMF increases its exposure to a bilaterally-connected European issuers by 0.35% of portfolio weight; in contrast, its portfolio weight on every other unconnected European issuer drops by 0.23% of portfolio weight. Next, to ensure that this finding is not driven by some observable or unobservable features of a certain issuer or a certain fund, I use difference-in-differences models to test the change of lending, with the control of characteristics and fixed effects at both the issuer-level and the fund-level. Multivariate regressions show that, after June 2011, holding the issuer fixed, European issuers receive more lending from the MMFs that are in a pre-existing CHR with them, but not from other MMFs; likewise, holding fixed the MMF,

[17]In Appendix I, I conduct a similar natural experiment in the context of the 2013 Dodd-Frank stress tests. The findings show that, if MMFs are involved in CHR with the bank holding companies (BHCs) who are revealed to have low tier 1 common ratio in the stress test, they increase their portfolio weights on these BHCs after the disclosure of test results.

funds finance less to unconnected European issuers, but lend more to their bilaterally-connected European partners. Although issuers who can build a CHR must be conglomerates, my main findings are robust after controlling for firm size. Therefore, the results are unlikely to be driven by the "too big to fail" phenomenon. MMFs' bias in connected European issuers is not present in placebo specifications before the 2011 European bank crisis. A broader comparison including non-European issuers proves further that the findings are not driven by some unobservable changes on all bilaterally-connected fund-issuer pairs.

Chernenko and Sunderam (2014) conducted a study of a negative relationship between fund flow and fund's *Euro Share*, and show that MMFs with greater exposure to European banks before mid-2011 suffer greater outflows in the June–August 2011 period. So it is possible that MMFs' bias toward bilaterally-connected European issuers is because these funds do NOT suffer outflows driven by their exposure to European banks. However, my test shows that MMFs involved in a CHR with European issuers suffer significant outflows driven by their increase in *Euro Share*, hence the negative flow-*Euro Share* relationship does, indeed, exist in those funds. A surprising implication of this finding is that, although bearing large outflows driven by *Euro Share* after June 2011, MMFs involved in a CHR with European issuers still bias the portfolio weights toward them.

Another possibility is that the securities issued by European banks to their bilaterally-connected MMFs are more secure, so that MMFs are willing to tilt to these issuers after June 2011. However, I do not find any evidence that securities issued by MMFs' bilaterally-connected European issuers are less risky than MMFs' other holdings after mid-2011. The results are robust after controlling for characteristics and fixed effects at both the issuer-level and the fund-level. Therefore, MMFs' holding bias on connected European issuers is also not likely to be driven by differences in money market instruments' riskiness.

At this point in the study, I test reciprocity behind a CHR, which motivates MMFs to tilt toward bilaterally-connected European issuers. To be specific, I analyze the *reverse* fund-issuer pairs in a bilateral connection—namely, the lending from the original issuer's affiliated MMF to the original fund's sponsor. For example, as shown with the blue arrow in Figure 7, the fund-issuer pair with Deutsche Bank-affiliated MMFs as the fund and JP Morgan as the issuer is a reverse pair. Testing with difference-in-difference models, I find that the *Holdings Risk* increases significantly more in reverse pairs than in any other fund-issuer pairs during June-August 2011. A deeper look into different holdings shows that portfolio weight of risky securities in reverse pairs increases by 10.17 basis points, while the portfolio weight of safest instrument decreases by 6.53 basis points. Together, the two changes contribute to the increase of *Holdings Risk* in reverse pairs. These findings provide direct evidence of reciprocity between connected financial conglomerates: a European bank, through its affiliated MMFs, accepts more risky securities issued by its connected partner, though risky securities are unpopular in the MMF market after mid-2011. This action can be interpreted as paying compensation for these partners' help in increasing their MMFs' lending to the European bank.

Lastly, I examine how the nature of a CHR is related the spillover effect on Non-European issuers who borrow money from the MMFs involved in a CHR with European firms. Funds only have limited funding on hand, especially after mid-2011, when many of them suffered significant net outflows. If a MMF decides to increase its portfolio weight on one issuer, it has to cut off financing to some other issuers. In a market that is not frictionless—because of the problem of information asymmetry—issuers that get a lending cut may have difficulty borrowing from other MMFs in a short period of time. The increase of lending from MMFs involved in a CHR to their bilaterally-connected European issuers affects a larger base of Non-European issuers, given that more than half of money market instruments are held by these funds in the MMF market. Echoing the spillover effect in Chernenko and Sunderam (2014), I find the Non-European issuers suffer reduction in financing after mid-2011, if they borrows from these MMFs before mid-2011.

My paper adds to the recent growing body of literature on shadow bank lending in the context of MMFs. To the best of my knowledge, it is the first paper to show how financial conglomerates coordinate with each other by building a cross-holding relationship in order to realize *quid pro quo*. The reciprocal cross-holding relation is different from the reciprocal bundling strategy between

MMFs and banks in Li (2017), which treats MMFs and banks as independent borrowers and lenders, respectively, and explores how they cooperate in the face of contradictory post-crisis regulations on liquidity. In my study, reciprocity is rooted in financial conglomerates' nature of serving dual roles as borrowers and lenders in a particular market.

One strand of the MMF literature focuses on implicit guarantees inside financial institutions. Both Kacperczyk and Schnabl (2011) and Parlatore (2016) show that financial institutions that sponsor money market mutual funds act as providers of implicit guarantee to those funds, thus MMFs' risk-taking incentives are affected by whether the funds can get sponsors' support. My findings show that reciprocity can serve as a driver of implicit guarantees between financial institutions.

My work also relates to the major body of MMF studies about risky yield-reaching behavior. Different reasons motivate MMFs to take risks before the 2007-2010 financial crisis, for example, expanding risk-taking opportunities and the positive flow-yield relation (Kacperczyk and Schnabl, 2013), low administrative fees (Chodorow-Reich, 2014a), the macro environment with zero-bound interest rate (Di Maggio and Kacperczyk, 2017), and tournament motivation of fund managers (La Spada, 2018).[18] My tests, though conducted in the post-crisis period, show that being involved in a pre-existing CHR with issuers of risky securities can also explain some risky holdings in MMFs' portfolios.

This paper also joins the broader literature on connections between different divisions under the umbrella of one financial conglomerate. For example, Ritter and Zhang (2007) find that investment banks allocate their underwritten hot IPOs to their affiliated funds to boost the funds' performance and thus attract more money; Massa and Rehman (2008) show that funds increase their portfolio weights on the firms that borrow from their affiliated banks in the period following the deal. Ivashina and Sun (2011) find that institutional participants in loan renegotiations subsequently trade in the stock of the same company. These papers focus on the Chinese-wall issue of the

[18] Other papers in MMFs studies focus on MMFs behaviors during crises, see, for example, McCabe (2010), Strahan and Tanyeri (2015), and Schmidt, Timmermann, and Wermers (2016).

conflict of interests within one financial institution.[19] Taking a slightly different tack, my study focuses on the cooperation between two financial institutions through their different departments.

The rest of the paper proceeds as follows: Section 2 provides the background information and develops two main testing hypotheses. Section 3 describes the data. The methodology and major results are presented in Section 4. I conclude in Section 5.

2 Background and Hypotheses Development

This section explains cross-holding relations in the MMF market, reviews the European bank crisis, and develops hypotheses that will be tested.

2.1 CHR in the U.S. MMFs Market

MMFs invest in high-quality assets like short-term securities, liquid debt, and monetary instruments, which are normally considered to be safe. Unlike other mutual funds, MMFs are allowed by the SEC's Rule 2a-7 to use the amortized cost pricing method to keep a constant $1 per share NAV; hence, they were always been viewed as safe as cash until the 2008 crisis, when MMFs experienced extraordinary stress originating from defaults of some short-term debt in their portfolio holdings. To improve MMFs' financial stability, a number of substantial reforms by the SEC were adopted in 2010 and 2014.[20] One important reform is that funds must report their portfolio details by filing form N-MFP every month. The SEC's N-MFP form classifies all U.S. MMFs into five categories: prime fund, treasury fund, government/agency fund, single state fund, and other tax exempt fund. The abbreviation "MMF" in this paper refers to prime money market funds because they mainly invest in non-government securities.

As shown in Figure 8, different financial firms in the MMF market play multiples roles:

[19] See Mehran and Stulz (2007) for a summary of the conflict of interest.

[20] For more details about these reforms see Gallagher, Schmidt, Timmermann, and Wermers (2015b) and Hanson, Scharfstein, and Sunderam (2015).

some, such as American Century Investment and Waddell & Reed Financial, only stand on the fund side, sponsoring MMFs; others, such as Barclays and RBS, stand on the issuer side only, issuing different money market instruments; the rest, for example, JP Morgan and Deutsche Bank, stand on both the fund and the issuer sides. For the third type, serving dual roles under the umbrella of one financial conglomerate, affiliated MMFs provide funding to other money market instruments issuers, while affiliated investment banks or security companies receive funding from other MMFs.[21]

Serving the dual roles of the fund and the issuer provides two financial firms opportunities to establish bilateral connections. For example, as shown in Figure 7, through its affiliated MMF, JP Morgan can hold short-term money market instruments issued by Deutsche Bank's banking department; meanwhile, Deutsche Bank's affiliated MMF can also hold short-term money market instruments issued by JP Morgan's banking department.

2.2 The European Bank Crisis in 2011

Since the 2008 crisis, MMFs experienced their most rapid period of outflows during the European bank crisis of 2011. The very beginning of this crisis can be traced back to 2009, when Greece's sovereign debt was revealed to be massively understated because of accounting issues. Investors kept worrying about high default chances of Greece and some other European countries, and panic soon spread. As a consequence, investors doubted European banks' solvency, because those banks were exposed to the European bank economy and held a large amount of sovereign debt from countries in trouble. On June 13, 2011, Standard and Poor's downgraded Greek sovereign debt to CCC; on June 15, Moody's placed large French banks BNP Paribas, Credit Agricole, and Societe Generale on review for possible downgrade because of their exposure to Greece; then, in July, Moody's downgraded Portugal and Ireland. Following that action, investors' worries spread

[21] This market also involves a small group of non-financial institutions: the U.S. government, which is the issuer of Treasuries, agencies or municipals who issue agency or municipal debt, and non-financial firms, whose non-financial commercial papers account for a very small proportion in MMFs portfolio holdings.

contagiously, covering much of the European continent. As a result, CDS premiums on banks in core European countries rose markedly.

This series of events generated a disaster for European financial institutions' creditworthiness in summer 2011. Right after mid-2011, concerns about European financial institutions' credit quality motivated U.S. investors to redeem from MMFs with high exposure to European bank risk. From June to July, prime MMFs lost roughly $113 billion as outflows (Gallagher et al., 2015a). By the end of August 2011, the assets under their management declined by 11% (Chernenko and Sunderam, 2014). Facing large redemptions, U.S. MMFs sharply reduced their investments in European banks.

2.3 Hypothese Development

This paper's interest is whether and how a CHR biases the lending practices of MMFs. However, it is insufficient to conduct a direct test, as a CHR could endogenously correlate with issuers' characteristics, especially with their creditworthiness. The timeframe around the European bank crisis in June 2011 presents a laboratory environment: money market instruments issued by European banks, though they had always been considered safe, suddenly raised fear among investors. An intuitive question following is thus: is there any difference in portfolio weights between MMFs' bilaterally-connected and -unconnected European issuers after the European bank crisis?

I focus on the March–August 2011 period and separate the entire sample into two symmetric parts: March–May and June–August 2011, which respectively represent the pre- and post-periods of Moody's put downgraded reviews of European banks.[22] Chernenko and Sunderam (2014) show that MMFs with greater exposure to European banks suffer greater outflows after June 2011. Thus, if the lending of MMFs is fully market-based, MMFs should have decreased their exposure to all European issuers so that they would not intensify further investor redemptions; in other words,

[22]The choose and separation of the same sample period follows Chernenko and Sunderam (2014).

all European issuers would have seen decline in MMFs' funding. However, the pre-existing CHR brings potential reciprocity, which is reflected in the lending from a bank's affiliated MMFs to the bank's bilaterally-connected European partners. As shown in Figure 9, J.P. Morgan's MMFs will treat two European issuers—Deutsche Bank which is bilaterally-connected with J.P. Morgan and RBS, which is not—differently.

Hypothesis One. In the post-period, MMFs increase their portfolio weights of the European banks that are in a pre-existing CHR with the funds' sponsors.

Of course, direct tests of Hypothesis One suffer from an endogeneity problem. It could simply be the case that the issuers involved in CHR are big financial firms so that their issued securities are much less risky, or that MMFs involved in CHR are affiliated with big financial firms so that they are still willing to hold risky securities. Therefore, this hypothesis should emphasize the control of the issuer-fixed effect and the fund-fixed effect. To be specific, after the European bank crisis: (1) the funding a given European bank receives from MMFs would be different, depending on whether the bank is in a CHR with a fund's sponsor; and (2) a given MMF's portfolio weights on European banks would be different, depending on whether the fund's sponsor is in a CHR with a bank.

Next, I directly investigate whether MMFs' bias toward bilaterally-connected issuers is driven by reciprocity. For each fund-issuer pair in CHR, there is always a reverse fund-issuer pair in which the fund is affiliated with the original issuer and the issuer is the original fund's sponsor. Given that two parties involved in a CHR have stakes in each other, the securities in the reverse pair can be the reflection of reciprocity. As shown in Figure 10, when J.P. Morgan's MMFs tilt their portfolio weight to Deutsche Bank, money market instruments issued by J.P. Morgan and held by Deutsche Bank's MMFs could also be different from money market instruments in other fund-issuer pairs. The second hypothesis discusses the motivation of the fund side if Hypothesis One is true.

Hypothesis Two. In the post-period, securities held in reverse fund-issuer pairs are different from securities in other fund-issuer pairs.

Hypothesis Two, if true, implies that the European side of a CHR should provide some benefits as a return to its connected partner, and that this compensation is reflected in the portfolio holdings of the European bank's affiliated MMFs.

3 Data and Summary Statistics

I collect data from different sources. This paper has a novel dataset based on the SEC form N-MFP, which all U.S. money market funds are required to report each month since November 2010.[23] N-MFP forms provide information on three levels: (1) fund-level data on gross yields, TNAs, maturities, advisors, etc.; (2) class-level data on Nasdaq tickers, net yields, shareholder flow activities (gross subscription and gross redemption) etc.; and (3) holdings-level data on each securitys issuer, yield, maturity date, value, maturity, type, and so forth. The detailed classification of different types of securities can be found in the Appendix B. N-MFP forms classify MMFs into five categories: "prime," "treasury," "government/agency," "single state fund," and "other tax exempt fund." My focus is prime MMFs because they are major MMFs investing in non-government securities. In addition, I filtered out 35 feeder funds that make almost all of their investments through master funds.

More fund information is complemented by the CRSP Mutual Fund Database; 89.34% of N-MFP class-level observations can be linked to CRSP, which gives class-level expense ratios, types (institutional or retail), ages, etc.[24] The study is conducted on the fund-series level so that all class-level characteristics (e.g., net yield, age, expense ratio) are finally aggregated to the fund level weighted by values of class assets. Names of funds and security issuers are not reported uniformly in N-MFP forms. The study uses Factset and Bloomberg to get funds and issuers formal names as well as headquarter locations. Issuers that are sovereign, agency, municipal, or non-financial firms are removed from the data. The study also obtains each funds sponsor names from the SEC form

[23] The SEC requires funds to file N-MFP within five business day after each month ends, but forms would not be publicly available until 60 days after. The same data are used by Chernenko and Sunderam (2014), Hu, Pan, and Wang (2015), and Li (2017).

[24] I match N-MFP data with CRSP Mutual Fund Database by Nasdaq tickers first; then I manually match the rest whose Nasdaq tickers are wrong or missing in N-MFP by checking class names and fund advisor names.

N-SAR. Lastly, the study collects European issuers CDS information from the Markit CDS pricing database as a control measure of European borrowers credit risk. Throughout this paper, I use five-year CDS rates measured in USD and have the "Modified-Modified" restructuring clause.[25]

The resulting dataset covers the November 2010-August 2013 period, but most of my analyses focus on the March-August 2011 period, during which there are 216 financial firms. Figure 11 gives a snapshot. In total, 77 financial firms are sponsoring funds and 163 financial firms are issuing money market instruments. The two sides overlapping are 24 financial firms serving dual roles, 19 Non-European and 5 European; their names are listed in Appendix F The fund-side financial firms own a total of 264 unique MMFs, which together manage monthly average assets of $1.76 trillion during the sample period. Although one third of financial firms on the fund side serve dual roles, they sponsor 40% of MMFs, and their total AUM occupies almost half of all MMFs AUM. The issuer-side financial firms issue securities with a monthly total value of $1.23 trillion. About 15% of financial firms on the issuer side are also fund-sponsors; these firms issue securities that account for 31% in value of all issued securities in the MMF market. These facts indicate that, no matter on the fund side or on the issuer side, only big financial firms are capable of holding dual roles, a feature even more pronounced for European firms. Securities issued by the five dual-role firms take around one-fourth of all European issuers security value. Comparing Panel A with Panel C, on the issuer side, European financial firms are fewer than non-European financial firms in numbers, but they account for more than 60% in the value of issued securities. This summary conforms to the documented fact by Ivashina, Scharfstein, and Stein (2015) that foreign banking entities issue a large share of dollar liabilities.

Panel A of Table 10 reports summary statistics of month-fund observations during the entire sample period. The average fund has $7051.88 million in net asset (TNA) and is 18.62 years old; 33.24% of its shares are for institutional investors, and its portfolio maturity is 38.40 days. Comparing stand-alone MMFs (lender only) and dual-role MMFs (whose sponsors also issue

[25] For CDS rates only shown in Euro in the Markit database, I convert them to USD ones using real-time exchange rates.

money market instruments in the MMF market), dual-role MMFs have larger TNA, younger fund age, more tilted ownership toward institutional investors, and slightly lower expense ratios. The fund flow calculated as the difference between *Subscription* and *Redemption* shows that the size of an average dual-role fund decreases by 0.40% monthly while the size of an average stand-alone fund increases by 0.16%; this difference may relate to the formers higher exposure to European debt (41.13%), which might be a main trigger of investors redemption. Moreover, dual-role funds invest 14.40% of their assets into their connected partners. Standard deviations of annualized *Gross Yield* and *Net Yield* show that MMFs are heterogeneous in reaching for yield, and dual-role funds are more prone to reach for yield than their stand-alone peers. In terms of portfolio holdings, the average fund invests 25.53% in *ABCP* (asset-backed commercial paper) and *Financial CP* (financial commercial paper) together, and 17.95% in Bank Obligation; portfolio holdings of dual-role funds and stand-alone funds are quite similar in these three categories. However, dual-role funds hold far fewer secure debts issued by governments or agencies. Detailed information of different types of securities in MMFs portfolio holdings is reported in Table 24 of the Appendix E

Panel B reports summary statistics of month-issuer observations during the whole sample period. The average issuer issues $8.63 billion market instruments, with an average yield of 30.48 bps and an average maturity of 38.88 days, and takes an average MMF portfolio weight of 2.39% from around 40 MMFs. Comparing issuers-only and dual-role issuers (who have affiliated MMFs), the latter issues more money market instruments to a larger numbers of MMFs, accounts for higher weight in MMF portfolios, and provides a lower average yield with a shorter maturity. In term of security types, the average issuer mainly issues *ABCP*, *Bank Obligation*, and *Financial CP*. Comparing issuers-only and dual-role issuers, *ABCP* and *Government/Agency Repo* occupy larger weight in a dual-role issuers security pool, while issuers-only weigh much more on *Bank Obligation*.

My detailed empirical analysis is conducted on the fund-issuer pair level; namely, one fund-issuer pair in every month is one observation in the sample. Lending is measured by the exposure of fund f to issuer i at month t:

$$Exposure_{f,i,t} = \frac{Outstanding_{f,i,t}}{\sum_i Outstanding_{f,i,t}},$$

where $Outstanding_{f,i,t}$ is the total value of money market instruments issued by issuer i and held by fund f in month t, and $\sum_i Outstanding_{f,i,t}$ is the total value of fund f's portfolio holding in month t. Therefore, $Exposure$ represents a given fund f's portfolio weights to different issuers i in month t. When t is one of the three months in the post-period, I use the average $\sum_i Outstanding_{f,i}$ of the pre-period as the denominator, so that $Exposure$ is not passively affected by the change in the total value of fund f's portfolio after June, 2011.

To measure the riskiness of each fund-issuer pair, I apply three risk measures suggested by Kacperczyk and Schnabl (2013). The first one is $Spread$, namely an asset's gross yield net of one-month T-bill rate. After adjusting for time varying interest rate, this measure largely reflects asset risk. The second one is $Maturity$, namely an asset's days-to-maturity. Intuitively, the longer the days-to-maturity, the larger the uncertainty in an asset. Each issuer may have multiple issued securities in one fund's portfolio; so for each fund-issuer pair, both $Spread$ and $Maturity$ are firstly measured on the fund-security level, and are then averaged to the fund-issuer level by weighing assets value. The last one is $Holdings\ Risk$, calculated as the weight of an issuer's bank obligations net of the weight of its safest securities in the same portfolio. The safest securities include government repo, agency repo and Treasury repo. All variable definitions appear in Appendix D

Table 11 reports summary statistics of pair-month observations during the whole sample period. The median fund-issuer pair has \$44.99 million outstanding, but the distribution is skewed, with a mean outstanding of \$2.16 billion. The median pair's MMF portfolio weight is 2.1%, with an average spread of 20.40 bps and an average maturity of 36.26 days. The distribution of $Holdings$ $Risk$ is also skewed with a mean of 25.61 bps and median of 0.00 bps.[26] In panel B, I list the

[26] Securities in pairs with zero $Holdings\ Risk$ are neither bank obligations nor safe assets like repos.

summary statistics of pairs whose issuers are from Europe. The above five characteristics of these pairs are quite similar to the ones of the entire pair sample.

4 Methodology and Empirical Results

In this section I describe the tests employed to estimate the hypothesized bias in MMFs' portfolio weights toward bilaterally-connected issuers (Hypothesis One), and the hypothesized difference of securities in reverse pairs (Hypothesis Two). I also add a discussion about how MMFs' tilt to connected European issuers is associated with negative lending spillovers to other issuers who also borrow money from these funds.

4.1 Construction of CHR Measures

According to the definition of CHR, a pair (f,i) has a dummy *BConnected* equal to one, if both $Exposure_{f,i,t}$ and $Exposure_{i,f,t}$ are larger than zero when t is one of the three months in the pre-period. It means that, before mid-2011,when fund f holds securities issued by issuer i, if i also has an affiliated MMF that simultaneously holds securities issued by f's sponsor, then this fund-issuer pair is called "bilaterally connected."

A fund-issuer pair (f,i) is called a "reverse pair" if the fund f is sponsored by a European financial firm and, simultaneously, this European firm's money market instruments are also owned by the issuer i's affiliated MMFs (for example, in Figure 7, the fund-issuer pair with Deutsche Bank affiliated MMFs as the fund and JP Morgan as the issuer is a reverse pair). Obviously, "reverse pair" is a bilaterally-connected pair in which MMFs are under the umbrella of European financial houses.

Table 12 gives an overview of connected and unconnected fund-issuer pairs in the sample during the whole March–August 2011 period. The observed number of bilaterally-connected pairs is far smaller than that of unconnected ones: only above 6% of fund-issuer pairs (1947 month-pairs) are reflections of CHR. This fact is reasonable given that the numbers in Figure 11 already show that not every entity in this market has the capacity to both sponsor MMFs and issue money market instruments. Generally speaking, a fund weighs 3.07% of its portfolio holdings on every bilaterally-connected issuer, more than the weight on unconnected ones; as a comparison, the lending value of $204.91 million per pair in connected pairs is higher than $160.70 million in unconnected ones, while risk exposure proxies such as yield, net yield and days-to-maturity are lower. These facts jointly imply that CHR is associated with lending at a larger dollar amount and lower risk exposure. It is worth noting that a fund's portfolio weight on a connected issuer can reach as high as 10.27%, which is far larger than the 5% issuer diversification limit required by the SEC since the 2014 MMF reform (which is launched later than this paper's testing period.)

4.2 Tests of Hypothesis One

4.2.1 Univariate Analysis

I start my empirical analysis by testing the first hypothesis. I investigate how MMFs' lending to bilaterally-connected and unconnected European issuers changes around the European bank crisis.

Panel A in Table 13 presents the univariate statistics and *t*-test of differences in MMFs' European exposure between the post- and pre-periods. Given the relatively small number of pairs involved in CHR, I use a bootstrap method to generate the empirical distribution of connected pairs' *Exposure* difference under the null hypothesis. Specifically, for each pair in the connected sample, I randomly select with replacement a pair that has a European issuer. This process continues until each pair in our original connected sample is represented by a pair with a European issuer in this pseudo-connected sample. Then I estimate the mean of *Exposure* difference in the pseudo-connected sample, which yields one observation of differences in MMFs' European exposure between the post- and pre-periods. This entire process is repeated until I have 1,000 pseudo-connected samples, and thus 1,000 mean *Exposure* difference observations. These 1,000 mean *Exposure* difference observations are used to approximate the empirical distribution of mean *Exposure* difference for connected pairs.

On average, if a European issuer is bilaterally-connected with a fund, after the European bank crisis, the fund's exposure to this connected partner increases by 0.35%, measured in portfolio weight; in contrast, a fund's portfolio weight on every unconnected European issuer drops by 0.23%. The corresponding economic implication is surprising: after Moody's review on European banks in June 2011, an average U.S. MMF financed every connected partner in Europe $29.58 million more while cut off $19.66 million in lending to every other European borrower. Both differences are statistically significant at less than 5% level. The other noteworthy fact is, in both the pre- and post-periods, the average exposure of connected pairs almost doubles that of unconnected ones.

For comparison, I show results of the same univariate test for non-European issuers in Panel B of Table 13. The empirical statistical reference of connected pairs is also generated by the similar bootstrap method in Panel A. Generally speaking, exposure in fund-issuer pair here is less than that in Panel A, which is in line with the fact that European securities take a large share in the dollar dominated MMF market. After the crisis, funds add weights to both connected and unconnected issuer, although the difference of exposure in connected pairs is statistically insignificant and much smaller than the difference in unconnected ones. This change is consistent with documented facts that MMFs turned to non-European borrowers after the crisis in Europe began.

4.2.2 Multivariate Analysis

A. The Difference-in-Differences Test

My first hypothesis focuses on the real effects of a CHR on MMFs' lending to European issuers. The univariate analysis above provides preliminary evidence that MMFs' lending to bilaterally-connected and unconnected European issuers changes in different directions after the European bank crisis. However, this phenomenon may be driven by issuers' or funds' other characteristics.

To control for these factors, in the following section, I use multivariate regressions to test the change in each fund-issuer pair's *Exposure*. The results are reported in Table 14. My analysis is based on the following multivariate regression model:

$$\begin{aligned} Exposure_{f,i,t} =& \alpha + \beta_1 BConnected_{f,i} \times Post + \beta_2 BConnected_{f,i} \\ & + \beta_3 Post + \lambda_1 Control_{f,t} + \lambda_2 Control_{i,t} + \varepsilon_{f,i,t}, \end{aligned} \tag{4}$$

where *Exposure* is fund-issuer pairs' exposure winsorized at the 5th and 95th percentiles;[27] *BConnected* is a dummy equal to one for all bilaterally-connected fund-issuer pairs in the pre-period; *Post* equals one when the month t is in the post-period; $Control_{f,t}$ and $Control_{i,t}$ form a group of control variables on the issuer side and the fund side respectively, including the natural logarithm of fund TNA ($Fund\ Size_{f,t}$), fund net yield ($Net\ Yield_{f,t}$), fund expense ratios ($Expense\ Ratio_{f,t}$) and fund-level institutional share proportions ($Institutional\ Share_{f,t}$), fund flows ($Fund\ Flow_{f,t-1}$) and issuer's five-year CDS rates ($CDS\ Rate_{i,t}$). The month-fixed effect accounts for any time differences that may drive risk differences across fund-issuer pairs. Similarly, unobserved time-invariant differences among issuers, funds, fund-sponsors or issuer type are controlled by the issuer-, the fund-, the sponsor-fixed or the issuer-type-fixed effect. All issuers are put into seven categories: "Conglomerate," "Bank," "Investment Company," "Insurance Company," "Government," "Agency," and "Non-financial Firms." I consider error terms to be within funds and within issuers; therefore, standard errors are two-way clustered at the fund level and the issuer level.

From Column 1 to Column 5, consistent with the univariate analysis, I find a strong positive relationship between the bilateral connection and fund-issuer pairs' exposure in the post-period: after mid-2011, CHR increases a MMF's exposure to the corresponding European issuer by 0.36%–0.45% of its portfolio holdings, which means the lending amount in per connected fund-issuer pair is inflated by \$34.76–\$42.95 million. The results are statistically and economically significant: in the post-period, CHR corresponds to a 18.9%–23.35% increase in *Exposure* relative

[27] The results are similar without winsorization and with it at different levels (1st and 99th, 10th and 90th).

to the cross-sectional standard deviation of *Exposure* to European issuers.

An identification concern is that bilaterally-connected issuers are less risky, and therefore became more popular in the post-period when MMFs were prone to escape from risky issuers. I address this problem by adding European issuers' five-year CDS rates across all columns as a control variable of issuers' default risk. Results show that MMFs' *Exposure* to European issuers is less for issuers with higher CDS rate. Plus, it is less for funds with larger size, higher expense ratio and lower institutional share.

Moreover, the issuer-fixed effect is included in Column 2 to Column 4, where *BConnected* and *Post* lose their statistical significance, indicating the positive (negative) relationship between the bilateral connection (the post-period), and *Exposure* mirrors some persistent nature from issuers. However, the positive coefficient of $BConnected \times Post$ remains statistically significant; therefore, MMFs' tilt of portfolio weight to bilaterally-connected European issuers is very unlikely to be associated with these issuers' creditworthiness. As predicted by Hypothesis One, in the post-period, holding fixed the issuer, MMFs finance less to unconnected European issuers but lend more to their bilateral connected European partners.

A similar identification concern exists on the fund side. Although funds' key characteristics have been controlled, my results might also be driven by unobserved time-invariant differences among funds or fund-sponsors. Further, these fund-level or sponsor-level characteristics may be associated with funds' building-up of bilateral connections. I address this problem by including the fund-fixed effect in Column 1 and Column 3 to Column 5, as well as the sponsor-fixed effect in the last two columns. These specifications do not change the quality of previous results but support Hypothesis One which also predicts that, in the post-period, holding fixed the MMF, European issuers receive more finance support from the MMFs belonging to their bilaterally-connected financial firms.

Undoubtedly, issuers who have the capacity to build CHR with MMFs are likely to be conglomerates with different departments running under their umbrellas. Complying with the "too big to fail" intuition, one explanation of MMFs' higher exposure on bilaterally-connected issuers after the crisis is that these issuers are secured because they are conglomerate. Although this feature of being conglomerate is controlled by the issuer-fixed effect, to further distinguish it from the bilateral connection, I control the issuer-type-fixed effect in Column 4. I also add a dummy *Conglomerate* in Column 5. My main findings are robust. Although the bilateral connection of this paper's focus is proven to be different from the conglomerate effect, Column 5 indicates that being a conglomerate also helps issuers to gain funding from MMFs in the post-period.

B. Placebo Tests

To ensure that the difference-in-differences (DD) test above is not biased, I conduct placebo tests in this section to analyze the DD test's sensitivity. The idea is to redo the same test using data prior to the post-period, although due to the limitation of the N-MFP data's time span, I can only track back to November 2010, when MMFs are required to disclose their portfolio holdings in detail to SEC for the first time.

Using the data from November 2010 to May 2011, I conduct two placebo tests following the specification 4. Both placebo tests, as the true one, are six months long and include all fund-European issuer pairs. The first(last) three months in each placebo sample are called the pre-(post-) period. The goal is to investigate whether we observe similar changes in MMF portfolio holdings surrounding placebo cutoffs as we do around the mid-2011 cutoff. These placebo tests provide evidence on the extent to which MMF portfolio weights of bilaterally-connected and -unconnected pairs are different before the 2011 European bank crisis.

Both Panel A and B in Table 15 indicate that there are no significant differences in MMF portfolio weight between bilaterally-connected and -unconnected pairs that have European issuers in the two placebo tests. The difference-in-differences in the two six-month placebo samples are both insignificant. Thus, it does not appear that our results are mechanically driven by a trend that took place before the 2011 European bank crisis.

C. Comparison among All Issuers

This section includes non-European issuers to show how fund-issuer pairs' *Exposure* changes in the entire sample between the pre- and post-periods. Table 16 presents the results of the following multivariate regression model:

$$\begin{aligned} Exposure_{f,i,t} =& \alpha + \beta_1 BConnected_{f,i} \times Post \times European\ \ Issuer_i \\ & + \beta_2 BConnected_{f,i} \times Post + \beta_3 BConnected_{f,i} \times European\ \ Issuer_i \\ & + \beta_4 Post \times European\ \ Issuer_i + \beta_5 BConnected_{f,i} + \beta_6 Post \\ & + \beta_7 European\ \ Issuer_i + \gamma Control_{f,t} + \varepsilon_{f,i,t}, \end{aligned} \tag{5}$$

where $Exposure$, $BConnected$ and $Control_{f,t}$ are the same as these defined in the specification 4; $European\ \ Issuer$ is a dummy equal to one if the issuer i is from Europe. The month fixed effect accounts for any time differences that may drive risk differences across fund-issuer pairs. Similarly, unobserved time-invariant differences among issuers, funds, or fund-sponsors are controlled by the issuer-, the fund- or the sponsor-fixed effect, and standard errors are two-way clustered at the fund level and the issuer level.

From Column 1 to Column 4, I find that, in the post-period, a MMF's portfolio weight on European issuer decreases by 0.13%–0.22%; however, the bilateral connection increases a fund's portfolio weight on a connected European issuer by 0.46%–0.54%. In comparison, the coefficients of the interaction terms between $BConnected$ and $Post$, and the one between $BConnected$ and $European\ \ Issuer$ are both close to zero. Hence, the bias in MMFs' portfolio weight is neither universal across all issuers in the post-period nor common for all European issuers during the entire sample period.

4.2.3 MMF Flows

MMFs' bias toward bilaterally-connected European issuers in the post-period is puzzling in this context as documented by Chernenko and Sunderam (2014). Before examining the motivation behind CHR, it is necessary to test whether the outflow consequences in the post-period of MMFs'

European exposure documented by Chernenko and Sunderam (2014) still hold among MMFs involved in CHR with European issuers. In other words, if the biased MMFs are not exposed to the outflow consequence, then it is not surprising that they increase stakes on bilaterally-connected European issuers.

To show how flows of different MMFs respond to funds' risk-taking activities in the two periods, I apply the following multivariate regression model:

$$Fund\ \ Flow_{f,t} = \alpha + \beta_1 Euro\ \ Share_{f,t} + \gamma Control_{f,t} + \varepsilon_{f,t}, \tag{6}$$

where $Fund\ Flow$s are funds' net flows scaled by one-month lagged fund assets, the ratios are winsorized at the 5th and 95th percentiles. *Euro Share* is the share of a fund's assets invested in European financial firms. $Control$ includes the monthly $Fund$ *Size*, *Institutional Share*, and *Net Yield*. The month fixed effect accounts for any time differences that may drive flow differences across MMFs.

Table 17 presents results. The tests are conducted in the pre- and post-periods separately. Panel A covers all MMFs, and Panel B and Panel C are subsamples of MMFs involved and not involved in CHR with European financial firms. As shown in Column 3 and 4 of Panel A, when we regress fund flows on *Euro Share* in the post-period, the effect of *Euro Share* is significantly negative. The same two columns in Panel B show similar results: for MMFs involved in CHR with European issuers, a one-standard-deviation increase in *Euro Share* is associated with annualized fund flows of -8.23% of assets. Given that their mean annualized fund flows in the post-period were -18.30%, the effect of *Euro Share* is not negligible. As a comparison, results in Columns 3 and 4 of Panel C are insignificant, though still negative. In sum, the negative *Flow-Euro Share* relation documented by Chernenko and Sunderam (2014) is concentrated in MMFs that are bilaterally-connected with European issuers. Combining this result with the findings of portfolio weight bias in the previous sections, it is surprising that, even though investors evaluate the exposures of their MMFs to European banks, these MMFs still increase their portfolio weight on bilaterally-connected European issuers while bearing large outflows driven by *Euro Share* in the post-period.

Another interesting finding in Table 17 is that net yield plays different roles in the two periods. In the pre-period, funds show a strong performance-flow relationship: higher-yielding funds attract more fund flows, and this relationship is prone to MMFs not involved in CHR with European issuers. In the post-period, however, net yield fails to drive flows.

4.2.4 Securities Comparison

A further look of relationship lending serves to check for association with differences in riskiness of securities issued by connected and unconnected issuers.

For fund-issuer pairs with European issuers, Table 18 presents the univariate statistics and *t*-test of differences in securities' riskiness between the post- and pre-periods. The empirical statistical reference of connected pairs is generated by the similar bootstrap method in Section 4.2.1. In Panel A and Panel B, both connected- and unconnected-pairs behave in the same pattern: surrounding the European bank crisis, the change of *Spread* is close to zero, while *Maturity* is reduced by 9 to 10 days. A slightly different pattern appears in Panel C: *Holdings Risk* does not change for connected pairs but increases by 3.42 base points for unconnected pairs. In a word, although the cross-holding relationship make a difference in lending, there is no differences in securities' riskiness. A further multivariate analysis using the difference-in-difference model in Appendix H confirms this finding.

4.3 Tests of Hypothesis Two

As shown above, MMFs increased exposures to bilaterally-connected European partners after the European bank crisis, but this bias is not related to securities' riskiness. In other words, it is not because their connected European issuers provided less risky money market instruments that makes MMFs tilt to these issuers after mid-2011. As such, we must ask: what other benefits could

MMFs get from helping their bilaterally-connected European partners after the crisis?

There is reciprocity between two financial firms involved in a CHR with each other. The nature of the bilateral connection is that both parties mutually hold each other's debt; therefore, MMFs of the European financial firms also have stakes in their bilaterally-connected partners. To test the reciprocity effect, I turned to the reverse lending, which is portfolio holdings of MMFs sponsored by European financial firms.

4.3.1 Univariate Analysis

Here, I compare "reverse pairs" with other fund-issuer pairs surrounding the European bank crisis.[28]

Four different variables are tested. Table 19 presents the corresponding univariate statistics and *t*-test of differences. The empirical statistical reference of reverse pairs is generated by the bootstrap method similar to that in Section 4.2.1. In Panel A, funds' exposure in reverse pairs increases by 0.13%, while that in other pairs does not change. Panel D shows stronger evidence: *Holdings Risk* increases by 5.74 base points for reverse pairs but decreases by 2.79 base points for other pairs. These findings suggest that, in the post-period, compared to other fund-issuer pairs, MMFs sponsored by European financial firms increase their portfolio holdings of money market instruments issued by their connected issuers. Moreover, these MMFs accept more risky securities than safest securities from their connected issuers. Panel B and Panel C do not show the similar pattern: both reverse and other pairs experience declines in securities' *Spread* and *Maturity*.

[28] Bilateral connected pairs with European issuers are excluded.

4.3.2 Multivariate Analysis

A more detailed comparison is made by estimating the following regression model:

$$
\begin{aligned}
Lending_{f,i,t} =& \alpha + \beta_1 Reverse\ \ Pair_{f,i} \times Post + \beta_2 Reverse\ \ Pair_{f,i} + \beta_3 Post \\
&+ \beta_4 BConnected_{f,i} + \beta_5 European\ \ Issuer_i + \beta_6 European\ \ Fund\ \ Sponsor_f \\
&+ \gamma Control_{f,t} + \varepsilon_{f,i,t},
\end{aligned} \tag{7}
$$

where *Lending* is measured by *Exposure*, *Spread*, *Maturity* and *Holdings Risk* respectively. *European Issuer* is a dummy equal to one if the issuer is a European firm. *European Fund Sponsor* is a dummy equal to one if the fund's sponsor is a European firm. Other independent variables are the same as those defined in specifications 4 and 5. I consider error terms to be within funds and within issuers; therefore, standard errors are two-way clustered at the fund level and the issuer level.

Table 20 reports the results when *Lending* is measured by *Holdings Risk*.[29] Across all columns, estimates of β_1 are positive and statistically significant at the level of 1%: *Holdings Risk* in reverse pairs increases 13.84-15.46 basis points after the European bank crisis. This finding is robust after controlling different fixed effects, especially the pair's feature of being bilaterally-connected (*BCoonected*); the issuer's feature of being a European firm (Column 4); and the fund-sponsor's feature of being a European firm (Column 5). As a comparison, estimates of β_3 are negative and statistically significant at the level of 10%: *Holdings Risk* generally decreases 3.17–5.57 basis points in the post-period.

These findings imply that, after the European bank crisis, although MMFs usually hold FEWER unsecured securities than secure ones, European financial firms that own MMFs accept MORE unsecured securities than secure ones from their bilaterally-connected partners. According to Chernenko and Sunderam (2014), unsecured money market instruments were popular in the pre-period because their high yields were what yield-reaching MMFs were chasing, but this popularity

[29] The results when *Lending* is measured by the other three measures are presented in 31.

soon went to the opposite side in the post-period when MMFs turned to less risky assets to avoid further redemption. Clearly, getting a MMF to accept unsecured securities is hard in the post-period. I interpret the surprising change in *Reverse Pair*s' *Holding Risk* as European firms' compensation for, as shown in Section 4, these bilaterally-connected partners' continual financing the corresponding European financial firms after mid-2011.

Holdings Risk is calculated as the weight of an issuer's bank obligations net of the weight of its safest securities in the same portfolio. To give a deeper look into *Holdings Risk*, in Table 21, I test the changes in the two components separately.

Columns 1 to 5 show that the portfolio weight of bank obligations in reverse pairs increases 7.35–10.17 basis points after the European bank crisis. Column 6 to 10 show that the portfolio weight of safest instrument in reverse pairs decreases 5.23–6.53 basis points after the European bank crisis. The two changes together contribute to the increase of *Holdings Risk* in reverse pairs.

The results above provide evidence in favor of Hypothesis Two about reciprocity. To be specific, the finding that financial firms tilt in their MMFs' portfolios to bilaterally-connected European issuers is associated with the corresponding European financial firms' acceptance of—through their affiliated MMFs—more risky bank obligation and less safest instruments like repos from these financial firms after the European bank crisis, a period when both European debt and risky securities are unwelcome while safe repos are popular in the MMF market.

4.4 Spillover Effects

Analyses in the previous two sections are all about the direct impacts of a CHR. Given the small ratio that bilaterally-connected pairs take (5%) in the full sample of fund-issuer pairs, people may question how deeply and widely CHR affects the overall MMF market. This section, discusses how the MMFs' tilt to connected European issuers relates to the influence on other issuers who also borrow money from these funds.

Due to limited available funding on MMFs' hand, especially in the post-period when many MMFs suffered big net outflows, if a MMF decides to increase its stake in one issuer, it must cut off financing to some other issuers due to financial constraints. These issuers may then meet difficulty borrowing money from other lenders in a short time due to frictions in lending.

Now I introduce a variable $SEuro\ \ Fund\ \ Share$. If an issuer is not held by any fund that has bilaterally-connected European issuers in the pre-period, then $SEuro\ \ Fund\ \ Share_i = 0$, otherwise $SEuro\ \ Fund\ \ Share_i = 1$. I then put all issuers in the sample into two groups based on $SEuro\ \ Fund\ \ Share$.

In Table 22, we can see that 165 financial firms borrow money from $SEuro\ \ Fund$s before mid-2011, namely more than half of issuers can be indirectly affected by CHR in the post-period. On average, issuers in this group are big borrowers in terms of their debt outstanding in the MMF market, indicating that influences on them may represent big impacts on the entire issuer side. Further, this group has more European issuers as well as high-yield securities.

Then I apply the following test from Chernenko and Sunderam (2014):

$$\Delta Outstanding_i = \alpha + \beta Issuer\ \ Euro\ \ Share_i + \varepsilon_i, \tag{8}$$

where $\Delta Outstanding$ is the percentage change in the issuer's average $Outstanding$ between the pre- and post-period; $Issuer\ \ Euro\ \ Share$ measures an issuer's indirect exposure to European financial firms, calculated as :

$$Issuer\ \ Euro\ \ Share_{i,t} = \frac{\sum_f Outstanding_{f,i,t} \times Fund\ \ Euro\ \ Share_{f,t}}{\sum_f Outstanding_{f,i,t}},$$

given $Fund\ \ Euro\ \ Share$ is a fund's total exposure to European issuers. In the regression, I use each issuer's average $Issuer\ Euro\ Share$ in the pre-period. To release the identification concern that issuers' $Issuer\ Euro\ Share$ and $SEuro\ Fund\ Share$ are associated with their creditworthiness, I also control for each issuer's $Yield$ and $European\ Issuer$ dummy.

As shown in Table 23, the negative effect of being financed by MMFs that have large European issuer exposure on other issuers, as Chernenko and Sunderam (2014) documented, is only found with issuers who borrow money from $SEuro\ Funds$. The inclusion of *Yield* and *European Issuer* does not change this impact, suggesting that the results are not driven by MMFs general aversion to risk in the post-period. However, I do not find significant similar results for issuers not relying on $SEuro\ Funds$. Plus, the distributions of $Issuer\ Euro\ Share$ in the two groups are very similar. These findings indicate that the two groups of issuers are very different in whether or not they are easily affected by their indirect exposure to European issuers. Those financial firms borrowing money from MMFs that are bilaterally-connected with European issuers are prone to having trouble borrowing money from other MMFs in the post-period if their old lenders cut off the financing.

5 Conclusion

In the context of the U.S. money market funds, this paper studies the existence and influence of a reciprocal cross-holding relation between financial conglomerates. Applying the market turmoil in European banks in mid-2011 as an exogenous event, I show that non-European financial firms increase their MMFs' stakes in bilaterally-connected European financial firms after Moody's review of some European banks in mid-2011 whereas MMFs generally reduce their exposure to European borrowers at the same time. I provide evidence that this change is motivated by reciprocity. I further show that CHR also creates negative spillovers on Non-European issuers.

My findings improve the current understanding of lending behaviors of "shadow banks," especially how financial conglomerates coordinate with each other to realize *quid pro quo* in shadow bank lending.

Appendices

A Essay One: 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

$\textit{Weak-Relation}^{freq}_{i,j,t}$	A lender-based weak-relationship-dummy equals one if $\textit{Lending Freq}_{i,j,t}$ is below the median for that lender j during the five-year window preceding the month t
$\textit{Lending Size}_{i,j,t}$	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: $\textit{Lending Size}_{i,j,t} = \frac{\text{\$ Amount of loans to borrower } i \text{ by bank } j}{\text{Total \$ amount of loans by lender } j}$
$\textit{Lending Freq}_{i,j,t}$	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: $\textit{Lending Freq}_{i,j,t} = \frac{\text{Number of loans to borrower } i \text{ by bank } j}{\text{Total number of loans by lender } j}$
$\textit{Reliance}_{i,j,t}$	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: $\textit{Borrowing Size}_{i,j,t} = \frac{\text{\$ Amount of loans to borrower } i \text{ by bank } j}{\text{Total \$ amount of loans by borrower } i}$
$\textit{Reliance}^{freq}_{i,j,t}$	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: $\textit{Borrowing Freq}_{i,j,t} = \frac{\text{Number of loans to borrower } i \text{ by bank } j}{\text{Total number of loans by borrower } i}$
$\Delta \textit{Lending}_{i,j,d}$	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: $\Delta \textit{Lending}_{i,j,d} = \sum_{t=dt-12}^{dt-1} \textit{Loan Amount}_{i,j,t} - \sum_{t=dt+1}^{dt+12} \textit{Loan Amount}_{i,j,t}$

Bank Variables

$\textit{Bank Size}_{j,y}$	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 $Bank\text{-}Disaster\text{-}Exposure^{freq}_{j,d} = \sum_{i \in I^d} Lending\ Freq_{i,j,dt}$.
$\Delta Lending\text{-}in\text{-}disaster\text{-}states_{j,d}$	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: $\Delta Lending\text{-}in\text{-}disaster\text{-}states_{j,d} = \sum_{i \in I^d} \sum_{t=dt-1}^{dt-12} Loan\ Amount_{di,j,t} - \sum_{i \in I^d} \sum_{t=dt+1}^{dt+12} Loan\ Amount_{di,j,t}$
$Disaster\text{-}Lending_{j,d}$	$Disaster\text{-}Lending_{j,d} = \frac{\Delta Lending\text{-}in\text{-}disaster\text{-}states_{j,d}}{N_{j,d}}$. $N_{j,d}$ 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.
$HHI^{deposits}_{j,y}$	the Herfindahl-Hirschman index based on bank j's annual deposits in dollars in each state s: $HHI^{deposits}_{j,y} = \sum_s (\frac{Deposit_{j,y,s}/Total\ Deposit_{j,y}}{N})^2$, where N is the total number of states.
$HHI^{branches}_{j,y}$	the Herfindahl-Hirschman index based on bank j's branch numbers in each state s: $HHI^{branches}_{j,y} = \sum_s (\frac{Branches_{j,y,s}/Total\ Branches_{j,y}}{N})^2$, 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.

$\widehat{Firm\text{-}Disaster\text{-}Exposuree}_{i,d}$	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 $\widehat{Firm\text{-}Disaster\text{-}Exposure}_{i,d} = \sum_j Borrowing\ Size_{i,j,dt} \times \frac{Disaster\text{-}Lending_{j,d}}{Asset_{i,dt}}$, the frequency-based $\widehat{Firm\text{-}Disaster\text{-}Exposure}^{freq}_{i,d} = \sum_j Borrowing\ Freq_{i,j,dt} \times \frac{Disaster\text{-}Lending_{j,d}}{Asset_{i,dt}}$. $N_{j,d}$ 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 months 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 months window after a natural disaster, and loans issued in non-disaster period. I drop "connected loans" –loans issued by connected firms during the 12 months 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 26 about here]

Table 26 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.

D Essay Two: Variable Definitions

$BConnected_{f,i}$	A dummy equal to one for a fund-issuer pair, of which fund f holds securities issued by issuer i and i also has an affiliated MMF that simultaneously holds securities issued by f's sponsor in the pre-period.
$CDS\ Rate_{i,t}$	Issuer's five-year CDS rates that are measured in USD and are with the "Modified-Modified" restructuring clause from the Markit CDS pricing database.
$Conglomerate_i$	A dummy equal to one for issuers who are conglomerate.
$Connceted\ Share_{f,t}$	The share of fund's assets invested in bilaterally-connected partners.
$Expense\ Ratio_{f,t}$	The fund-level expense ratio, which is the value-weighted average of the class-level expense ratios from CRSP.
$Exposure_{f,i,t}$	The fund f's portfolio weight of money market instruments issued by issuer i in month t, $Exposure_{f,i,t} = \frac{Outstanding_{f,i,t}}{\sum_i Outstanding_{f,i,t}}$.
$European\ \ Issuer_i$	A dummy equal to one if the issuer i is from Europe.
$European\ \ Fund\ \ Sponsor$	A dummy equal to one if the fund's sponsor is a European firm.
$Euro\ Share_{f,t}$	The share of a fund's assets invested in European financial firms.
$Fund\ Flow_{f,t}$	Net subscriptions scaled by lagged fund assets. Net subscription is the sum of class-level difference between subscription and redemption from N-MFP. The ratios are winsorized at the 5th and 95th percentiles.
$Fund\ Size_{f,t}$	The natural logarithm of fund TNA.
$Gross\ Yield_{f,t}$	The annualized fund-level 7-day gross yield reported on form N-MFP.
$Holdings\ Risk_{f,i,t}$	The fund f's portfolio weight on the issuer i's bank obligations net of the weight of its safest securities in the same portfolio. The safest securities include government repo, agency repo and Treasury repo.
$Institutional\ Share_{f,t}$	The fund-level institutional share proportion, which is the value-weighted average of the class-level institutional shares from CRSP.
$Maturity_{f,i,t}$	Maturity is firstly measured at the security level as a security's days-to-maturity. $Maturity_{f,i,t}$ is the value-weighed average maturity of securities issued by issuer i and held by fund f in month t.
$Net\ Yield_{f,t}$	The value-weighted average of annualized class-level 7-day net yield from N-MFP.
$Outstanding_{f,i,t}$	The total value of money market instruments that are issued by issuer i and held by fund f in month t.
$Reverse\ Pair_{f,i}$	A dummy equal to one for a fund-issuer pair, of which fund f is sponsored by a European financial firm and, simultaneously, this firm's money market instruments are also owned by the issuer i's affiliated MMFs.
$Spread_{f,i,t}$	Spread is firstly measured at the security level as a security's gross yield net of one-month T-bill rate. $Spread_{f,i,t}$ is the value-weighed average spread of securities issued by issuer i and held by fund f in month t.
$SEuro\ \ Fund_f$	A dummy equal to one if a MMF has bilaterally-connected European issuers.
$SEuro\ \ Fund\ \ Share_{i,t}$	$SEuro\ \ Fund\ \ Share_{i,t} = \frac{\sum_f Outstanding_{f,i,t} \times SEuro\ \ Fund_f}{\sum_f Outstanding_{f,i,t}}$, it reflects how heavily an issuer relies on these $SEuro\ \ Fund$s to borrow money.

E Investment and Issuer Categories

Based on investment categories reported in N-MFP, I classify portfolio holdings into 12 investment categories: "asset backed commercial paper (ABCP)", "bank obligation", "financial commercial paper", "non-financial commercial paper", "government or agency repo", "Treasury repo", "other repo", "investment company", "Treasury", "government or agency debt", "municipal or agency debt", and "other".

As for issuers categories: firstly, I search in Factset and Bloomberg formal names and business categories for issuers of securities in the first eight investment categories, 99.5% of which find matched records. This group of issuers is classified into five types: "finance", "consumer", "health", "high tech", and "manufacturing". Except for "finance", the other four types of firms only issue non-financial commercial paper in the sample. Secondly, I name issuers of securities in the last four investment categories after the corresponding investment's category name.

Table 24 reports summary statistics of securities in MMFs portfolio holdings. Panel A lists non-government securities. On average, *ABCP*, *Bank Obligation*, *Financial CP* and *Other Repo* pay higher yields with larger maturities than *Government/Agency Repo*, *Treasury Repo* and *Nonfinancial CP* do. Of special note is *Other Repo*, which is a special type of repo collateralized by equities, corporate bonds or even financial derivatives, and therefore not considered as secure as normal repos which are backed by very safe assets such as Treasuries or government debt. In terms of issuing sources, there are more European issuers than U.S. issuers for repos, *Bank Obligation* and *Financial CP*, and vice versa for *ABCP* and *Non-financial CP*. Panel B shows that government or agency securities have lower yields but longer maturities than those in Panel A.

F Financial Firms Serving Dual-Roles in the MMFs Market

The following lists the 19 Non-European financial entities who both sponsor dollar-dominated MMFs and issue money market fund instruments.

Bank of America Corp.	New York Life Insurance Co.
Bank of Montreal	PNC Financial Services Group, Inc.
BlackRock, Inc.	Prudential Financial, Inc.
General Electric	Royal Bank of Canada
Guggenheim Partners, LLC	State Street Corporation
Invesco	The Bank of New York Mellon Corp.
JPMorgan Chase & Co.	The Goldman Sachs Group, Inc.
MetLife, Inc.	The Toronto-Dominion Bank
Mitsubishi UFJ Financial Group, Inc.	Wells Fargo & Company
Morgan Stanley	

The following lists the five European financial entities who both sponsor dollar-dominated MMFs and issue money market fund instruments.

AXA SA	UBS AG
Deutsche Bank AG	ING Bank NV
HSBC Holdings Plc	

G Bilateral Connection and Past Relationship

"Relationship" in the banking literature usually refers to the one in a long time period. The relationship strength is measured by proxies based on prior lending activities rather than being detected directly. As a comparison, CHR documented in this paper implies an important channel that financial institutions use to build relationship. To show that my above findings cannot simply be captured by indirect relationship measures in existing literature, I run a multivariate regression model which is similar to the specification 4 but includes *Past Relation*, which is measured by the following four measures at the fund-issuer pair level used in Chernenko and Sunderam (2014):

- *Frequency*: a dummy equal to one if a fund lends more frequently to an issuer than the median fund does;
- *Maturity*: a dummy equal to one if a fund-issuer pair's maturity is longer than the issuer's median borrowing maturity;
- *Quantity (Issuer Based)*: a dummy equal to one for the fund-issuer pair (f, i) if its portfolio share is above that issuer's median portfolio share;
- *Quantity (Fund Based)*: a dummy equal to one for the fund-issuer pair (f, i) if its portfolio share is above that fund's median portfolio share.

These four measures are built based on prior lending activities in the MMF market from November 2010 to February 2011. The tests include month-fixed effects, issuer-fixed effect, fund-fixed effects, sponsor-fixed effects, and issuer-type fixed effects. Standard errors are clustered at both the issuer- and the fund- levels. Regression results are reported in Table 25.

As shown in column (1), (3), (5) and (7), a strong *Past Relation* is associated with 0.26%-1.39% increase in MMF's exposure to a European issuer, but the coefficients of the interaction term *Past Relation* $\times$ *Post* are statistically and economically insignificant except for column (7), which means that MMFs' lending difference around the European bank crisis is not conditional on indirect relationship measures in existing literature. Moreover, in column (2), (4), (6) and (8), the coefficients of $BConnected \times Post$ remain positive and statistically significant after the control of $Past\ Relation$, therefore confirms that similar results in Table 14 are not simply dominated by indirect relationship measures in existing literature. These findings suggest that CHR is not simply a reflection of documented relationship strength by previous researches but helpful to deepen the understanding about the relationships mechanism.

H Multivariate Analysis of Securities Comparison

The following multivariate regression model tests changes of riskiness in depth.

$$\begin{aligned} Risk_{f,i,t} =& \alpha + \beta_1 BConnected_{f,i} \times Post + \beta_2 BConnected_{f,i} + \beta_3 Post \\ & + \lambda_1 Control_{f,t} + \lambda_2 Control_{i,t} + \varepsilon_{f,i,t}, \end{aligned} \tag{A.1}$$

where *Risk* is measured by *Spread*, *Maturity* and *Holdings Risk* at the fund-issuer-month level; independent variables are the same as these defined in the specification 4. I consider error terms to be within funds and within issuers, therefore standard errors are two-way clustered at the fund level and the issuer level.

Results of this difference-in-difference model are presented in Table 30. Except for Columns (2), all estimates of β_1 are close to zero, denoting that changes in riskiness of securities issued by connected and unconnected European issuers surrounding the European bank crisis are the same. In other words, although the cross-holding relationship makes a difference in lending, there is no difference in securities' riskiness.

However, Table 30 conveys information about fund-issuer pairs' other features that affect *Risk*: (1) the bilateral connection is associated with lower *Risk*; (2) the post-period is associated with lower *Risk*. These two findings indicate that, securities in the connected fund-issuer pairs are less risky across the entire sample period, and MMFs hold less risky securities after the European bank crisis.

I The Dodd-Frank Banking Stress Test

In the wake of the financial crisis, the U.S. Congress enacted the Dodd-Frank Wall Street Reform and Consumer Protection Act (Dodd-Frank Act). The act requires the Federal Reserve to conduct an annual stress test of large bank holding companies (BHCs) to evaluate whether they have sufficient capital to absorb losses resulting from adverse economic conditions. The Federal Reserve adopted rules implementing these requirements since October 2012. The results of the first Dodd-Frank banking stress test were released in March 2013 with 18 BHCs under the supervisory stress test. The 18 BHCs are: Ally Financial, American Express, Bank of America, the Bank of New York Mellon, BB&T, Capital One Financial, Citigroup, Fifth Third Bancorp, the Goldman Sachs Group, JPMorgan, KeyCorp, Morgan Stanley, the PNC Financial Services Group, Regions Financial Corporation, State Street Corporation, SunTrust Banks, U.S. Bancorp, and Wells Fargo.

The 2013 test examined how bank balance sheets would hold up under the pressure of an extremely adverse economic scenario, which included a severe recession in the U.S. combined with a housing market drop, rising unemployment, a global financial shock, and marked slowdowns in major foreign financial markets.

Of particular focus in the Dodd-Frank test is the tier 1 common ratio. The mandated minimum level by regulators was 5% and the median among tested BHCs was 7.7% in 2013. Though only Ally Financial failed the test seriously, many of the rest 17 BHCs who passed the test had their tier 1 common ratios quite close to 5% and much lower than 7.7%, including Bank of America, the Goldman Sachs Group, JPMorgan, Morgan Stanley, and Wells Fargo. These BHCs' creditworthiness was affected by the release of the stress test results in March 2013, though not as severely as European banks in the European bank Crisis.

Among the 18 BHCs tested by the first Dodd-Frank Stress Test in 2013, six BHCs have their tier 1 common ratios quite close to the mandated minimum level 5% and much lower than the median 7.7%. This six BHCs are Ally Financial, Bank of America, the Goldman Sachs Group, JPMorgan, Morgan Stanley, and Wells Fargo. Except for the first one, the rest five are all involved in CHR in the MMF market. Though the release of the stress test results in March 2013 is less impactful than the series of events happened on European banks in mid-2011, the creditworthiness of these BHCs that showed low capital ratios was also affected. In this section, I conduct the tests that are similar to specification 4, using December 2012 to February 2013 as the pre-period and March-May 2013 as the post-period. Changes of *Exposure* are reported in Table 32.

From Column 1 to Column 5, though weaker in statistical significance (10%) than those in Table 16, I find a positive relationship between the bilateral connection and fund-issuer pairs' exposure in the post-period: after the 2013 Dodd-Frank Stress Test, a MMF's exposure to their bilaterally-connected issuers which are disclosed with low tier 1 common ratios increases by 0.51%-0.60% of its portfolio holdings. The tests reflect CHR influences MMFs' lending after the 2013 Dodd-Frank stress test, in a similar though weaker pattern that it influences MMFs surrounding the 2011 European bank crisis.

Tests of *Holdings Risk* in the reverse pairs are shown in Table 33. The results are much weaker given the stress test results do not create a shock as big as the one by Moody's downgrading review in 2011, plus, financial firms involved in this event are all very large BHC, which are much robust and less volatile.

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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
Book Leverage	169116	0.291	0.301	0.026	0.214	0.436
Market Leverage	145265	0.373	0.467	0.011	0.164	0.544

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 Δ*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 $\Delta Lending$ 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 $\Delta Borrowing$, the total change of loan borrowing of each non-shocked firm surrounding natural disasters, on $Firm\text{-}Disaster\text{-}Exposure$, 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×Year FE	N	Y	Y	N	Y	Y
Disaster Operations & Suppliers	N	N	Y	N	N	Y
Fixed Effects	Borrower, Industry × Year					
Control Variables	Size-, Age-, ROA-tercile×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-$\widehat{\text{Disaster}}$-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× 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)
$\widehat{\text{Firm-Disaster-Exposure}}$× 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×Year, State×Year, Industry×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× 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)
$\widehat{\text{Firm-Disaster-Exposure}}$× 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×Year, State×Year, Industry×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

Panel A reports summary statistics of prime money market funds in the sample during the whole March-August 2011 period. *Total Net Asset*, *Portfolio Maturity* are as reported in N-MFP. *Age*, *Institutional Shares* and *Expense Ratio* are value-weighted averages of class-level characteristics from CRSP. *Fund Flow* is the difference between *Subscription* and *Redemption*, which are value-weighted averages of the same class-level items from N-MFP. *Gross Yield* is the annualized fund-level 7-day gross yield from N-MFP. *Net Yield* is the value-weighted average of annualized class-level 7-day net yield from N-MFP. *Connceted Share* is the share of fund's assets invested in bilaterally-connected partners. *Euro Share* is the share of fund's assets invested in European banks. Standard deviations are presented in the parentheses. Panel B reports summary statistics of issuers that are financial firms in the sample during the whole March-August 2011 period. For an issuer, $Outstanding$ is the total value of its issued money market instruments, *Portfolio Weight*,*Yield*, *Net Yield* and *Maturity* are value-weighted averages of these instruments' MMF portfolio weight, yield, net yield and maturity, respectively. Standard deviations are presented in the parentheses.

Table 10: Summary Statistics: Funds and Issuers

	Mean	SD	Mean	SD	Mean	SD
Panel A: Funds						
	All		Stand-Alone Funds		Dual-Role Funds	
			Fund Characteristics			
Total Net Assets ($billions)	7.05	16.23	2.26	5.14	9.63	19.29
Institutional Share(%)	33.24	43.23	22.91	37.28	39.14	45.26
Age(years)	18.62	8.36	19.81	8.29	17.94	8.32
Portfolio Maturity(days)	38.40	11.08	38.34	11.51	38.43	10.85
Expense Ratio(bps)	28.35	9.40	30.01	11.95	27.56	7.76
Gross Yield(bps)	22.76	7.50	20.74	7.52	23.87	7.25
Net Yield(bps)	3.43	7.83	2.59	5.34	3.88	8.85
Fund Flow(bps)	-20.82	2237.97	15.78	946.20	-40.50	2687.24
Connected Share (%)	7.22	10.29	0.00	0.00	14.40	10.38
Euro Share (%)	36.38	16.57	27.02	17.07	41.13	14.11
			Instrument Shares(%)			
ABCP	10.41	11.86	9.67	13.11	10.81	11.10
Bank Obligation	17.95	16.22	10.79	13.21	21.84	16.38
Financial CP	15.12	10.78	15.05	12.32	15.16	9.84
Government/Agency	23.53	18.91	32.01	24.25	18.94	13.14
Non-financial CP	8.50	14.21	13.85	16.19	5.59	12.06
Government/Agency Repo	8.50	11.51	6.43	11.96	9.63	11.11
Treasury Repo	3.13	7.26	2.12	5.33	5.59	12.06
Other Repo	2.14	5.03	0.63	4.03	9.63	11.11
Other	7.98	8.09	6.28	7.92	8.89	8.04
Panel B: Issuers						
	All		Issuers Only		Dual-Role Issuers	
			Issuers Characteristics			
Outstanding ($billions)	8.63	15.17	7.18	14.10	15.81	18.02
Exposure (%)	2.39	2.3	2.22	2.52	3.22	1.61
Weighted Average Yield (bps)	30.48	20.42	32.7	21.69	20.13	6.28
Weighted Average Net Yield (bps)	26.1	20.07	28.3	21.32	15.88	6.08
Weighted Average Maturity (days)	48.5	42.97	50.44	44.79	39.11	31.22
Number of Funds	40.01	53.34	32.88	49.78	75.14	56.48
			Issuers Shares (%)			
ABCP	10.46	26.22	8.55	25.11	19.69	29.45
Bank Obligation	39.16	42.23	43.62	43.49	17.51	26.51
Financial CP	26.62	36.35	27.47	37.23	22.51	31.49
Non-financial CP	11.2	27.69	12.42	29.76	5.25	12.23
Government/Agency Repo	3.71	12.94	1.61	9.21	13.88	21.1
Treasury Repo	0.01	0.08	0.01	0.08	0.03	0.06
Other Repo	2.25	8.22	0.87	4.04	8.96	16.23

Table 11: Summary Statistics: Fund-Issuer Pairs

	N	Mean	SD	Percentile 25	50	75
Panel A: All						
Outstanding ($1M)	34129	215.78	514.47	10.00	44.99	190.09
Exposure (%)	34129	2.73	2.71	1.05	2.10	3.64
Spread (bp)	29398	21.04	12.30	13.80	20.40	27
Maturity (days)	33918	54.27	58.85	11.62	36.26	75
Holdings Risk (bp)	34129	25.61	55.30	0.00	0.00	93.14
Panel B: European Issuers						
Outstanding ($1M)	17385	256.75	570.57	12.30	53.99	230.00
Exposure (%)	17385	2.97	2.75	1.21	2.35	3.93
Spread (bp)	14924	23.05	12.39	16.00	22.20	29.2
Maturity (days)	17317	50.66	52.03	12.94	36.10	70.41
Holdings Risk (bp)	17385	27.78	54.06	0.00	0.00	89.68

This table reports summary statistics of fund-issuer pairs in the sample during the whole March-August 2011 period. For each fund(f)-issuer(i) pair, *Exposure* is the value weight of an issuer's securities in a fund's portfolio holdings, *Outstanding* is the total value of money market instruments that are issued by issuer i and held by fund f in month t, *Spread* is a security's gross yield net of one-month T-bill rate. *Maturity* is a security's days-to-maturity. For each fund-issuer pair, both *Spread* and *Maturity* are value-weighed average. *Holdings Risk* is the weight of an issuer's bank obligations net of the weight of its safest securities in the same portfolio. The safest securities include government repo, agency repo and Treasury repo.

Table 12: Connected versus Unconnected Fund-Issuer Pairs

					Percentile				
		N	Mean	SD	Min	25	50	75	Max
CON	Exposure (%)	1947	3.07	2.74	0.25	0.98	2.21	4.25	10.27
	Outstanding ($1M)	1947	204.91	300.31	1.94	16.50	72.01	250.06	1129.00
	Yield (bps)	1674	19.99	8.67	5.00	13.58	19.97	26.23	35.44
	Net Yield (bps)	1674	15.07	8.46	0.00	9.00	15.00	21.14	30.82
	Maturity (days)	1947	34.77	38.14	1.00	3.53	20.64	52.75	133.00
UCON	Exposure (%)	32182	2.49	1.75	0.30	1.06	2.10	3.61	6.66
	Outstanding ($1M)	32182	160.70	253.76	0.79	10.00	43.00	185.71	956.86
	Yield (bps)	27724	25.98	10.63	6.86	18.90	26.00	32.42	47.81
	Net Yield (bps)	27724	21.03	10.33	2.64	14.00	20.88	27.30	42.60
	Maturity (days)	31971	52.38	49.95	1.00	12.06	37.41	76.00	178.58

This table reports distributions of key variables across different fund-issuer pairs in the sample during the whole March-August 2011 period. Variable definitions appear in Appendix D A fund-issuer pair (f,i) is called "connected" if the issuer i has an affiliated MMF that simultaneously holds securities issued by the financial firm who owns fund f in the pre-period.

Table 13: Changes of MMF's Exposure between the Pre- and Post-Periods

	Pair	Post		Pre			
	Number	Mean(%)	SD(%)	Mean(%)	SD(%)	Diff(%)	SD(%)
Panel A: European Issuers							
Connected	148	4.013***	3.906	3.660***	3.465	0.352**	1.564
Unconnected	3714	2.174***	1.802	2.408***	1.717	-0.234***	1.408
Panel B: Non-European Issuers							
Connected	278	2.112***	1.928	2.021***	2.032	0.091	1.350
Unconnected	3583	1.990***	1.600	1.811***	1.547	0.179***	1.214

This table reports changes of *Exposure* in fund-issuer pairs surrounding Moody's review. For each fund-issuer pair, *Exposure* is the value weight of an issuer's securities in a fund's portfolio holdings, calculated as: $Exposure_{f,i,t} = \frac{Outstanding_{f,i,t}}{\sum_i Outstanding_{f,i,t}}$, where $Outstanding_{f,i,t}$ is the total value of money market instruments that are issued by issuer i and held by fund f in month t, and $\sum_i Outstanding_{f,i,t}$ is the total value of fund f's portfolio holding in month t. "Pre" is the period from March to May in 2011, "Post" is the period from June to August in 2011. ***, **,* indicate statistical significance at 1%, 5% and 10% respectively, and connected pairs' statistical significance is based on bootstrapped p-values.

Table 14: Changes in MMFs' Exposure to European Borrowers between the Pre- and Post-Periods

	(1)	(2)	(3)	(4)	(5)
BConnected × Post	0.379***	0.446***	0.403***	0.403***	0.361**
	(0.134)	(0.134)	(0.132)	(0.133)	(0.140)
BConnected	1.121*	0.063	0.215	0.215	0.923**
	(0.585)	(0.283)	(0.279)	(0.280)	(0.387)
Post	-0.320**	-0.056	-0.034	-0.112*	-0.296*
	(0.157)	(0.083)	(0.077)	(0.061)	(0.166)
Conglomerate × Post					0.591**
					(0.288)
Conglomerate					0.075
					(0.096)
Fund Size	-0.175	-0.176***	-0.203	-0.203	-0.178
	(0.210)	(0.043)	(0.227)	(0.227)	(0.212)
Net Yield (bps)	-0.016	0.012	-0.013	-0.013	-0.015
	(0.010)	(0.017)	(0.011)	(0.012)	(0.009)
Age(years)	-0.027	0.004	-0.033	-0.033	-0.031
	(0.032)	(0.007)	(0.033)	(0.033)	(0.032)
Expense Ratio(bps)	-0.017*	-0.003	-0.019*	-0.019*	-0.016
	(0.010)	(0.009)	(0.010)	(0.010)	(0.010)
Institutional Share(%)	3.806**	0.202	3.931***	3.931***	3.883**
	(1.441)	(0.156)	(1.407)	(1.411)	(1.482)
Fund Flow(bps)	-0.002	-0.001	-0.001	-0.001	-0.002
	(0.003)	(0.006)	(0.004)	(0.004)	(0.003)
CDS Rate(%)	0.252***	-0.027	-0.060	-0.060	0.210***
	(0.091)	(0.062)	(0.056)	(0.056)	(0.071)
Month-Fixed Effects	Y	Y	Y	Y	Y
Fund-Fixed Effects	Y	N	Y	Y	Y
Issuer-Fixed Effect	N	Y	Y	Y	N
Sponsor-Fixed Effects	N	N	N	Y	Y
Issuer-Type-Fixed Effects	N	N	N	Y	N
Observations	10835	10835	10835	10835	10835
Adjusted R^2	0.268	0.276	0.421	0.421	0.289

The sample is fund-issuer pairs with European issuers for the whole March-August 2011 period. The dependent variable is fund-issuer pairs' exposure winsorized at the 5th and 95th percentiles. Variable definitions appear in Appendix D All regressions are at the monthly level. Reported in the parentheses are two-way clustered standard errors at the fund- and the issuer- level. ***, **,* indicate statistical significance at 1%, 5% and 10% respectively.

Table 15: Changes in MMFs' Exposure to European Borrowers: Placebo Tests

	(1)	(2)	(3)	(4)	(5)
Panel A: November 2010-April 2011					
BConnected × Post	-0.138	-0.073	-0.070	-0.070	-0.133
	(0.156)	(0.126)	(0.115)	(0.115)	(0.150)
Bconnected	0.584	-0.417	-0.278**	-0.277**	0.382
	(0.586)	(0.264)	(0.136)	(0.135)	(0.378)
Post	-0.081	0.152	0.034	0.137	-0.066
	(0.076)	(0.098)	(0.022)	(0.090)	(0.077)
Conglomerate × Post					0.826**
					(0.362)
Conglomerate					-0.075
					(0.071)
Observations	9772	9773	9772	9772	9772
R^2	0.239	0.272	0.429	0.429	0.272
Panel B: December 2010-May 2011					
BConnected × Post	-0.097	-0.002	-0.011	-0.013	-0.058
	(0.155)	(0.109)	(0.094)	(0.090)	(0.104)
Bconnected	0.622	-0.425	-0.268	-0.266	0.410
	(0.644)	(0.302)	(0.177)	(0.176)	(0.424)
Post	0.075	0.135	0.068	0.068	0.123
	(0.100)	(0.100)	(0.097)	(0.096)	(0.117)
Conglomerate × Post					0.875**
					(0.396)
Conglomerate					-0.221**
					(0.110)
Observations	11818	11819	11818	11818	11818
R^2	0.232	0.274	0.426	0.426	0.264
Controls	Y	Y	Y	Y	Y
Month-Fixed Effects	Y	Y	Y	Y	Y
Fund-Fixed Effects	Y	N	Y	Y	Y
Issuer-Fixed Effects	N	Y	Y	Y	N
Sponsor-Fixed Effects	N	N	N	Y	Y
Issuer-Type-Fixed Effects	N	N	N	Y	N

The sample is fund-issuer pairs with European issuers for periods before Moody's review in 2011, November 2010-April 2011 for Panel A, December 2010-May 2011 for Panel B. The dependent variable is fund-issuer pairs' exposure winsorized at the 5th and 95th percentiles. *Post* equals one when *t* represents a month in the post-period, which is defined as the first three months of the corresponding placebo sample. Other variables are the same with the ones in Table 14. All regressions are at the monthly level. Reported in the parentheses are two-way clustered standard errors at the fund- and the issuer- level. ***, **,* indicate statistical significance at 1%, 5% and 10% respectively.

Table 16: Changes in Exposure to All Borrowers between the Pre- and Post-Periods

	(1)	(2)	(3)	(4)
BConnected × Post × European Issuer	0.458*	0.510**	0.542**	0.542**
	(0.245)	(0.231)	(0.241)	(0.241)
BConnected × Post	-0.143	-0.101	-0.158	-0.158
	(0.186)	(0.176)	(0.186)	(0.187)
BConnected× European Issuer	0.673	0.119	0.321	0.321
	(0.560)	(0.481)	(0.388)	(0.389)
Post × European Issuer	-0.130**	-0.209***	-0.220***	-0.220***
	(0.057)	(0.051)	(0.052)	(0.052)
BConnected	0.368	-0.022	-0.025	-0.025
	(0.249)	(0.392)	(0.289)	(0.289)
Post	0.082*	0.165***	0.146***	0.146***
	(0.045)	(0.049)	(0.045)	(0.045)
European Issuer	0.436***			
	(0.156)			
Fund Size	-0.163	-0.213***	-0.115	-0.115
	(0.149)	(0.034)	(0.132)	(0.132)
Net Yield (bps)	-0.017**	0.008	-0.009	-0.009
	(0.007)	(0.013)	(0.006)	(0.006)
Age (years)	0.011	0.005	-0.009	-0.009
	(0.027)	(0.006)	(0.024)	(0.024)
Expense Ratio(bps)	-0.002	-0.008	-0.003	-0.003
	(0.007)	(0.007)	(0.008)	(0.008)
Institutional Share(%)	1.564	0.060	1.325	1.325
	(0.974)	(0.130)	(0.956)	(0.957)
Fund Flow (%)	-0.000	0.002	0.000	0.000
	(0.002)	(0.004)	(0.002)	(0.002)
Month-Fixed Effects	Y	Y	Y	Y
Fund-Fixed Effects	Y	N	Y	Y
Issuer-Fixed Effect	N	Y	Y	Y
Sponsor-Fixed Effects	N	N	N	Y
Issuer-Type-Fixed Effects	N	N	N	Y
Observations	23018	23018	23018	23018
Adjusted R^2	0.246	0.282	0.405	0.405

The sample is all fund-issuer pairs for the whole March-August 2011 period. The dependent variable is fund-issuer pairs' exposure winsorized at the 5th and 95th percentiles. *European Issuer* is a dummy equal to one for issuers who are from Europe. Variable definitions appear in Appendix D Reported in the parentheses are two-way clustered standard errors at the fund- and the issuer- level. ***, **,* indicate statistical significance at 1%, 5% and 10% respectively.

Table 17: Fund Flows during the Pre- and Post-periods

	March-May 2011		June-August 2011	
	(1)	(2)	(3)	(4)
Panel A: All Funds				
Fund Euro Share	1.220	0.946	-3.099***	-2.269*
	(1.155)	(1.191)	(1.178)	(1.226)
Fund Size	0.367***	0.117	-0.303***	-0.142
	(0.090)	(0.103)	(0.114)	(0.130)
Net Yield (bps)		0.080*		-0.027
		(0.043)		(0.089)
Institutional Share		1.098**		-2.185***
		(0.494)		(0.594)
Constant	-8.582***	-4.154**	7.805***	5.328**
	(1.822)	(2.080)	(2.331)	(2.595)
Month-Fixed Effects	Y	Y	Y	Y
Observations	678	591	680	589
Adjusted R^2	0.031	0.046	0.048	0.081
Panel B: Funds Involved in CHR with European Issuers				
Fund Euro Share	1.420	3.654	-4.287*	-4.899**
	(3.011)	(3.504)	(2.381)	(2.386)
Fund Size	0.371**	0.254	-0.689***	-0.689**
	(0.153)	(0.258)	(0.191)	(0.271)
Net Yield (bps)		0.096		-0.037
		(0.179)		(0.284)
Institutional Share		-0.279		-2.442**
		(1.377)		(1.165)
Constant	-7.224**	-6.002	15.763***	17.034***
	(3.446)	(5.597)	(4.258)	(5.633)
Month-Fixed Effects	Y	Y	Y	Y
Observations	171	134	173	135
Adjusted R^2	0.040	0.051	0.106	0.193
Panel C: Funds not Involved in CHR with European Issuers				
Fund Euro Share	0.376	-0.653	-2.148	-1.973
	(1.293)	(1.353)	(1.584)	(1.684)
Fund Size	0.349***	0.077	-0.149	0.049
	(0.107)	(0.115)	(0.143)	(0.156)
Net Yield (bps)		0.088**		-0.021
		(0.044)		(0.092)
Institutional Share		1.513***		-1.916***
		(0.558)		(0.726)
Constant	-7.960***	-2.864	2.614	-0.495
	(2.117)	(2.264)	(2.886)	(3.099)
Month-Fixed Effects	Y	Y	Y	Y
Observations	507	457	507	454
Adjusted R^2	0.025	0.051	0.041	0.065

The dependent variable is the monthly net flow ratio ($Fund\ Flow$), the pre-period in columns 1-2, the post-period in columns 3-4. $Fund\ Flow$s are winsorized at the 5th and 95th percentiles. Variable definitions appear in Appendix D All regressions are at the monthly level. Reported in the parentheses are robust standard errors. ***, **,* indicate statistical significance at 1%, 5% and 10% respectively.

Table 18: Changes of Securities' Riskiness between the Pre- and Post-Periods

	Pair	Post		Pre			
	Number	Mean	SD	Mean	SD	Diff	SD
Panel A: Spread (bps)							
Connected	148	17.670***	13.318	17.675***	12.028	-0.005	6.730
Unconnected	3714	22.628***	11.479	22.694***	11.742	-0.066	6.568
Panel B: Maturity (days)							
Connected	148	24.854***	25.096	34.552***	28.920	-9.698***	29.875
Unconnected	3714	42.452***	45.234	53.037***	50.218	-10.585***	36.182
Panel C: Holding Risk (bps)							
Connected	148	-7.808	61.080	-7.034	63.261	-0.774	32.837
Unconnected	3714	24.813***	54.062	28.237***	52.328	3.424*	27.725

This table reports changes of securities' riskiness in fund-issuer pairs surrounding Moody's review. The sample is fund-issuer pairs with European issuers for the whole March-August 2011 period. Variable definitions appear in Appendix D "Pre" is the period from March to May in 2011, "Post" is the period from June to August in 2011. ***, **,* indicate statistical significance at 1%, 5% and 10% respectively, and connected pairs' statistical significance is based on bootstrapped p-values.

Table 19: The Comparison between Reverse Pairs and Other Fund-Issuer Pairs

	Pair	Post		Pre			
	Number	Mean	SD	Mean	SD	Diff	SD
Panel A: Exposure (%)							
Reverse Pairs	500	1.577***	1.803	1.445***	1.860	0.132*	1.533
Other Pairs	6474	2.124***	2.382	2.110***	2.429	-0.014	2.194
Panel B: Spread (bps)							
Reverse Pairs	500	15.221***	7.943	16.000***	8.880	-0.779*	4.853
Other Pairs	6474	18.655***	12.068	19.581***	12.284	-0.926*	6.125
Panel C: Maturity (days)							
Reverse Pairs	500	43.642***	53.506	51.364***	64.691	-7.722***	37.835
Other Pairs	6474	43.208***	48.348	50.396***	54.084	-7.188***	38.509
Panel D: Holding Risk (bps)							
Reverse Pairs	500	25.109	61.080	19.372	63.261	5.737***	30.797
Other Pairs	6474	19.756***	54.062	22.544***	52.328	-2.788**	24.094

This table compares securities in reverse fund-issuer pairs and those in other fund-issuer pairs (excluding bilateral connected pairs with European issuers) surrounding Moody's review. A fund-issuer pairs is called a reverse pair if, in the pre-period, the fund is sponsored by a European financial firm, and money market instruments issued by this firm are also held by the issuer's affiliated MMFs. Variable definitions appear in Appendix D ***, **,* indicate statistical significance at 1%, 5% and 10% respectively, and reverse pairs' statistical significance is based on bootstrapped *p*-values.

Table 20: Reciprocity: Changes in *Holdings Risk*

	(1)	(2)	(3)	(4)	(5)
Reverse Pair × Post	13.837***	13.901***	13.798***	15.464***	13.878***
	(4.011)	(1.923)	(3.231)	(3.998)	(2.251)
Reverse Pair	-25.939***	-0.438	-5.134	-24.778***	2.785
	(7.188)	(8.771)	(8.883)	(6.521)	(8.916)
Post	-5.013**	-3.170*	-2.556*	-5.566*	-3.188*
	(2.511)	(1.834)	(1.405)	(2.810)	(1.834)
BConnected	-24.992*	-4.512	3.542	-23.582**	-3.690
	(12.777)	(4.155)	(4.331)	(11.613)	(4.225)
European Issuer				-2.571	
				(8.642)	
European Fund Sponsor					-4.366
					(3.539)
Fund Size	1.844**	3.491***	1.656**	1.747**	3.421***
	(0.858)	(0.882)	(0.719)	(0.836)	(0.896)
Net Yield (bps)	-0.530	-0.266	-0.333	-0.514	-0.260
	(0.496)	(0.336)	(0.339)	(0.495)	(0.342)
Age (years)	-0.387***	-0.181	-0.269**	-0.379***	-0.186
	(0.130)	(0.153)	(0.119)	(0.132)	(0.151)
Expense Ratio(bps)	0.087	0.282	0.138	0.092	0.261
	(0.171)	(0.241)	(0.161)	(0.183)	(0.235)
Institutional Share(%)	-1.915	5.105	-0.567	-1.736	4.111
	(3.811)	(4.287)	(3.487)	(3.737)	(4.134)
Fund Flow (%)	0.086	0.142	0.032	0.089	0.148
	(0.069)	(0.128)	(0.063)	(0.072)	(0.127)
Month-Fixed Effects	Y	Y	Y	Y	Y
Fund-Fixed Effects	Y	N	Y	Y	N
Issuer-Fixed Effect	N	Y	Y	N	Y
Sponsor-Fixed Effects	N	N	N	Y	N
Issuer-Type-Fixed Effects	N	N	N	Y	Y
Observations	21843	21831	21831	21843	21831
Adjusted R^2	0.140	0.428	0.490	0.161	0.428

The sample is fund-issuer pairs (excluding bilateral connected pairs with European issuers) for the whole March-August 2011 period. The dependent variable is the portfolio weight difference between risky and risk-less assets holdings (*Holdings Risk*) per fund-issuer pair. Variable definitions appear in Appendix D All regressions are at the monthly level. Reported in the parentheses are two-way clustered standard errors at the fund- and the issuer- level. ***, **,* indicate statistical significance at 1%, 5% and 10% respectively.

Table 21: Reciprocity: the Decomposition of Changes in *Holdings Risk*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
			Bank Obligation					*Repo*		
Reverse Pair × Post	7.638**	7.380**	7.476***	10.171***	7.348**	-6.199***	-6.521***	-6.322***	-5.293**	-6.530***
	(3.457)	(3.237)	(2.709)	(3.305)	(3.184)	(2.242)	(1.227)	(1.305)	(2.345)	(1.254)
Reverse Pair	-18.491**	0.998	-0.508	-17.307**	5.447	7.447**	1.435	4.627	7.472***	2.663
	(8.266)	(6.371)	(6.310)	(7.823)	(6.702)	(3.730)	(4.299)	(5.014)	(2.737)	(4.008)
Post	-2.638	-1.331	-1.600	-2.809	-1.356	2.375	1.840*	0.956	2.757*	1.833*
	(1.620)	(1.357)	(0.987)	(1.813)	(1.350)	(1.483)	(0.992)	(0.677)	(1.422)	(1.005)
BConnected	-11.461	-1.370	4.832	-10.839	-0.234	13.531*	3.142	1.291	12.743*	3.455
	(9.094)	(3.923)	(4.759)	(8.524)	(3.364)	(7.891)	(3.801)	(3.252)	(7.545)	(3.709)
European Issuer				-2.101					0.469	
				(6.471)					(3.709)	
European Fund Sponsor					-6.029*					-1.663**
					(3.225)					(0.755)
Fund Size	2.321***	3.537***	2.088***	2.254***	3.441***	0.477	0.046	0.432	0.506	0.020
	(0.751)	(0.722)	(0.674)	(0.703)	(0.733)	(0.491)	(0.372)	(0.348)	(0.450)	(0.384)
Net Yield (bps)	-0.256	-0.026	-0.143	-0.259	-0.017	0.274	0.241	0.190	0.255	0.243
	(0.247)	(0.210)	(0.177)	(0.256)	(0.211)	(0.281)	(0.193)	(0.198)	(0.269)	(0.216)
Age (years)	-0.302**	-0.138	-0.240**	-0.301**	-0.145	0.085	0.043	0.030	0.078	0.041
	(0.128)	(0.139)	(0.117)	(0.129)	(0.136)	(0.095)	(0.064)	(0.068)	(0.089)	(0.068)
Expense Ratio(bps)	0.161	0.221	0.172	0.161	0.192	0.074	-0.061	0.033	0.069	-0.069
	(0.156)	(0.176)	(0.144)	(0.161)	(0.170)	(0.079)	(0.104)	(0.058)	(0.074)	(0.108)
Institutional Share(%)	-0.641	3.254	0.051	-0.513	1.881	1.274	-1.851	0.618	1.223	-2.230
	(3.747)	(3.442)	(3.384)	(3.573)	(3.139)	(1.258)	(1.629)	(0.978)	(1.074)	(1.598)
Fund Flow (%)	0.042	0.102	0.015	0.046	0.110	-0.044	-0.040	-0.017	-0.043	-0.038
	(0.059)	(0.108)	(0.050)	(0.053)	(0.110)	(0.032)	(0.038)	(0.031)	(0.034)	(0.051)
Observations	21843	21831	21831	21843	21831	21843	21831	21831	21843	21831
Adjusted R^2	0.151	0.421	0.488	0.189	0.423	0.102	0.387	0.441	0.138	0.387

The sample is fund-issuer pairs (excluding bilateral connected pairs with European issuers) for the whole March-August 2011 period. The dependent variable is the portfolio weight in *Bank Obligation* per fund-issuer pair. Variable definitions appear in Appendix D All regressions are at the monthly level. Reported in the parentheses are two-way clustered standard errors at the fund- and the issuer- level. ***, **,* indicate statistical significance at 1%, 5% and 10% respectively.

Table 22: Characteristics of Issuers in Different Issuer Groups

	$SEuro\ \ Fund\ \ Share$=0	$SEuro\ \ Fund\ \ Share$=1
Outstanding ($millions)	106.728	7917.022
Yield	0.016	0.023
European Issuer	21	65
Conglomerate	15	29
Number	130	165

This table reports characteristics of issuers in different $SEuro\ \ Fund\ \ Share$ groups, where $SEuro\ \ Fund\ \ Share$ is decided as: $SEuro\ \ Fund\ \ Share_{f,i,t} = \frac{\sum_f Outstanding_{f,i,t} \times SEuro\ \ Fund_f}{\sum_f Outstanding_{f,i,t}}$. $Outstanding$ is the value of each issuer's total shares across all MMFs. $Yield$ is the value-weighed average yield of each issuer's securities. $European\ \ Issuer$ is a dummy equal to one if the issuer comes from Europe. $Conglomerate$ is a dummy equal to one if the issuer's financial house is a conglomerate that also owns MMFs. $Number$ is the number of financial houses in each group.

Table 23: Spillover Effects on Different Issuer Groups

	$SEuro\ \ Fund\ \ Share$=0			$SEuro\ \ Fund\ \ Share$=1		
	(1)	(2)	(3)	(4)	(5)	(6)
Issuer Euro Share	-0.102	-0.118	-0.117	-1.129***	-0.821**	-0.804**
	(-0.367)	(-0.411)	(-0.404)	(-4.986)	(-3.254)	(-3.169)
European Issuer		0.035	0.036		-0.186*	-0.187*
		(0.246)	(0.250)		(-2.597)	(-2.605)
Yield			1.230			0.654
			(0.657)			(0.639)
Observations	130	130	130	165	165	165
Adjusted R^2	0.001	0.002	0.006	0.134	0.170	0.172

This table reports spillover effects on different $SEuro\ \ Fund\ \ Share$ groups, where $SEuro\ \ Fund\ \ Share$ is decided as: $SEuro\ \ Fund\ \ Share_{f,i,t} = \frac{\sum_f Outstanding_{f,i,t} \times SEuro\ \ Fund_f}{\sum_f Outstanding_{f,i,t}}$. The dependent variable is $\Delta Outstanding$, the percentage change in the issuer's average $Outstanding$ between the pre-and post-period. $Issuer\ \ Euro\ \ Share$ is calculated as: $Issuer\ \ Euro\ \ Share_{i,t} = \frac{\sum_f Outstanding_{f,i,t} \times Fund\ \ Euro\ \ Share_{f,t}}{\sum_f Outstanding_{f,i,t}}$, given $Fund\ \ Euro\ \ Share$ is a fund's total exposure to European issuers. $European\ \ Issuer$ is a dummy equal to one if the issuer comes from Europe.$Yield$ is the value-weighed average yield of each issuer's securities. Robust standard errors are applied. T-statistics are reported in the parentheses. ***, **,* indicate statistical significance at 1%, 5% and 10% respectively.

Table 24: Summary Statistics: Securities

Security Type	Yield(bps)		Maturity(days)		U.S.(%)		Europe(%)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Panel A: Non-Government Securities								
ABCP	25.46	3.31	43.74	7.49	52.52	6.04	40.06	8.22
Bank Obligation	27.52	3.67	62.7	18.67	31.02	6.19	40.12	12.87
Financial CP	26.91	4.49	57.1	5.64	22.7	1.34	43.87	6.28
Government/Agency Repo	15.12	5.20	3.82	1.73	43.25	3.81	53.77	5.69
Treasury Repo	10.17	5.36	8.81	38.94	36.76	8.41	61.91	7.84
Other Repo	38.19	3.76	18.87	13.70	43.76	2.36	50.72	4.20
Non-financial CP	17.84	2.57	49.72	5.25	60.71	4.61	32.78	3.19
Panel B: Government or Agency Securities								
Government/Agency	15.45	2.02	117.36	74.10				
Treasury	16.53	2.06	120.58	10.95				
Municipal/Agency Debt	18.21	5.40	176.67	811.87				

This table reports summary statistics of non-government securities in panel A and that of government/agency securities in panel B. The sample period is the whole March-August 2011 period. *Yield* and *Maturity* are value-weighted average of corresponding security-level characteristics. *U.S. (%)* and *Europe (%)* represents the dollar ratio of one type of security issued in the U.S. and Europe respectively. Standard deviations of the given characteristics are presented in the parentheses.

Table 25: Bilateral Connection and Past Relation

	Frequency		Maturity		Quantity (Issuer Based)		Quantity (Fund Based)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
BConnected		0.407***		0.408***		0.416***		0.470***
× Post		(0.146)		(0.126)		(0.125)		(0.175)
BConnected		0.216		0.207		0.194		0.164
		(0.220)		(0.295)		(0.310)		(0.179)
Post	0.112	0.094	-0.009	-0.030	0.033	0.016	0.147	0.129
	(0.096)	(0.090)	(0.099)	(0.094)	(0.084)	(0.080)	(0.095)	(0.088)
Past Relation	-0.137	-0.142	0.087	0.089	0.034	0.026	-0.293***	-0.309***
× Post	(-0.093)	(-0.094)	(-0.064)	(-0.063)	(-0.079)	(-0.078)	(-0.082)	(-0.083)
Past Relation	1.083***	1.085***	0.271***	0.269***	0.940***	0.943***	1.385***	1.391***
	(-0.097)	(-0.097)	(-0.087)	(-0.088)	(-0.115)	(-0.116)	(-0.098)	(-0.099)
Fund Size	-0.164	-0.173	-0.138	-0.146	-0.178	-0.189	-0.143	-0.153
	(0.240)	(0.232)	(0.239)	(0.230)	(0.248)	(0.239)	(0.248)	(0.239)
Net Yield (bps)	-0.015	-0.014	-0.013	-0.012	-0.011	-0.010	-0.014*	-0.013
	(0.009)	(0.010)	(0.011)	(0.012)	(0.009)	(0.010)	(0.008)	(0.009)
Age (years)	-0.031	-0.029	-0.032	-0.030	-0.032	-0.030	-0.027	-0.025
	(0.033)	(0.033)	(0.031)	(0.031)	(0.033)	(0.032)	(0.037)	(0.036)
Expense	-0.020*	-0.020*	-0.020*	-0.020*	-0.018*	-0.018*	-0.021*	-0.021*
Ratio(bps)	(0.011)	(0.011)	(0.011)	(0.011)	(0.010)	(0.010)	(0.011)	(0.011)
Institutional	4.234***	4.213***	3.926***	3.899***	4.121***	4.103***	3.651**	3.616**
Share(%)	(1.425)	(1.402)	(1.419)	(1.398)	(1.459)	(1.432)	(1.551)	(1.526)
Fund Flow (%)	-0.002	-0.001	-0.002	-0.002	-0.002	-0.001	-0.002	-0.001
	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)
CDS Rate (%)	-0.065	-0.058	-0.063	-0.056	-0.068	-0.061	-0.039	-0.030
	(0.056)	(0.056)	(0.056)	(0.056)	(0.058)	(0.057)	(0.056)	(0.056)
Observations	10833	10833	10833	10833	10833	10833	10833	10833
Adjusted R^2	0.463	0.464	0.422	0.424	0.440	0.442	0.494	0.495

The sample is fund-issuer pairs with European issuers for the whole March-August 2011 period. The dependent variable is fund-issuer pairs' exposure winsorized at the 5th and 95th percentiles. $Past\ Relation_{f,i}$ is measured in the October 2010-February 2011 period using different measures: *Frequency* is a dummy equal to one if a fund lends more frequently to an issuer than the median fund does; *Maturity* is a dummy equal to one if a fund-issuer pair's maturity is longer than the issuer's median borrowing maturity; $Quantity\ (Issuer\ Based)$ is a dummy equal to one if a fund-issuer pair's portfolio share is above that issuer's median portfolio share; $Quantity\ (Fund\ Based)$ is a dummy equal to one if a fund-issuer pair's portfolio share is above that fund's median portfolio share. Other variable definitions appear in Appendix D All regressions are at the monthly level, include month-fixed effects, issuer-fixed effect, fund-fixed effects, sponsor-fixed effects, and issuer-type fixed effects. Reported in the parentheses are two-way clustered standard errors at the fund- and the issuer- level. ***, **,* indicate statistical significance at 1%, 5% and 10% respectively.

Table 26: 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 months 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. $Disaster\text{-}Firm_{i,t}$ is a firm-loan-level dummy equals one to denote loans issued during the 12 months window after the firm is hit by a natural disaster. $Strong\text{-}Relation_{i,j,t}$ is the lender-based strong relationship variable measured either in lending size or in lending frequency. Control 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 27: 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-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***		
×Weak Relation^{size}			(-4.242)	(-4.207)		
Weak Relation^{freq}					-0.447	-0.411
					(-1.175)	(-1.151)
Disaster-Lending					-0.355***	-0.368***
×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×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 28: 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. *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	-0.147*	-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 ×Weak Relation		-0.373***				4.150**		
		(-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} ×Weak Relation^{freq}				-0.312**				4.774**
				(-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 29: 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 $\times$Weak Relation		-0.314***			-0.253***	
		(-4.384)			(-4.490)	
Weak Relation^{freq}			-0.495			-0.367
			(-1.052)			(-1.234)
Bank-Disaster-Exposure^{freq} $\times$Weak Relation^{freq}			-0.380***			-0.196***
			(-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

Table 30: Changes in Securites' Risk among Different Fund-Issuer Pairs between the Pre- and Post-Periods

	Spread			Maturity			Holding Risk		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
BConnected × Post	0.018	-1.250*	-1.175	-1.052	-0.127	0.879	7.892	5.294	5.949
	(0.779)	(0.658)	(0.803)	(7.192)	(7.029)	(6.974)	(5.632)	(5.359)	(5.298)
BConnected	-5.413***	-0.431	0.097	-18.411**	-7.550*	-0.498	-48.791***	-22.500***	-20.731***
	(1.709)	(0.928)	(1.639)	(8.353)	(4.061)	(6.107)	(14.506)	(5.494)	(7.236)
Post	0.549	-1.496***	0.518	-5.538	-12.966**	-5.371***	-1.858	-2.818	1.306
	(1.156)	(0.478)	(0.599)	(4.136)	(5.764)	(1.312)	(4.301)	(2.420)	(2.815)
Fund Size	-3.494***	0.596**	-4.022***	-22.242***	1.676*	-20.605**	-4.315	-3.582***	-6.500
	(1.047)	(0.290)	(0.817)	(8.250)	(0.990)	(8.248)	(6.107)	(1.105)	(6.188)
Net Yield (bps)	0.066	0.441**	0.072	-0.104	0.444	-0.017	0.499	-0.488	0.483*
	(0.088)	(0.199)	(0.103)	(0.380)	(0.475)	(0.356)	(0.315)	(0.495)	(0.281)
Age (years)	-0.283	-0.015	-0.274	-1.619	0.079	-1.271	-0.066	0.218	-0.019
	(0.248)	(0.051)	(0.259)	(1.377)	(0.151)	(1.285)	(0.848)	(0.204)	(0.916)
Expense Ratio(bps)	0.086	0.392***	0.086	0.178	0.479*	-0.007	0.000	-0.193	0.069
	(0.079)	(0.098)	(0.068)	(0.356)	(0.279)	(0.347)	(0.414)	(0.267)	(0.343)
Institutional Share(%)	3.072	0.689	5.329	26.705	-0.200	16.951	9.401	3.813	5.878
	(10.204)	(1.683)	(10.635)	(36.666)	(3.040)	(42.034)	(37.309)	(4.654)	(38.807)
Fund Flow(bps)	-0.004	-0.090**	-0.009	0.054	-0.124	0.074	0.024	-0.028	-0.006
	(0.025)	(0.040)	(0.025)	(0.078)	(0.145)	(0.072)	(0.095)	(0.132)	(0.099)
CDS Rate(%)	1.571***	-0.541	-0.785	-8.233***	-5.061**	-5.871**	-3.819	-3.686**	-3.554**
	(0.582)	(0.556)	(0.483)	(3.052)	(2.209)	(2.248)	(2.480)	(1.640)	(1.693)
Month-Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fund-Fixed Effects	Y	N	Y	Y	N	Y	Y	N	Y
Issuer-Fixed Effect	N	Y	Y	N	Y	Y	N	Y	Y
Sponsor-Fixed Effects	N	N	Y	N	N	Y	N	N	Y
Observations	9065	9063	9063	10812	10811	10810	10835	10834	10833
Adjusted R^2	0.304	0.285	0.454	0.161	0.238	0.332	0.190	0.330	0.444

The sample is fund-issuer pairs with European issuers for the whole March-August 2011 period. As defined in Table 8, the dependent variables are *Spread* in columns (1) to (3), *Maturity* in columns (4) to (6), and *Holdings Risk* in columns (7) to (9). Other variable definitions appear in Appendix D All regressions are at the monthly level. In the parentheses are two-way clustered standard errors at the fund- and the issuer- level. ***, **,* indicate statistical significance at 1%, 5% and 10% respectively.

Table 31: Reciprocity: Changes in *Exposure*, *Spread*, and *Maturity*

	(1)	(2)	(3)						
	Exposure			Spread			Maturity		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Reverse Pair × Post	-0.127	-0.129	-0.165	-0.977*	-0.386	-1.320*	2.956	3.355	1.942
	(0.183)	(0.131)	(0.125)	(0.583)	(0.636)	(0.721)	(3.414)	(3.631)	(4.237)
Reverse Pair	0.489	0.424	0.568	-1.285	-2.021	-0.931	0.450	-10.402***	4.498
	(0.317)	(0.405)	(0.381)	(1.772)	(1.550)	(1.951)	(8.698)	(3.477)	(8.725)
Post	0.001	0.050	0.063	-2.259***	-0.221	-1.693***	-9.324***	-9.578***	-4.246
	(0.026)	(0.050)	(0.068)	(0.317)	(0.589)	(0.506)	(1.943)	(2.870)	(2.625)
BConnected	-0.232	0.082	-0.242	-0.435	-4.047***	-0.710	-3.521	-18.778***	-6.190**
	(0.238)	(0.288)	(0.334)	(1.519)	(1.255)	(1.459)	(4.484)	(5.680)	(2.366)
European Issuer		0.476***			3.257***			-14.513*	
		(0.162)			(1.149)			(7.979)	
European Fund Sponsor			-0.477***			-0.107			2.434
			(0.134)			(0.820)			(3.574)
Fund Size	-0.090**	-0.102**	-0.197***	0.173	0.195	0.594**	1.422**	1.256	2.174**
	(0.041)	(0.043)	(0.039)	(0.131)	(0.172)	(0.269)	(0.646)	(0.791)	(0.931)
Net Yield (bps)	-0.011*	-0.009	0.007	-0.055	-0.088	0.347**	-0.338	-0.385	0.412
	(0.006)	(0.006)	(0.011)	(0.119)	(0.131)	(0.170)	(0.408)	(0.449)	(0.405)
Age (years)	0.003	0.005*	0.005	-0.048	-0.052	0.029	-0.205*	-0.239**	0.013
	(0.003)	(0.003)	(0.006)	(0.033)	(0.035)	(0.049)	(0.107)	(0.112)	(0.153)
Expense Ratio(bps)	-0.008**	-0.008*	-0.006	0.040	0.033	0.345***	0.065	0.078	0.699**
	(0.004)	(0.004)	(0.008)	(0.051)	(0.049)	(0.058)	(0.193)	(0.242)	(0.295)
Institutional Share(%)	0.023	0.036	0.132	0.279	0.407	1.673	-1.657	-1.534	2.166
	(0.069)	(0.072)	(0.125)	(0.549)	(0.550)	(1.154)	(2.702)	(2.727)	(2.465)
Fund Flow (%)	-0.000	-0.002	0.001	-0.027	-0.028	-0.065***	0.034	0.025	0.025
	(0.002)	(0.002)	(0.006)	(0.021)	(0.022)	(0.024)	(0.070)	(0.083)	(0.141)
Month-Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Issuer-Fixed Effect	Y	N	Y	Y	N	Y	Y	N	Y
Sponsor-Fixed Effects	Y	Y	N	Y	Y	N	Y	Y	N
Issuer-Type-Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	21831	21843	21831	18742	18754	18742	21803	21815	21803
Adjusted R^2	0.356	0.230	0.255	0.470	0.304	0.363	0.332	0.116	0.282

The sample is fund-issuer pairs (excluding bilateral connected pairs with European issuers) for the whole March-August 2011 period. Following the same definition in Table 19, the dependent variables are *Exposure* in columns (1) to (3), *Spread* in columns (4) to (6), and *Maturity* in columns (7) to (9). Other variables follow the same definition in Table 19. All regressions are at the monthly level. Reported in the parentheses are two-way clustered standard errors at the fund- and the issuer- level. ***, **,* indicate statistical significance at 1%, 5% and 10% respectively.

Table 32: The 2013 Dodd-Frank Test: Changes in Exposure

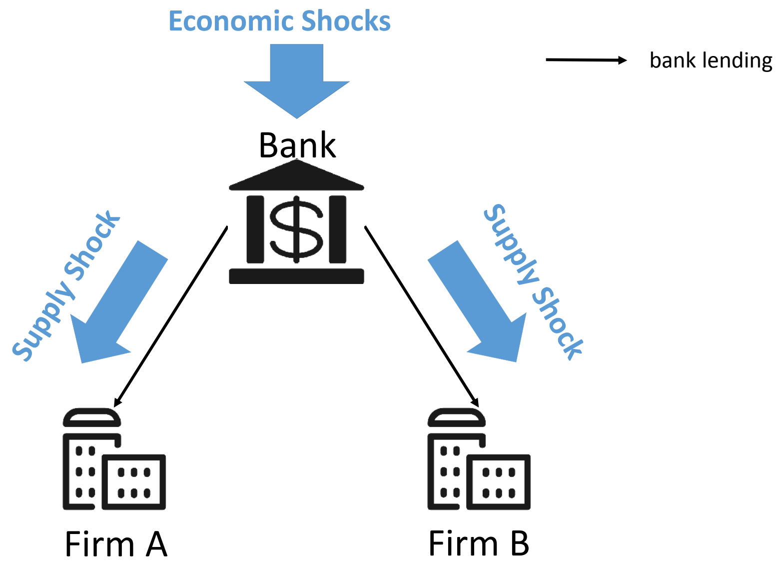
	(1)	(2)	(3)	(4)
BConnected × Post × LBHC	0.600*	0.508	0.516*	0.534*
	(0.332)	(0.311)	(0.311)	(0.311)
BConnected × Post	-0.325**	-0.332**	-0.389***	-0.407***
	(0.140)	(0.149)	(0.146)	(0.146)
BConnected× LBHC	-0.725	-0.790*	-0.636	-0.648
	(0.473)	(0.464)	(0.447)	(0.444)
Post × LBHC	-0.248	-0.299*	-0.255	-0.453**
	(0.164)	(0.164)	(0.163)	(0.189)
BConnected	0.215	0.812***	0.548*	0.562*
	(0.321)	(0.294)	(0.298)	(0.296)
Post	-0.154***	0.020	-0.078	-0.091
	(0.047)	(0.067)	(0.063)	(0.064)
LBHC	0.419*	0.747***	0.315	0.469
	(0.232)	(0.243)	(0.243)	(0.333)
Post × DFBHC				0.209*
				(0.111)
DFBHC				-0.164
				(0.283)
Fund Size	-0.277***	-1.046***	-1.010***	-1.009***
	(0.039)	(0.331)	(0.315)	(0.314)
Net Yield (bps)	0.000	-0.020	-0.019	-0.019
	(0.020)	(0.025)	(0.023)	(0.023)
Age (years)	-0.001	-0.111	-0.127	-0.126
	(0.009)	(0.174)	(0.169)	(0.169)
Expense Ratio(bps)	-0.002	-0.018	-0.017	-0.016
	(0.009)	(0.018)	(0.017)	(0.017)
Institutional Share(%)	0.474***	0.100	-0.186	-0.196
	(0.153)	(2.190)	(2.097)	(2.093)
Fund Flow (%)	-0.001	0.003	0.003	0.003
	(0.005)	(0.002)	(0.002)	(0.002)
Month-Fixed Effects	Y	Y	Y	Y
Fund-Fixed Effects	N	Y	Y	Y
Issuer-Type-Fixed Effects	Y	N	Y	Y
Observations	17243	17277	17242	17242
Adjusted R^2	0.087	0.157	0.201	0.201

The sample is all fund-issuer pairs for the whole December 2012 to May 2013 period. The dependent variable is fund-issuer pairs' exposure winsorized at the 5th and 95th percentiles. *LBHC* is a dummy equal to one for the six BHCs who performed bad in the Dodd-Frank test, *DFBHC* is a dummy equal to one for the 18 BHCs who were tested in the Dodd-Frank test. Other variables follow the same definition in Table 14. All regressions are at the monthly level. Reported in the parentheses are clustered standard errors at the fund-level. ***, **,* indicate statistical significance at 1%, 5% and 10% respectively.

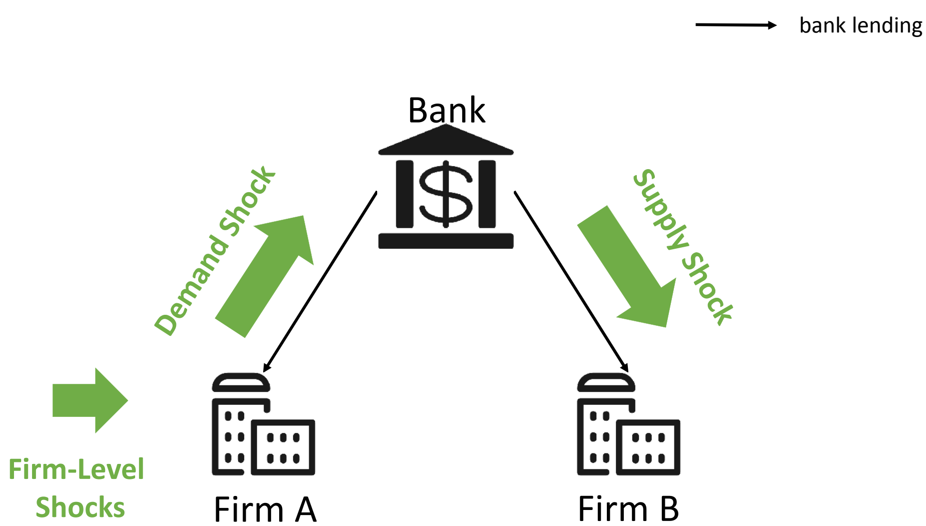
Table 33: The 2013 Dodd-Frank Test: Changes in *Holdings Risk*

Reverse Pair × Post	1.676	7.565	2.921
	(4.869)	(6.178)	(4.348)
Reverse Pair	1.076	-17.481	-2.548
	(8.910)	(10.657)	(7.446)
Post	0.541	2.340**	2.666***
	(0.587)	(1.028)	(0.893)
BConnected	-25.597***	-10.844*	-18.350***
	(6.097)	(6.089)	(5.863)
Fund Size	-1.563*	-1.519**	-1.579**
	(0.819)	(0.661)	(0.731)
Net Yield (bps)	-0.389	-0.354	-0.355
	(0.371)	(0.463)	(0.336)
Age (years)	-0.022	-0.264	-0.008
	(0.214)	(0.185)	(0.196)
Expense Ratio(bps)	-0.077	0.055	-0.057
	(0.173)	(0.165)	(0.162)
Institutional Share(%)	-0.668	-1.017	-0.540
	(3.514)	(3.548)	(3.173)
Fund Flow (%)	0.059	-0.064	0.059
	(0.069)	(0.096)	(0.067)
Month-Fixed Effects	Y	Y	Y
Fund-Fixed Effects	Y	N	Y
Issuer-Type-Fixed Effects	N	Y	Y
Observations	18461	18427	18426
Adjusted R^2	0.087	0.113	0.176

The sample is fund-issuer pairs (excluding bilateral connected pairs with European issuers) for the whole December 2012 to May 2013 period. The dependent variable is the portfolio weight difference between risky and risk-less assets holdings (*Holdings Risk*) per fund-issuer pair. Variable definitions appear in Appendix D All regressions are at the monthly level. Reported in the parentheses are clustered standard errors at the fund-level. ***, **,* indicate statistical significance at 1%, 5% and 10% respectively.



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.

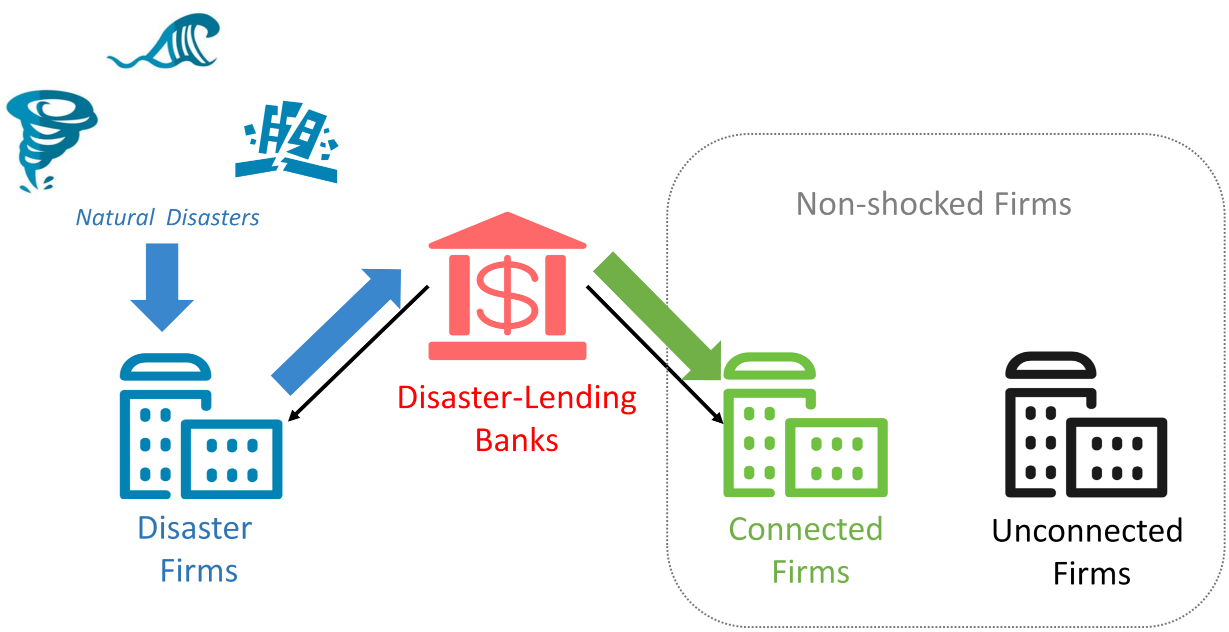
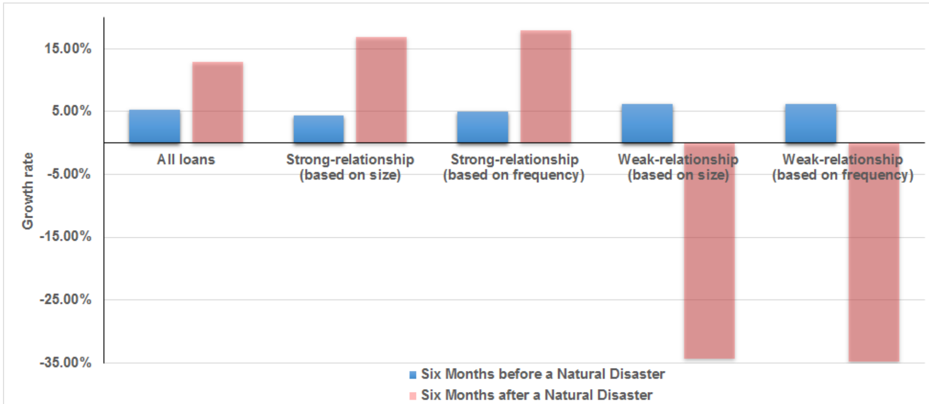
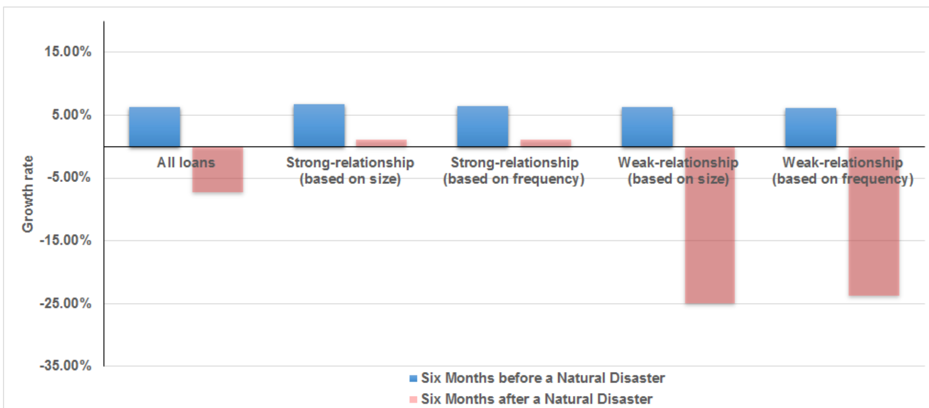


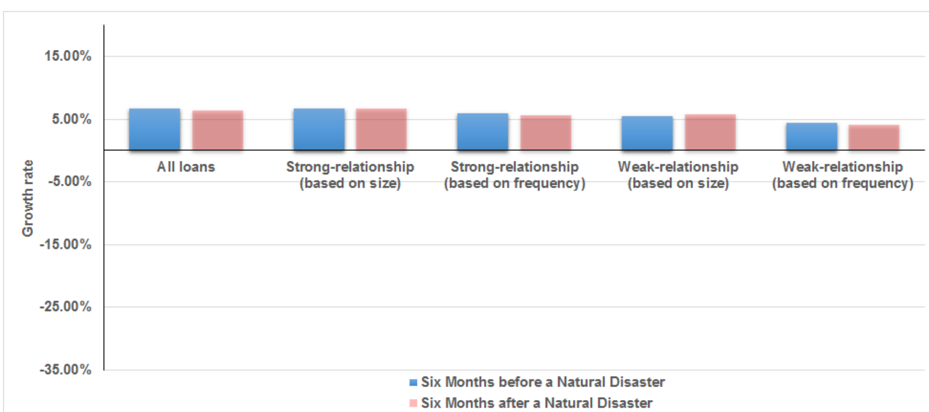
Figure 2: Borrowers and lenders when regional natural disasters hit
This figure illustrates the identification of different borrowers right after a natural disaster hit. Firms headquartered in the disaster county are flagged as "disaster firms"; banks that once lent to these firms in the past five years 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.

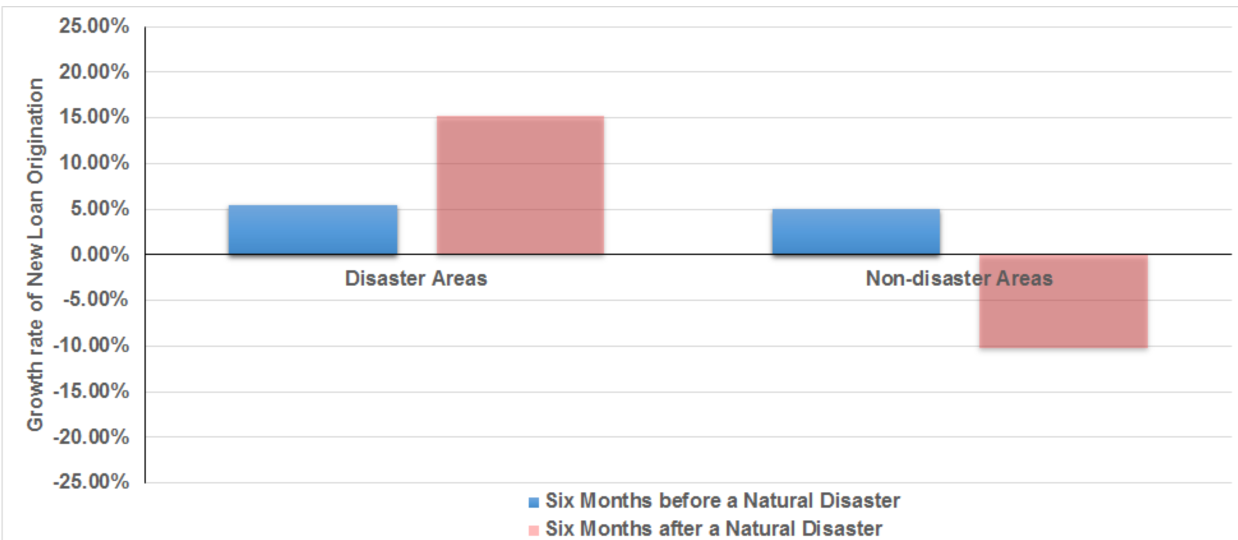


Figure 4: Bank-level lending change

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.

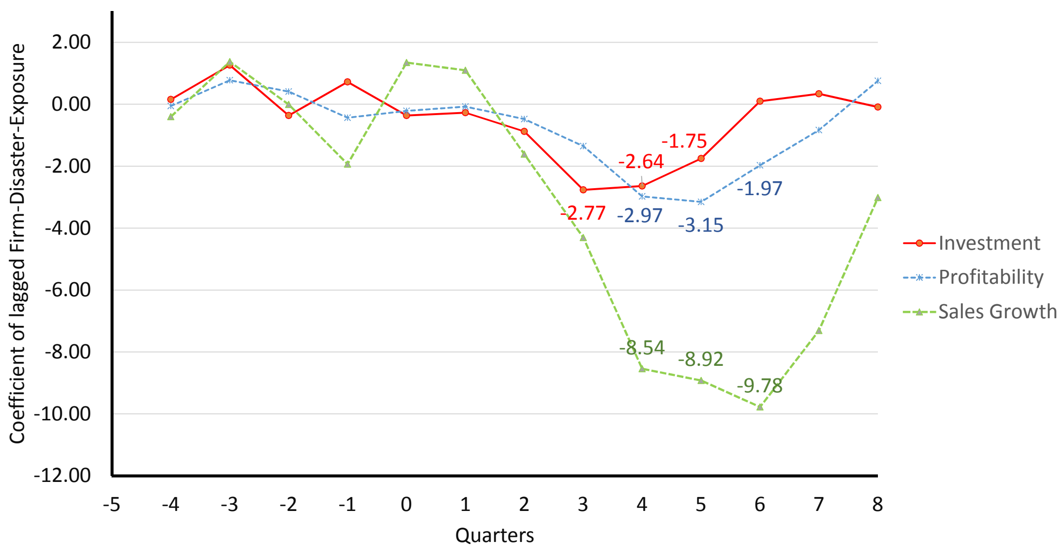


Figure 5: The real effects of natural disaster strikes on non-shocked firms through bank lending

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.

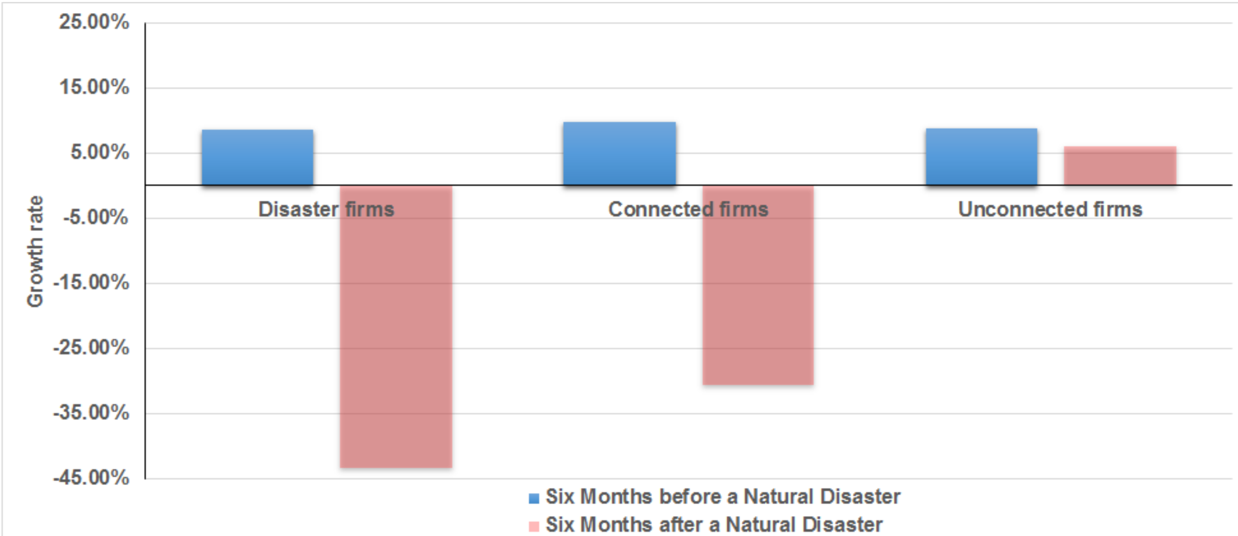


Figure 6: Growth in transaction loans
The figure plots the average growth rates in the total amount of transaction loans around the 28 natural disasters. A transaction loan is a new loan made to a firm which the bank never lent to during the previous five years. I apply data for loans made during six months before a natural disaster and six months after. The period-to-period growth rate is calculated by comparing to previous six months.

Figure 7: An example of cross holding relation (CHR) of two financial firms in the MMF market

Figure 8: An illustration of different financial firms in the MMF market

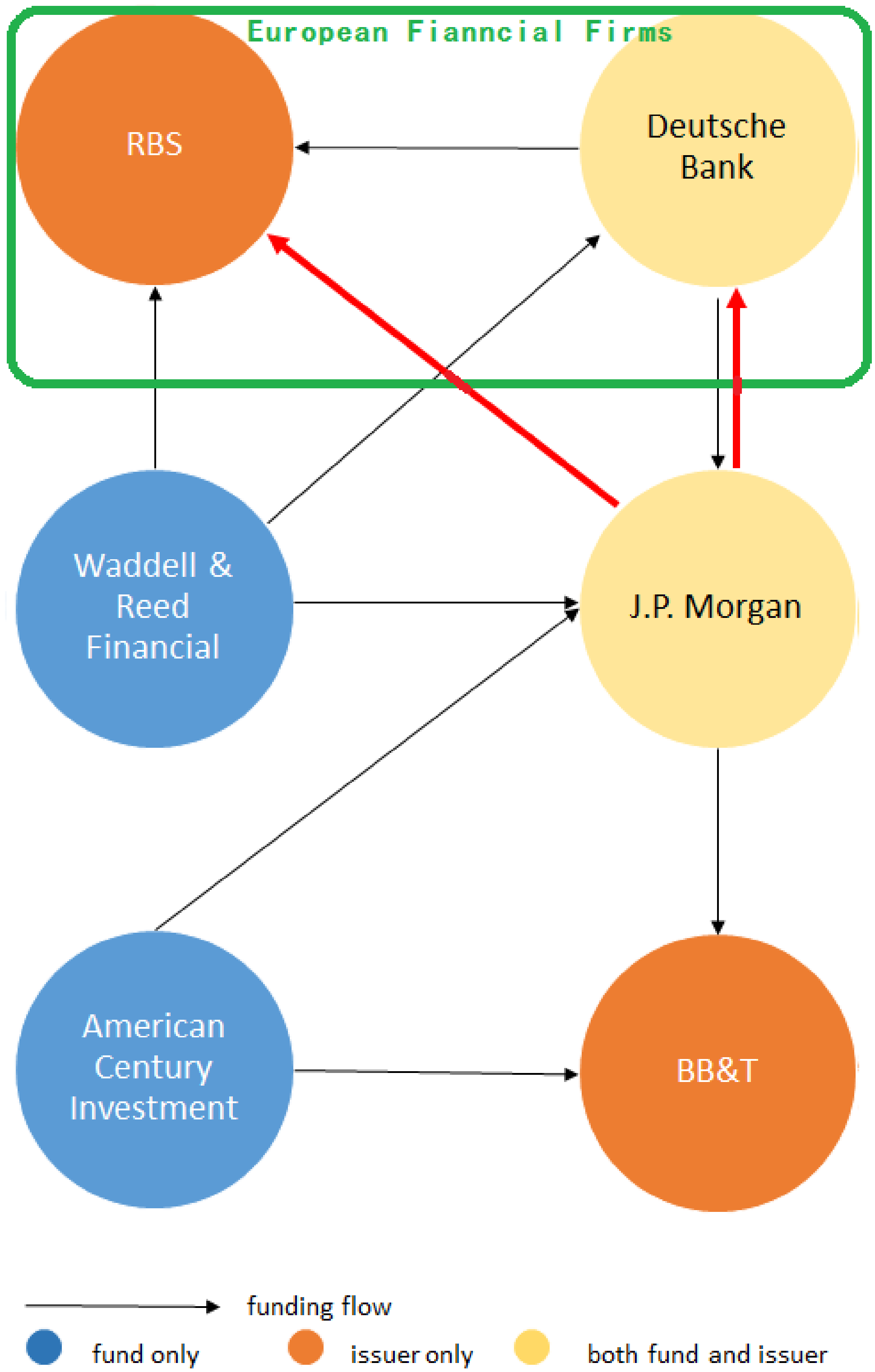


Figure 9: An illustration of Hypothesis One

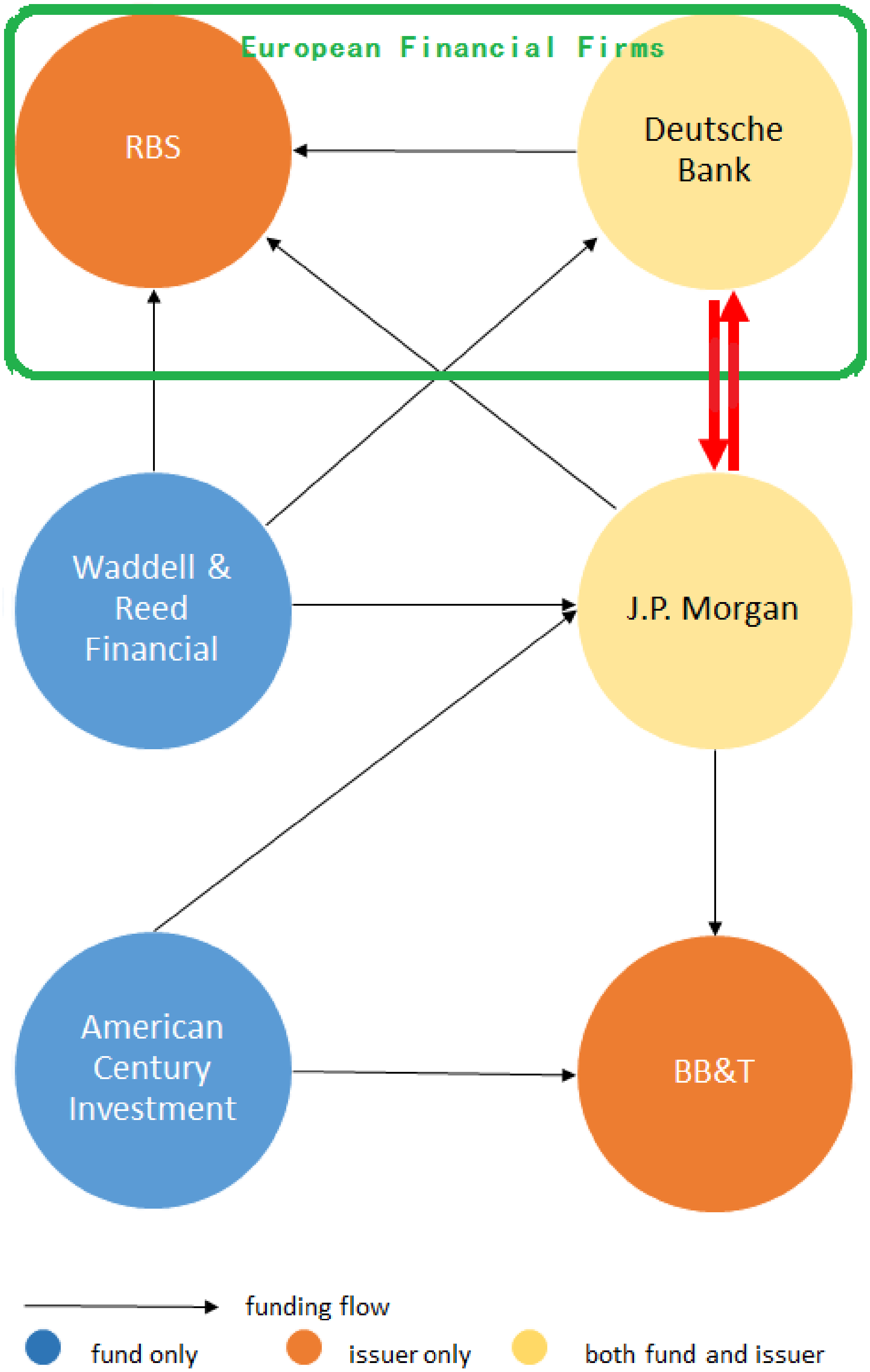
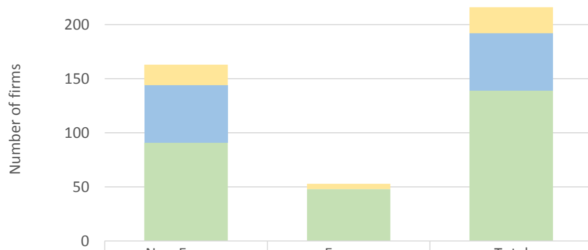
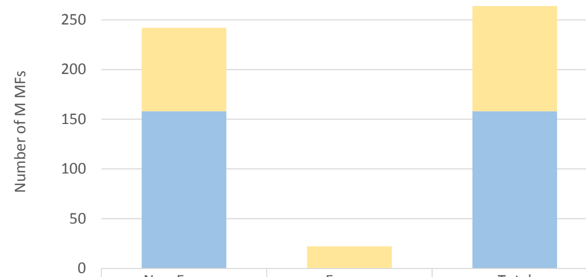


Figure 10: An illustration of Hypothesis Two



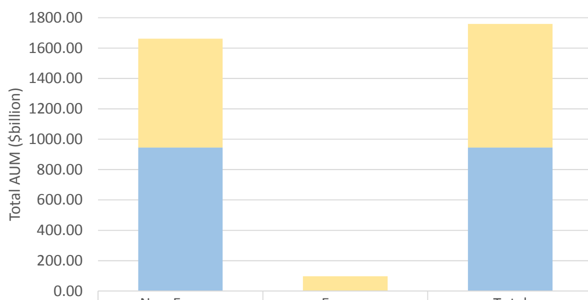
	Non-Europe	Europe	Total
both	19	5	24
fund only	53	0	53
issuer only	91	48	139

(a) Number of financial firms



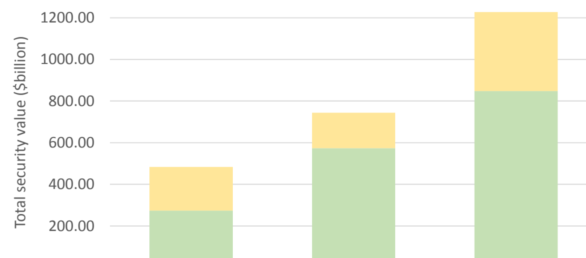
	Non-Europe	Europe	Total
both	84	22	106
fund only	158	0	158

(b) Number of MMFs



	Non-Europe	Europe	Total
both	716.98	97.81	814.79
fund only	944.39	0.00	944.39

(c) Total assets under management of MMFs ($ billions, monthly average)



	Non-Europe	Europe	Total
both	209.51	170.00	379.52
issuer only	273.95	573.94	847.89

(d) Securities' total value ($ billions, monthly average)

Figure 11: Financial firms in the MMF market during the whole March-August 2011 period