WORKING PAPER 24-05

Global Banks and Natural Disasters

OFFICE OF FINANCIAL RESEARCH

July 23, 2024

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Why These Findings Are Important

Natural disasters can generate large economic losses for global financial institutions, and these shocks can propagate across global banking networks. When these events occur in low-income countries, international banks with operations in those countries lower their cross-border lending to the affected countries. In this paper, the authors examine how natural disasters affect the financial system and how multinational lenders reallocate capital following these events.

Key Findings

1. **Not only are lower income countries directly affected by disasters, but they also suffer an indirect impact from reduced lending by global banks.**

2. **Reductions in past-disaster cross-border lending depend on bank connections to the countries affected.**

How the Authors Reached These Findings

The authors use bank-by-country-level data to control for loan demand following natural disasters. They construct two different measures of how connected a bank is to the affected country pre-disaster. By controlling for changes in post-disaster loan demand and the disaster's effect on banks' general lending decisions, the variation in pre-disaster lending relationships by banks within affected countries works to identify heterogeneous lending responses. The paper shows that the reduction in aggregate lending is driven by banks with weaker economic connections to the affected countries.

GLOBAL BANKS AND NATURAL DISASTERS

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July 23, 2024

Abstract.

Natural disasters can generate large economic losses and disruptions for global financial institutions, raising the concern that these disasters may increase financial systemic risk. We use detailed data on the foreign claims and liabilities of large U.S. regulated banks to study how multinational lenders reallocate capital following large natural disasters. We find little evidence that international banks increase lending to countries after destructive disasters, which should increase the demand for funds. Instead, difference-in-differences estimates suggest that natural disasters lower cross-border lending to affected countries by 9% two years after large natural disasters. We hypothesize that damaging natural disasters exacerbate cross-border information frictions. To test this mechanism, we exploit within-country heterogeneity in monitoring costs between banks. Consistent with this mechanism, our results show that declines in aggregate lending are driven by banks with weaker economic connections to the affected countries. These findings suggest that information frictions both dampen the transmission of natural disasters and reduce the reallocation of capital through the international financial system.

Keywords: International Lending, Global Banks, Climate Finance, Natural Disasters, Information Frictions
JEL Codes: G15, F34, G14, G32, Q54

We would like to thank Dasol Kim, Greg Phelan, Thomas Ruchti, Samuel Hughes, Jon Pogach, Sunjin Park, Robin Lumsdaine, Mark Paddrik, Stacey Schreft and Valentina Bruno for helpful comments and suggestions. We thank all participants at the American University Kogod School of Business brownbag seminar, and participants at the OFR brownbag seminar.

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1. Introduction

Increasingly extreme natural disasters can generate large economic losses and disruptions for global financial institutions, raising the concern that natural disasters may exacerbate financial systemic risk (Curcio et al. (2023); Hsiang and Kopp (2018)). U.S. banks are an important set of global financial institutions and have historically played a key role in global finance by allocating capital to where it is most needed. U.S. banks benefit the global economy by allowing for more efficient capital allocation, but interconnectedness can be costly as it can provide a channel for the transmission of economic shocks across regions. Recent literature on how banks respond to domestic climate events within the U.S. shows that banks transmit credit shocks following domestic natural disasters (Blickle et al. (2021); Cortés and Strahan (2017); Zhou et al. (2023)), but how U.S. banks respond to natural disasters in other countries has not been explored. These disasters may adversely impact financial stability if they subject global banks or their foreign subsidiaries to insolvency via bank runs, loan losses, or collateral destruction. Disaster events can also expose banks to pressures on asset quality and capital adequacy, as well as liquidity risk, and could expose the global economy to contagion risk if U.S. Banks transmit these shocks across borders (D'Hulster and Ötker-Robe (2015); Do et al. (2023)). This work seeks to fill a current gap in understanding how drivers of climate risk affect transmission channels and bank's financial risk by providing evidence on bank reactions to past shocks.

In this paper, we bridge this gap by using confidential regulatory data and a quasi-experimental design to analyze how U.S. regulated global banks react following large natural disasters in foreign countries. Contrary to repeated findings in the U.S. context where banks increase lending into disaster-affected domestic markets (Barth et al. (2019); Blickle et al. (2021); Cortés and Strahan (2017); Ivanov et al. (2022); Rehbein and Ongena (2022)), our main results show that banks *lower* their cross-border lending into disaster-affected foreign countries. We document four main facts from our results. First, following the shock, there's a decline in aggregate cross-border claims (i.e., loans) of countries hit by large natural disasters. Second, this decline is partially cancelled out by a small increase in local claims from foreign branches located inside affected countries. Third, these post-disaster declines depend on country characteristics and the connectedness between the bank and the affected country. Lastly, liabilities, intra-bank lending, and loans made by local affiliate bank branches within affected countries show little change.

To disentangle the demand-side and supply-side factors driving our empirical results, we follow Khwaja and Mian (2008) and use country-by-time fixed effects to control for loan demand, and we test for post-disaster lending heterogeneity by the strength of a bank's pre-disaster lending relationship with the disaster-stricken country. We quantify ties both by looking at how much pre-shock lending the bank did in the affected country (Cetorelli and Goldberg (2012b)), and the level of bilateral trade between the affected country and the home country of the parent bank (Borchert et al. (2021, 2022); Correa et al. (2023)). Our main result shows that, after a natural disaster, lending decreases are driven by the banks with the weakest ties to the affected countries. The aggregate decline in total lending is explained almost completely by a decline in cross-border claims on residents of the affected country, rather than changes in lending by the U.S. bank's local affiliate. We hypothesize that the heterogeneity we observe is consistent with an information friction channel where monitoring costs increase post-disaster. Banks without pre-existing lending relationships in a country withdraw from that country after a natural disaster as the uncertainty around loan quality increases.

These results show that, among our sample of U.S. regulated banks, disasters abroad are treated differently from disasters at home. Rather than increasing the amount of funds lent to meet the higher demand for capital, banks on average withdraw from foreign countries after a disaster – particularly where they have the weakest pre-disaster lending relationships. Although our study cannot speak to other potential sources of capital inflows after natural disasters, such as international aid or domestic banks, our results illustrate an important limitation to the international flow of capital after natural disasters. Also, the muted lending response also suggests that the international financial spillover risk from international disasters is limited.

Our analyses utilize regulatory data on global banks from the Federal Financial Institutions Examination Council (FFIEC) 009 Cross Country Exposure Report. We merge this with data on large natural disasters from the Emergency Events Database (EM-DAT) to create a quarterly country-bank panel[1]. Combining these datasets allows us to see how bank lending patterns change after large natural disasters occur in foreign countries. Shifts in bank lending can be attributed to both supply and demand factors, so we use a formal quasi-experimental design with various fixed-effects techniques in order to attribute the changes in lending shifts in bank loan supply, rather than bank loan demand.

This formal empirical strategy is based on a difference-in-differences research design that compares changes in bank lending to countries affected by natural disasters against unaffected countries. However, since disasters happen in different countries at different times,

[1]Our panel has foreign affiliate borrowing and lending into a country in a given quarter, as well as whether a large natural disaster occurred in that country within that quarter. When the Centre for Research on the Epidemiology of Disasters (CRED) compiles the EM-DAT they collect information on the severity of the event from a variety of sources. The EM-DAT flat files can be found at www.emdat.be. How the EM-DAT data is used, including any author manipulations of the data, is described in section 2.2.

traditional difference-in-differences estimates with staggered treatment may result in biased estimates (Baker et al. (2022)). We adjust for this by using the stacked difference-in-differences research design of Cengiz et al. (2019), which corrects for these biases. This stacked difference-in-differences design corrects biases driven by the asymmetric nature of the shocks in a staggered difference-in-differences design by using an identical size time window around each natural disaster in our sample and then stacking these windows on top of each other so that each treatment window is given equal weight in our regressions.

First, we aggregate our samples to the country level and use our stacked difference-in-differences design to document the first facts mentioned above. Two years post-disaster, impacted countries see a statistically significant 9% decline in cross-border lending by the banks in our sample, but this is partially canceled out by a 4.5% increase in local lending. Low GDP countries see a substantially larger decline in cross-border lending of 16.3%, with little increase in local lending, which translates into a 13.7% decline in total lending to affected countries.

These facts are at odds with existing research on how bank lending changes in response to domestic natural disasters. Previous studies using disaster shocks in the U.S. have shown that banks lend into affected areas by pulling funds from unaffected banks in their network. However, this might not generalize to international lending. Domestic markets have relatively homogeneous institutions that domestic banks can more easily navigate while monitoring loans to businesses and households affected by disasters. If a foreign country experiences a large natural disaster, however, banks may withdraw their resources if they face uncertainty about their ability to monitor and enforce contracts in the future. We hypothesize that banks with the weakest lending relationships – those with the least experience and highest monitoring costs – will decrease their post-disaster lending by the most.

To formally test this hypothesis, we use our bank-by-country level data to control for loan demand following natural disasters and construct two different measures of how connected the bank is to the affected country pre-disaster. In the main heterogeneity tests, we run our specifications as in Khwaja and Mian (2008) to control for both country-by-time and bank organization-by-time interacted fixed effects. The country-by-time fixed effects control for changes in post-disaster loan demand, while our bank organization-by-time fixed effects control for effects of the disaster on banks that could affect their general lending decisions. Thus, our identification of heterogeneous lending responses comes from variation in pre-disaster lending relationships by banks within affected countries.

Following Cetorelli and Goldberg (2012b), our first measure of lending relationships is based on pre-disaster bank investment in the affected country constructed from our bank-country-quarter sample. The second measure is constructed using the International Trade and Production Database for Estimation (ITPD-E) gravity dataset. This measure proxies for economic closeness by summing up total bilateral trade flows between the affected country and the home country of the bank, which the literature has shown is related to the entry and capital decisions of international banks (Borchert et al. (2021, 2022); Correa et al. (2023)). We perform stacked triple difference-in-differences estimators, using these measures to isolate banks with higher monitoring costs.

These test results suggest that banks with weaker ties to the affected country are driving the previously documented aggregate decline. Banks with low pre-shock investment levels see an immediate 15% decline in total lending into the affected country that continues for up to two years after the shock. Banks with low pre-shock bilateral trade flows see an 8% decline during the first post-shock year that increases to over 20% during the second year after the natural disaster. Consistent with the monitoring costs hypothesis, both of these results suggest that banks with weaker pre-event relationships with the affected country tend to drive the post-disaster decrease in aggregate lending.

These results contribute primarily to three strands of literature. First, they directly contribute to the climate finance literature studying how capital flows respond to disasters. Our main result – a decline in post-disaster international lending – contrast with other research illustrating that domestic banks respond to climate shocks by lending to affected areas (Barth et al. (2019); Cortés and Strahan (2017); Ivanov et al. (2022); Rehbein and Ongena (2022)). Given the ubiquity of U.S. banks in the global financial system (Cetorelli and Goldberg (2012a,b); Houpt (1999); Spiegel (2022)), and the importance of capital access to disaster recovery (Duqi et al. (2021); Gallagher and Hartley (2017); Koetter et al. (2020); Schüwer et al. (2019)), declines in lending by U.S. banks into foreign countries may have a material impact on their ability to recover from large natural disasters.

The post-disaster lending declines also contrast with other studies that look at the effects of climate shocks on cross-border economic activity. Gu and Hale (2022) show that climate shocks do not impact foreign direct investment (FDI), and Friedt and Toner-Rodgers (2022) find that FDI in India was lower following natural disasters and instead went to unaffected regions. Berg and Schrader (2012) show that lenders rationed credit after an Ecuadorian volcanic eruption, an effect that was attenuated for relationship borrowers. Supporting the information frictions hypothesis, recent work has also shown that climate disasters can have negative effects on asset quality, reduce intermediation efficiency, lower liquidity, and increase regulatory ratios (Nie et al. (2023)). Natural disasters can also negatively impact domestic bank stability (Collier et al. (2011); Collier and Babich (2019); Do et al. (2023)), because deposits and equity become more volatile and banks lose their competitiveness. In contrast, Blickle et al. (2021) find muted effects of U.S. natural disasters on domestic bank stability. Our work shows, at an international scale and across a large sample of banks, that natural disasters attenuate cross-border lending. This finding is relevant to international policy debates on the allocation of aid following climate shocks and potential spillovers from natural disasters to the international financial system (D'Hulster and Ötker-Robe (2015)).

Our paper also contributes to the literature on cross-border shock transmission through the global financial system. It is well known that global banks transmit shocks from the U.S. to periphery countries (Acharya and Schnabl (2010); Cetorelli and Goldberg (2012a,b); Shin (2012)), but less is known about how banks react to shocks originating in periphery countries. Our results extend this literature by providing direct evidence of how banks adjust their operations following shocks originating in foreign countries. Previous results in the international finance literature suggest that cross-border banking decisions are driven by international factors, such as bilateral trade flows, and our results align with this view (Borchert et al. (2021, 2022)).

Finally, our paper contributes directly to the banking literature. Banking theory suggests that bank lending solves different financial frictions from the internal capital market consideration of firms (Gertner et al. (1994); Houston et al. (1997); Stein (1997)), which implies that bank lending may respond in a distinct way to large natural disasters. Banks may also alter their behavior following disasters depending on their structure (Schüwer et al. (2019)). As mentioned above, previous literature has shown that FDI does not react to natural disasters in other countries, and in the international context, FDI is similar to a firm's internal capital market decision. The decline in bank lending that we document suggests that international banking may respond to different incentives than FDI. Some factors suggested by the literature that may make banking unique are sensitivity to changes in the information environment (Berger et al. (2005); Choudhary and Jain (2022); Loutskina and Strahan (2009)), and the use of "arms-length" loans that may respond to changes in the institutional environment of the country (Agarwal and Hauswald (2008); Rajan (1992)). We also contribute to the literature on the relationship between real bilateral trades and bank lending decisions such as Niepmann (2015) and Brüggemann et al. (2011), which suggests that stronger ties between the economies of a bank's home and affected countries may lower their incentive to decrease lending into the affected country. We show that banks whose home countries have low levels of bilateral trade with the affected country tend to lower their lending, which is consistent with the findings from these previous studies.

The rest of the paper is organized as follows: section 2 gives a detailed data description, section 3 discusses our methodology, section 4 presents the main results, and section 5 concludes.

2. Data

2.1. **International Bank Data.** The data on country level exposures of internationally active banks in the U.S. come from the FFIEC009 Country Exposure Report[2]. Banks with over \$30 million in claims[3] on residents of foreign countries must file an FFIEC009 report with regulators if their exposure to a given country exceeds 1% of total assets or 20% of capital of the reporting institution, and has at least a branch, a consolidated subsidiary, and Edge or Agreement subsidiary, or an International Banking Facility. In addition, reporting is also required by every U.S. bank holding company that is required to file the FR Y-6 Bank Holding Company Annual report and has a subsidiary that is required to file this report. In this form, U.S. banks report total claims on the households, banks, corporations, or public sector of a given non-U.S. country. They also report the total liabilities of their foreign offices in that country, as well as the net position of that foreign office to the rest of the banking organization, which is referred to as Net Due[4]. A full description of how each variable is derived from the report, as well as a brief description of its economic interpretation, is provided in Table A2. The advantage of our data is that it gives us a detailed look at bank level cross country exposures which allows us to explore the importance of bank-country connections, which we would be unable to do with the publicly available aggregates.

The primary outcome variable of interest for the majority of the tests will be claims on a foreign country. A claim can be, among other things, vault cash, deposit balances (both interest bearing and noninterest bearing), balances with central banks and official institutions, securities, federal funds sold, and loans. Claims broadly represents lending by the bank and we can think of it as a net cash flow into a country by a bank. For example, if a U.S. bank extends a loan to a German small business, this will provide an influx of cash to the German economy and will be reflected by an increase in total claims on Germany in the bank's FFIEC009 filing. There are two forms of reported claim in the form, *Local Claims* and *Cross Border Claims*. *Local Claims* are claims on a resident of the country by the bank's foreign affiliate in that country, and *Cross Border Claims* are claims on a resident of the country by any other part of the banking organization. In certain tests these two types of claims will be added together to express a bank's *Total Claims* on a country.

[2]See https://www.ffiec.gov/forms009_009a.htm for detailed FFIEC009 reporting forms and instructions.

[3]The definition of claim used in the FFIEC009 form is broad. Its technical definition is any claim on a future cash flow. For example, a claim could potentially include a government bond, a traditional bank loan, or a consumer credit card

[4]More specifically, Net Due refers to the amount that an affiliate bank is in debt to the rest of the banking organization. If Net Due is positive, then this means they are net borrowers from the rest of the banking organization, so an increase in Net Due reflects a cash inflow to the foreign affiliate bank.

The FFIEC009 dataset is at the affiliate level, so it is important to aggregate to the highest holder level in order to accurately capture ownership decisions. We use National Information Center (NIC) data in order to link the highest holder to the affiliate in the dataset. Once we have identified each affiliates unique bank identifier with their highest holder, we aggregate to the bank-country-quarter level. Certain tests will also be performed over a country-level sample, and this sample is created by aggregating over the sample of banks to the country-quarter level.

2.2. **Natural Disaster Data.** Data on natural disasters come from the Emergency Events Database (EM-DAT) compiled by the Centre for Research on the Epidemiology of Disasters (CRED).[5] This database compiles all natural disasters from 1900 to the present that occurred anywhere in the world in which either ten or more people were reported killed, one hundred or more people were reported affected, there was a declaration of a state of emergency, or there was a call for international assistance. This database is publicly available, and compiled based on various sources, including U.N. Agencies, NGOs, insurance companies, research institutes, and press agencies. For each natural disaster, the CRED reports the total number of deaths, total number of people impacted, and the total property damage as a result of the disaster.

Our analysis considers large natural disasters between 1986 and 2017. We subset to disasters that damage physical capital: earthquakes, floods, landslides, mass movement, storms, volcanic activity, and wildfires. For each country in each quarter, we aggregate the total number of deaths, the total number of people affected, total property damage, and total property damage as a share of GDP measured by purchasing power parity[6]. For each of these four measures of economic damage, we calculate its percentile within the dataset across all years. Because each damage measure is not consistently reported, we categorize a country as being affected by a "large" natural disaster if it exceeds the 90th percentile on any of the four measures. In total we classify 892 country-quarter observations as large disasters, an average rate of about one large disaster every five years across the reporting countries. A full time series of the disasters used in our paper is given in Figure 1a. Disasters are evenly distributed over time. The majority of the disasters belong to either the flood or storm category, likely due to these categories being broader in scope than the other categories.

2.3. **Measures of Economic Closeness.** A core hypothesis of our paper is that a bank's pre-shock relationship to a country will impact their lending decisions after a natural disaster. For example, a bank with low pre-shock levels of lending into the country may have less information about the country's institutions and ability to recover from damages, and this

[5]The EM-DAT flat files can be found at www.emdat.be.

[6]We assign disasters to quarters according to their start dates.

uncertainty will cause them to decrease lending. To test such hypotheses, we create time-varying measures of connectedness between each bank and country in our sample.

Our first measure of connectedness identifies "high investment" bank-country pairs in a given quarter as those where the country constitutes a high share of the bank's foreign lending. Following Cetorelli and Goldberg (2012a), we define bank i's investment share in country v in quarter t as $I_{ivt} = \frac{CLAIMS_{ivt}}{\sum_{s \in S} CLAIMS_{ist}}$, that is the percent of bank i's claims in country v out of all their local and cross-border claims to all countries. Intuitively, banks with higher I_{ist}'s are expected to be relatively more invested in and more well informed about country v, and so less likely to pull out of the country following a natural disaster[7].

The second measure of connectedness between bank i and country s uses the amount of trade between bank i's parent country and s. Let $TRADE_{isy}$ be the sum of agricultural and manufacturing imports and exports between bank i's parent country and country s in year y, measured from the International Trade and Production Database for Estimation (ITPD-E) gravity dataset (Borchert et al. (2021)). We measure the strength of the trade tie as the share of i's parent country's trade occuring in country v: $T_{ivt} = \frac{TRADE_{ivt}}{\sum_{s \in S} TRADE_{ist}}$. The motivation for this measures comes from the aforementioned literature on the relationship between real bilateral trades and bank lending decisions.

For our analysis, we take pre-disaster measures of I_{ist} in the five to eight quarters before the disaster and T_{ist} in the calendar year preceding the disaster. All other macroeconomic data used are sourced from the IMF International Financial Statistics, OECD, and Thomson Reuters Eikon.

2.4. **Summary Statisics.** Excluding all tax haven countries as classified by the IMF and subsetting to countries that consistently report in both EM-DAT and FFIEC009, our data contain 320,376 quarterly reports between 1984 and 2019 by 374 banking organizations across 95 countries.[8]

We report summary statistics for our bank and country sample, bank and country and trade sample, and bank and country and investment sample in Tables 1, 2, 3 respectively. All statistics are reported for 1985q1, 2019q1, and the full sample separately. The average bank was active in 6 foreign countries in 1985, but this number increases in the sample over time. Local lending by these internationally active banks is highly concentrated within a few banks in a given country. The average and median country in our sample have approximately 8 banks operating within its borders in 1985, but this number increases to 12 by the end of our

[7]By relatively more invested and well informed, we mean compared to other countries in the bank's portfolio, not compared to other bank's in the affected country. There are many instances of banks categorized as *low investment* with above average lending in the affected country.

[8]The EM-DAT flat files can be found at www.emdat.be. How the EM-DAT data is used, including any author manipulations of the data, is described in section 2.2.

sample. Average total claims for bank-country pairs increase tenfold through our sample, from 6.93 million per quarter to around 67 million by 2019.

High trade banks tend to perform significantly more lending to other countries, which is consistent with prior literature on this topic. High trade banks also tend to have a positive net due, while low trade banks are the opposite, suggesting that the high trade banks see other countries as a source of net investment rather than net funding. Similar results hold for the high investment vs. low investment bank sample, and are broadly consistent with the interpretation that low trade/investment banks have a weaker general relationship with the countries they are lending into.

3. Methodology

This paper's methodology is similar to a traditional difference-in-differences regression. Intuitively, we compare changes in bank lending or other outcomes in a country after a natural disaster occurs against changes in a control country that didn't experience a natural disaster in the same event window in order to derive the causal effect of natural disasters on bank activity.

However, in our framework natural disasters are staggered across different times in different countries, raising concerns as highlighted in a recent econometrics literature that TWFEs will be biased (Baker et al. (2022)). We adopt a "stacked" difference-in-differences design, described in detail below.

3.1. **Stacked Difference-in-Differences Sample.** We construct a stacked dataset of "clean" treated and control units to avoid the documented biases that can arise in two-way fixed effects (TWFE) difference-in-differences estimation with staggered treatment timing and dynamic and heterogeneous treatment effects mentioned above. In such settings, TWFE inappropriately uses recently treated units as controls and returns an average treatment effect where some of the heterogeneous treatment effects can enter with negative weights. Following Cengiz et al. (2019), the stacked difference-in-differences (stacked DD) estimates a series of TWFE regressions that only considers control units that are not treated over the estimation window and treated units that experience only one disaster over the estimation window, which we set at two years. By combining these clean treated and control units into a set of quarterly stacks, average dynamic treatment effects can be estimated.

Let $D_{st} = 1$ if country s experiences a large disaster in quarter t. We include country s as a clean control in quarter Q's stack if $D_{sk} = 0$ for $Q - 8 \leq k \leq Q + 8$. Country s is a clean treated unit in quarter Q's stack if $D_{sk} = 0$ for $Q - 8 \leq k < Q$ and $D_{sk} = 1$ for $Q < k \leq Q + 8$. Any countries not qualifying as a clean control or treated unit are excluded from the stack.

We include data from four quarters before to eight quarters after Q for each stack. All bank observations where the bank misses any FFIEC009 reporting quarter (i.e., reports no claims or liabilities in any country for a given quarter) are excluded and we subset to countries where at least one bank reports some liabilities or claims in every quarter between 1984 and 2019. In our country-level regressions we exclude any country that reports zero claims or zero liabilities in the five to eight quarters before Q, and correspondingly drop such banks in the bank-level regressions. Our estimation data contain 91 treated countries with 1,543 reporting banks and 2,218 control countries with 3,952 reporting banks across 76 stacks.

3.2. **Country Level Tests.** To estimate the country-level effects of natural disasters, we aggregate all the claims, liabilities, and net due variables at the country by quarter level. The country-level estimating equation for some normalized outcome Y can be expressed:

$$Y_{stQ} = \alpha_{sQ} + \alpha_{tQ} + \beta^t D_{st} + \epsilon_{stQ} \tag{1}$$

where we normalize Y_{stQ} such that $Y_{stQ} = \frac{Y_{stQ}}{\frac{1}{4}\sum_{k=Q-8}^{Q-5} CLAIMS_{sk}}$ so that treatment effects are estimated as percent changes relative to pre-disaster average total claims. The specification includes country-by-stack and quarter-by-stack fixed effects and standard errors are clustered by country. β^t traces out the dynamic treatment effects of large disasters for two years after the disaster as well as one year before to test for pre-trends. Additionally, we run our stacked DD specification with post-treatment indicators rather than a fully dynamic specification:

$$Y_{stQ} = \alpha_{sQ} + \alpha_{tQ} + \beta^1 I[Q \le t \le Q+4] X D_{st} + \beta^2 I[Q+5 \le t \le Q+8] X D_{st} + \epsilon_{stQ}.$$

A key advantage of our data is the ability to observe bank-level country exposures. We exploit this data granularity to test for the mechanisms driving our results, in particular whether banks with close economic connections to disaster-affected countries respond differently. Disaggregating outcomes by reporting bank i, our bank-level regressions can be expressed:

$$Y_{istQ} = \alpha_{stQ} + \alpha_{itQ} + \lambda^t LowRelationship_{isQ} + \beta^t LowRelationship_{isQ} \times D_{st} + \epsilon_{istQ} \tag{2}$$

where Y_{istQ} is normalized as a share of pre-disaster country total claims: $Y_{istQ} = \frac{Y_{istQ}}{\frac{1}{4}\sum_{k=Q-8}^{Q-5} CLAIMS_{sk}}$. Key to the identification strategy in Equation 2 is the country-by-quarter and bank-by-quarter fixed effects. Thus, all of our identification of the key coefficients of interest, β^t, comes from within-country differences between banks operating in the same country but with different economic closeness to the affected country.

We use our investment and trade proxies for the *LowConnected* variable as described above. In the investment specifications, $LowConnected_{isQ} = 1$ if the pre-disaster investment share variable is less than the median pre-disaster investment share for that bank in the stack. In the trade specification, $LowConnected_{isQ} = 1$ if the pre-disaster trade share is less than i's pre-disaster median trade share across all FFIEC009 reporting countries with non-zero trade.

As in Equation 2, bank-level regressions are estimated with one- and two-year post-treatment indicators to summarize our findings.

4. Results

4.1. **Country Level Treatment Effect.** We start by examining aggregate lending outcomes at the country level following natural disasters. We do this by running equation (1) over our stacked difference-in-differences country-level sample. Baseline results are reported in Table 4. This table reports the treatment effect for Total Claims, Cross-Border Claims, Local Claims, and Net Due as dependent variables in columns 1 through 4.

In column (1), we see that total lending by U.S. banks into affected countries is flat in the four quarters following a large natural disaster. During the second year after the natural disaster, Total Claims decline by a statistically insignificant 4% relative to its pre-shock level. We break Total Claims into its two components, Cross-Border Claims and Local Claims, in columns (2) and (3), and see that the second year effect is driven by a statistically significant 8.7% decline in cross-border lending that is partially offset by a 4.5% increase in local lending by foreign branches. For an affected country that receives sample mean of $168 million in cross-border loans per quarter, our estimates imply a $ 58 million decline in loans from banks in our sample in the second year after a large natural disaster.

We next consider whether the decline in cross-border lending and increase in local lending is driven by banks reallocating capital internally so that their branches located in affected countries can make more loans. We see little evidence that net lending to foreign branches increases in Column (4) of Table 4, with only small and statistically insignificant increases in Net Due in the first and second years after the disaster.

Finally, we flexibly estimate the lending dynamics of U.S. banks around natural disasters with separate coefficients for each quarter one year before to two years after each disaster. These results are shown across the four outcomes in Figure 3. The quarterly coefficients are consistent with the results in Table 4. Cross-Border claims begin to decline five quarters after the disaster, reaching a statistically significant decrease in seven and eight quarters post-disaster. Reassuringly for our parallel trends assumption, none of the outcomes show any significant pre-trends in the year before the shock.

As a proxy for the capacity for post-disaster recovery, we run the same tests as in 4, split based on high vs. low GDP. The results are presented in Table 5, with above-median GDP countries in panel A and below-median GDP countries in panel B. For higher-income countries, there is no evidence of a statistically significant decline in any of the lending outcomes. In addition, we see evidence of 5.6% and 14.2% increases in Net Due in the first and second years post-disaster, respectively, that are significant at $p < 0.1$. In contrast, Panel B shows that the declines in our overall results are driven by lower-income countries, who see a 16.3% decline in cross-border lending two years post-disaster.

These estimates suggest that lower income countries are directly impacted by disasters and also suffer an indirect effect of reduced lending international banks. This is consistent with assessments by international agencies that highlight the vulnerability of lower-income nations relative to higher-income countries to climate change.[9]

Broadly, our results suggest that banks do not increase lending into other countries affected by physically destructive natural disasters. In fact, they reduce cross-border lending while their local branches only modestly increase loans. These findings contrast sharply with other papers showing that U.S. banks reallocate capital internally to increase lending to areas within the U.S. affected by natural disasters (Barth et al. (2019); Cortés and Strahan (2017); Ivanov et al. (2022); Rehbein and Ongena (2022)).

Why do our results differ so markedly from other results on post-disaster lending in the U.S. context? Our results are especially surprising given that large and globally connected banks might be in the best position to meet increased demand for capital in a foreign country. We hypothesize that information frictions, exacerbated by natural disasters, make it more costly for internationally active banks to lend to disaster stricken countries. Berg and Schrader (2012) shows that natural disasters can increase monitoring costs, consistent with post-disaster increases in loan nonperformance documented in Nie et al. (2023). Other research has shown that monitoring costs, mediated by lending relationships and the economic distance between borrowers and lenders, are important determinants of both lending levels and the responsiveness of lending to economic shocks (Rajan (1992),Agarwal and Hauswald (2008), Hashimoto and Wacker (2012)).

Asymmetric information can explain several of the patterns across our results. Under this hypothesis we would expect to see larger declines in arms-length lending, just as we see greater declines in cross-border claims relative to local loans made by foreign branches. It is also consistent that we see greater declines in low-income countries that may have weaker institutions to enforce contracts post-disaster.

[9] See https://www.un.org/en/content/common-agenda-report/assets/pdf/Common_Agenda_Report_English.pdf for an example

However, while suggestive, our empirical results do not identify the monitoring costs channel. For example, lending declines may be driven by post-disaster declines in economic growth or because foreign aid or government investment supplanted bank activity. Alternatively, the decline in lending may reflect deteriorating bank balance sheets caused by disaster damages. To formally test the post-disaster information frictions hypothesis, we use our bank-by-country level data to exploit within-country and within-bank variation in monitoring costs between bank and country pairs.

4.2. **Using Bank-Level Variation in Monitoring Costs to Identify Post-Disaster Information Frictions.** The results in this section test whether post-disaster lending declines are driven by banks with higher monitoring costs. As described in section 3 we construct two monitoring cost proxies. The first is the pre-disaster share of a bank's lending in a given country. When banks concentrate more of their investment in a market, they are likely to have more lending relationships and private information that lower monitoring costs. Our second proxy is constructed from the pre-disaster share of the bank's parent country's trade with a given country, motivated by the literature linking cross-border banking to international trade (Borchert et al. (2021), Borchert et al. (2022)). For both proxies, banks are grouped into below-median and above-median connectedness.

We test the significance of our monitoring cost proxies by estimating Equation 2. A key advantage of this specification is that given within-country and within-bank variation in monitoring costs, country-by-time and bank-by-time fixed effects can be included. These controls absorb demand side factors related to post-disaster economic growth or credit demand that might otherwise explain our findings, as well as disaster impacts on the bank organization balance sheet that may affect lending. If information frictions explain a substantial part of the aggregate lending decline, we predict that the triple interaction terms between below-median connectedness, affected, and post-disaster will be negative.

First, we compare banks with high versus low pre-disaster investment levels in affected countries, with results given in Table 6. Panel A includes bank-country and disaster-year-quarter fixed effects, while Panel B adds more saturated bank-year-quarter and country-year-quarter time fixed effects to absorb any country-level or bank-level factors that might drive our results.

Panel A shows that banks with low pre-disaster investment levels see a 15% decline in total claims during the first year after the natural disaster and an even lower 18% decline during the second year, both statistically significant at the 1% level.[10] This decline is driven almost

[10]Note that if lending declines were driven by tighter capital constraints due to physical damages, as found by Collier and Babich (2019), we would expect to see larger declines for banks with higher pre-disaster investment.

completely by cross-border claims, which experience a 13% and a 17% decline in the first and second years after the disaster, respectively. Low investment banks show statistically insignificant and small declines in local claims and net due.

Adding country-by-time and bank-by-time fixed effects in Panel B does little to change the relative declines in total claims and cross-border claims.[11] Although the declines in local claims are of similar magnitude as in Panel A, we do see a statistically significant 5.7% relative decline in local claims by low investment lenders. We also see first-year 6.2% and second-year 9.7% relative declines in low investment net due.

The full dynamics in low investment and high investment bank-country during the event window around the disasters are presented in Figure 4, which plot quarterly coefficients from Equation 2 with bank-country and disaster-year-quarter fixed effects. This figure shows that the negative coefficient in Table 6 on total claims is not only being driven by an approximately 10% decline in lending by low investment bank-country pairs, but also a 20% increase in total claims for high investment bank-country pairs. Cross-border and local claims demonstrate similar dynamics, with high investment bank lending levels statistically indistinguishable from their pre-disaster means two years after the disaster. It is notable, however, that total claims and cross-border claims remain significantly lower in low investment bank-country pairs even two years post-disaster. although cross-border claims for high investment countries decreases to pre-event levels by the end of the second year after the event.

Interestingly, Figure 4 suggests not only that low investment banks pull back their lending to affected countries, but high investment banks increase their lending. The dynamics displayed by high investment banks is closer to the lending patterns we see in Cortés and Strahan (2017). The previously documented aggregate decline in lending differs from their results, however. The patterns in Figure 4 may be because low investment banks have fewer ties to the affected country, a phenomenon that is not as prevalent in the domestic setting used in Cortés and Strahan (2017).

Next, we turn to our monitoring costs trade proxy, with results in Table 7. As in Table 6, Panel B adds bank-time and country-time fixed effects.

The results in Panel A are broadly similar to those in Panel A of Table 6, albeit weaker in the first post-disaster year and stronger in the second. Two years after the disaster, low trade bank-country pairs experience a 22.3% larger decline in total claims that is primarily driven by a 21.5% relative decline in cross-border claims. Similar to the previous investment results, adding the saturated time fixed effects in Panel B does little to change these results.

[11]Note that the bank-by-time fixed effects absorb any bank covariates that might explain differences in lending between bank-country pairs.

In contrast with the investment specification, we do not see evidence that low trade bank-country pairs have lower local claims or net due.[12]

Figure 5 shows dynamic results from the trade proxy estimation, plotting quarterly coefficients with bank-country and disaster-year-quarter fixed effects. As in Figure 4, declines in total claims for low trade bank-country pairs increase over time, are driven by declines in cross-border lending, and remain statistically significant two years post-disaster. However, there is less evidence of an increase in lending by high trade bank-country pairs.

These results support the hypothesis that post-disaster cross-border lending declines are driven by information frictions. Consistently across our two proxies, declines in total lending to disaster-affected countries are larger for the less connected U.S. regulated banks operating there and driven by declines in cross-border rather than local loans. U.S. regulated banking organizations also do not internally move capital into their foreign branches as indicated by our net due results. While there is some evidence that more connected banks increase their post-disaster lending along some margins, it is not enough to offset the declines from the less connected banks. This finding suggests that the organizational pecking order described in Cetorelli and Goldberg (2012b) is not symmetric with respect to domestic and foreign shocks. Whereas U.S. based banks pulled in liquidity from their affiliates abroad during the 2008 crisis, funds do not flow into foreign offices when they are hit by natural disasters.

5. Conclusion

We test whether global banks react to large natural disasters abroad, and find that they tend to lower their cross-border lending into affected countries, and that this result is strongest for low GDP countries. This aggregate decline is not uniform among all banks in the country, but is concentrated in banks with low levels of pre-shock investment in the affected country and whose parent country has low levels of pre-shock trade with the affected country. These results are consistent with the literature on bank lending, which predicts that relationship loans are more robust to negative shocks.

Previous literature has shown that banks tend to lend to affected areas following domestic natural disasters, and has suggested that banks can play an important role in assisting affected populations. Our results show that this fact may not hold at the international level. Policy-makers in international organizations such as the UN have proposed extra support for developing countries following natural disasters, and our results are consistent with that policy goal.

[12]Appendix Table A1 shows that our results are consistent when we include both the low trade and low investment indicators simultaneously.

Looking at the broader context of international finance, while previous research has shown that large banks relied on their foreign affiliates for funding during the Global Financial Crisis and regulated banks propagate shocks from the U.S. to other countries, our results give little evidence of reciprocity when those same foreign entities suffer natural disasters. On the one hand, this suggests that the U.S. financial system is at least somewhat insulated from disaster shocks abroad, at least through a direct lending channel. On the other hand, these findings also suggest that international lending is not always a two-way street and that global banks can react differently to foreign and domestic shocks. Evaluating the causes and consequences of such asymmetries in cross-border capital flows is an important area for future research.

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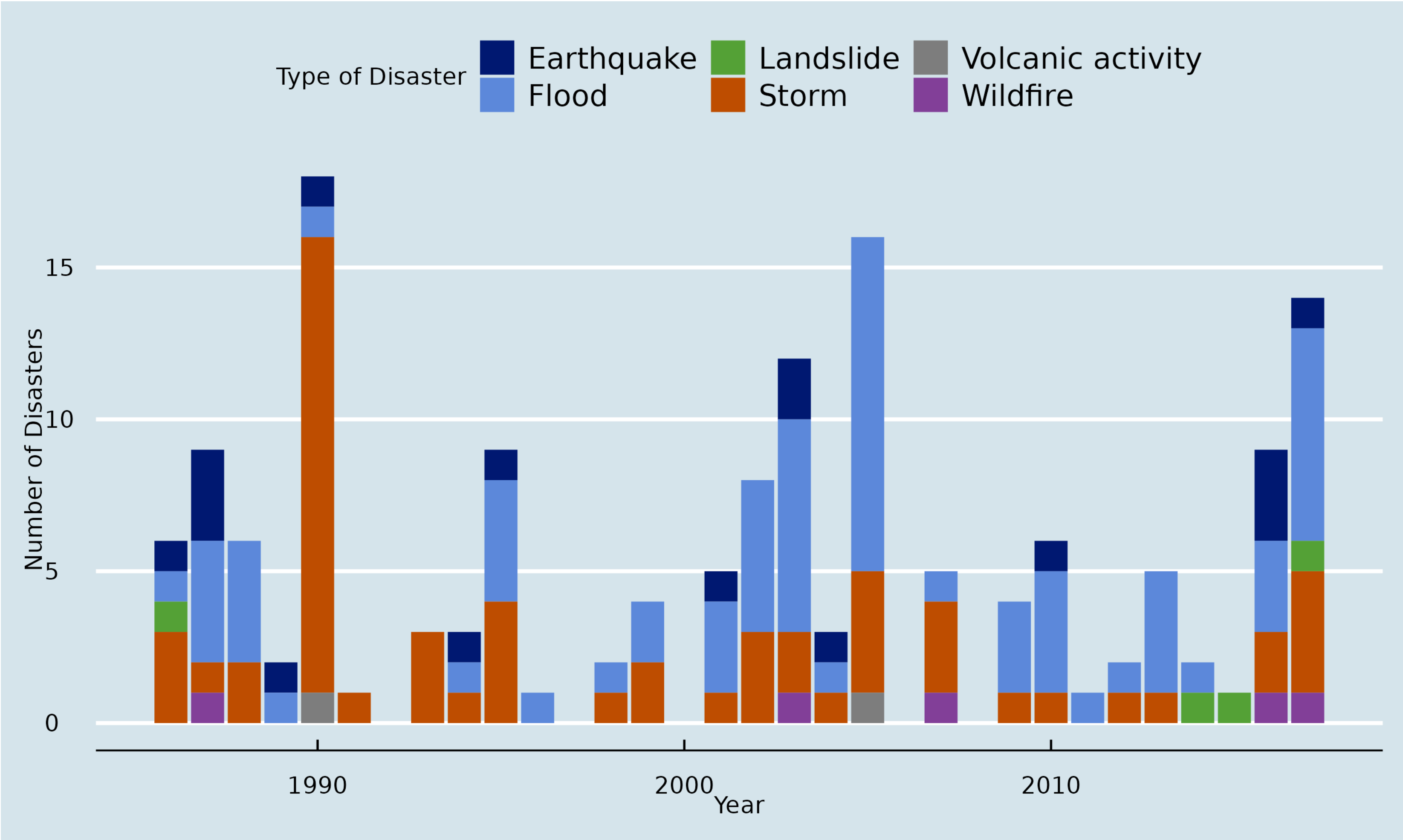
Figure 1. Time Series of Disasters by Category

(a) The frequency of natural disasters is provided for each year in the dataset (1985-present). In each year, disasters are split into the six categories at the top of the table and the number for each category is given. These categorizations are specified in the EM-DAT as downloaded from the international disasters database site.



Source: EM-DAT, Authors' analysis. The EM-DAT flat files can be found at www.emdat.be. How the EM-DAT data is used, including any author manipulations of the data, is described in section 2.2.

Table 1. Bank & Country Summary Statistics

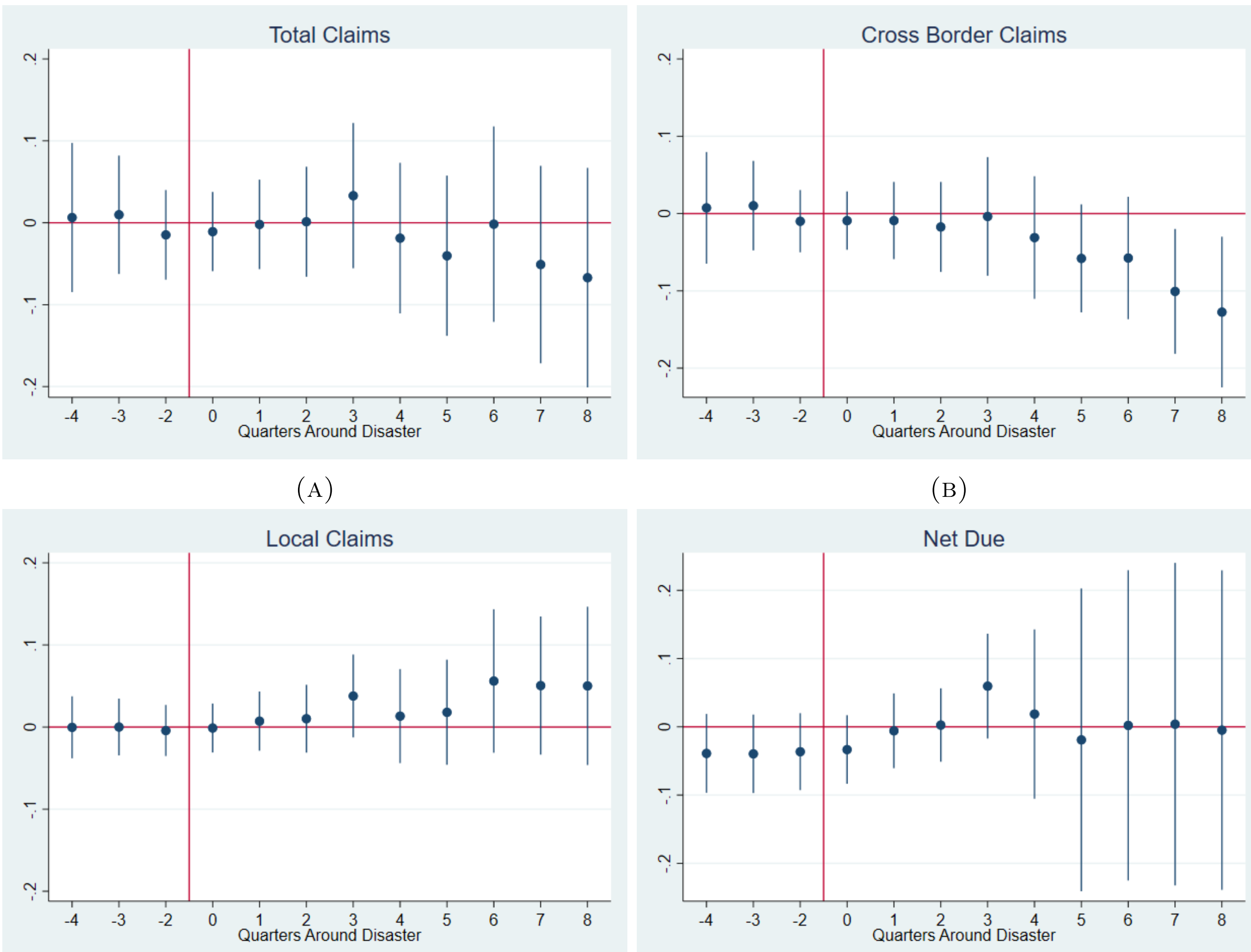
This table displays summary statistics for variables of interest aggregated at the bank and country level. Statistics are displayed for quarters at the beginning and end of the sample, as well as for the entire sample.

		Bank		Country	
		Mean	Median	Mean	Median
Number of Offices	1985Q1	6	3	8	8
	2019Q1	9	5	12	11
	Sample	6	3	11	9
Average Local Claims	1985Q1	6.93	0	15.43	3.89
	2019Q1	66.99	0	140.54	25.21
	Sample	49.3	0	108.96	25.95
Average Total Claims	1985Q1	29.11	8.11	48.52	35.62
	2019Q1	240.39	18.22	461.14	239.05
	Sample	158.72	20.68	276.70	113.46
Average Cross Border Claims	1985Q1	22.15	8.11	33.09	19.2
	2019Q1	173.4	18.23	320.60	105.32
	Sample	109.41	17.32	167.74	56.69
Average Net Due	1985Q1	2.45	0	2.75	0.23
	2019Q1	42.83	0	67.73	7.92
	Sample	10.88	0	5.35	1.85

Source: FFIEC 009 Cross Country Exposure Report, IMF IFS, Thomson Reuters Eikon, OECD, Authors' Analysis. The EM-DAT flat files can be found at www.emdat.be. How the EM-DAT data is used, including any author manipulations of the data, is described in section 2.2.

Figure 2. Dynamic Country-Level Disaster Treatment Effects

These figures present the stacked difference-in-differences country-level estimates of the dynamic effects of natural disasters one year pre-disaster to two years post-disaster. Results are shown for total claims (a), cross-border claims (b), local claims (c), and net due (d) at the country level. The red vertical line represents the disaster event quarter, with the coefficient on the quarter before the disaster (not shown) normalized to zero. 95% standard errors are clustered at the country level.

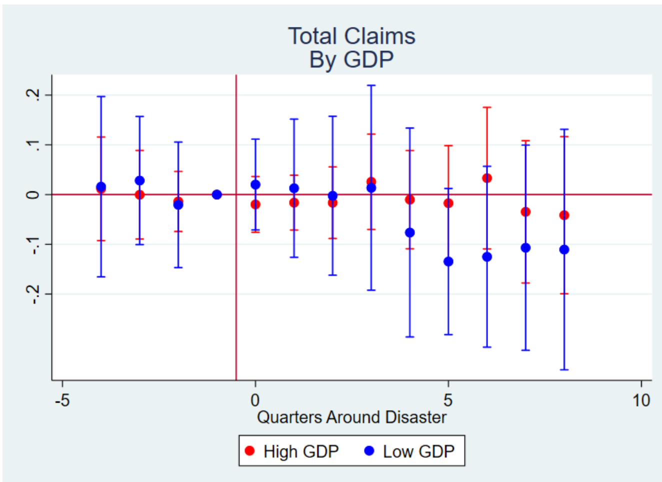


(a) (b) (c) (d)

Source: FFIEC 009 Cross Country Exposure Report, EM-DAT, IMF IFS, Thomson Reuters Eikon, OECD, Authors' Analysis. The EM-DAT flat files can be found at www.emdat.be. How the EM-DAT data is used, including any author manipulations of the data, is described in section 2.2.

Figure 3. Dynamic Disaster Treatment Effects by Country GDP

These figures present the stacked difference-in-differences country-level estimates of the dynamic effects of natural disasters one year pre-disaster to two years post-disaster split by countries having an above-median (red) or a below median (blue) GDP. The red vertical line represents the disaster event quarter, with the coefficient on the quarter before the disaster (not shown) normalized to zero. 95% standard errors are clustered at the country level.



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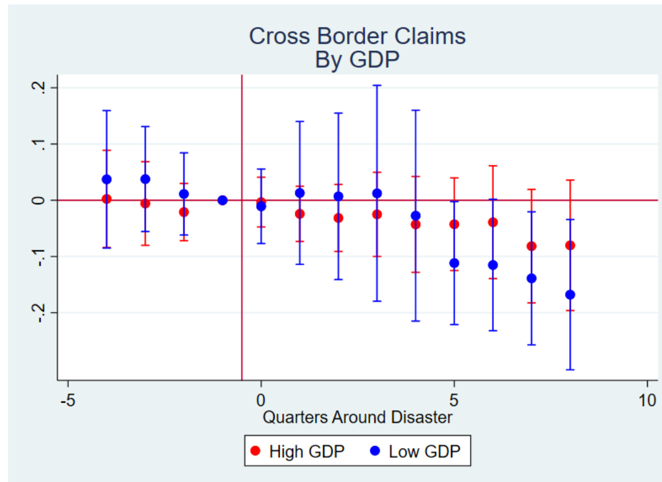

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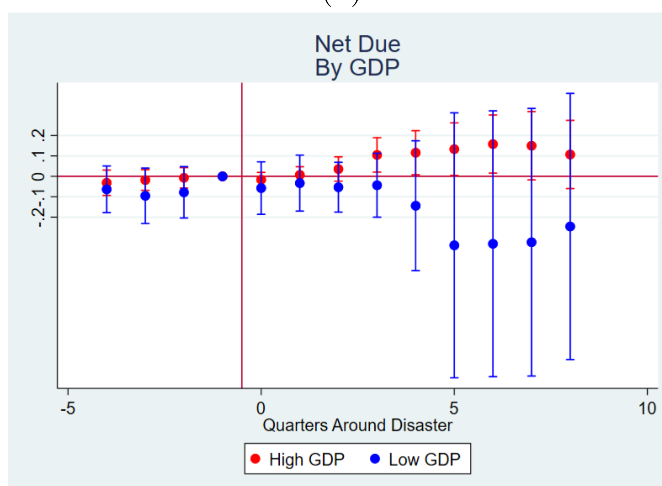

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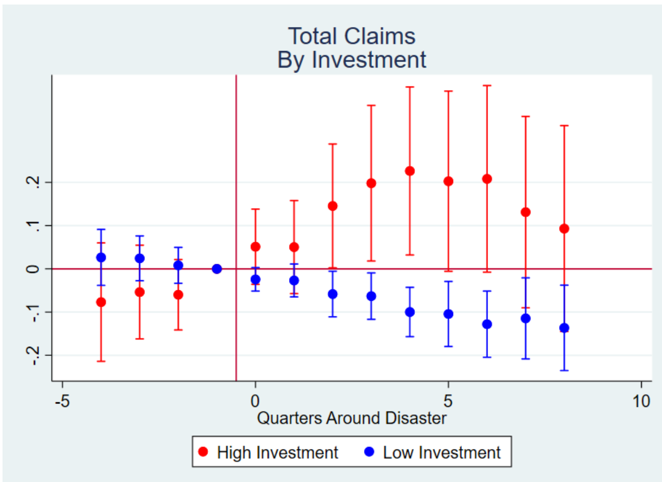
Source: FFIEC 009 Cross Country Exposure Report, EM-DAT, IMF IFS, Thomson Reuters Eikon, OECD, Authors' Analysis. The EM-DAT flat files can be found at www.emdat.be. How the EM-DAT data is used, including any author manipulations of the data, is described in section 2.2.

Figure 4. Dynamic Bank-Level Disaster Treatment Effects by Pre-Disaster Investment Share

These figures present the stacked difference-in-differences bank-level estimates of the dynamic effects of natural disasters one year pre-disaster to two years post-disaster split by banks having an above-median (red) or a below median (blue) share of their pre-disaster investment in the treated country. The red vertical line represents the disaster event quarter, with the coefficient on the quarter before the disaster (not shown) normalized to zero. 95% standard errors are clustered at the country level.



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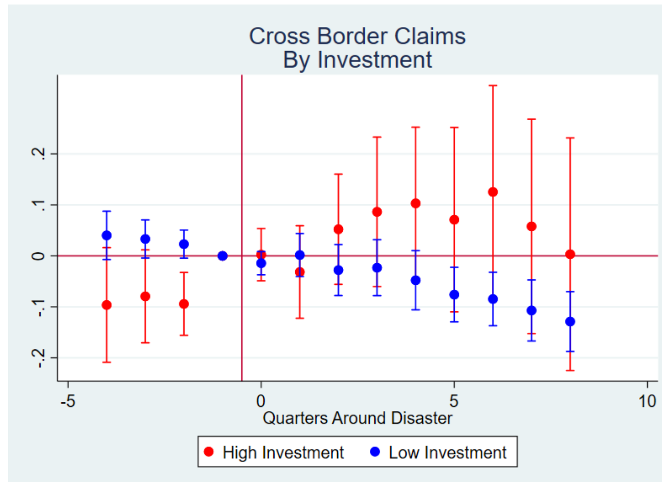

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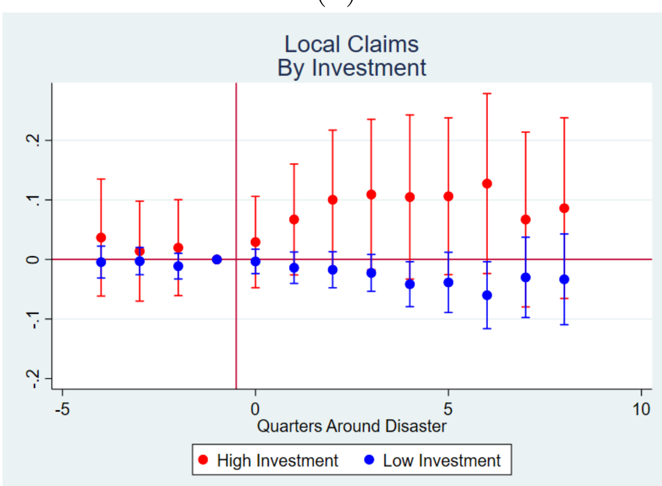

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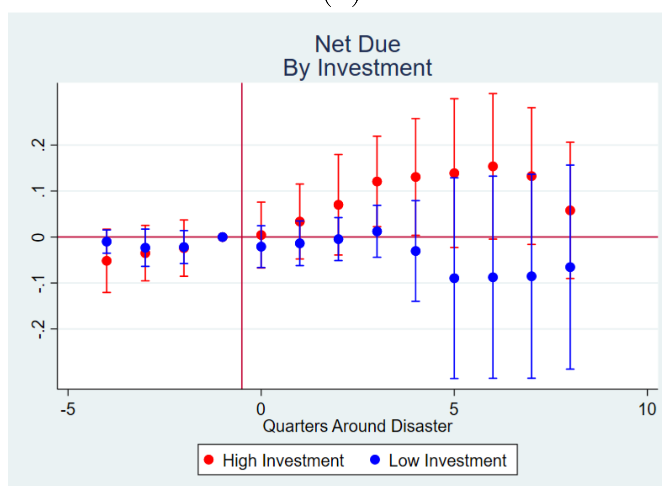

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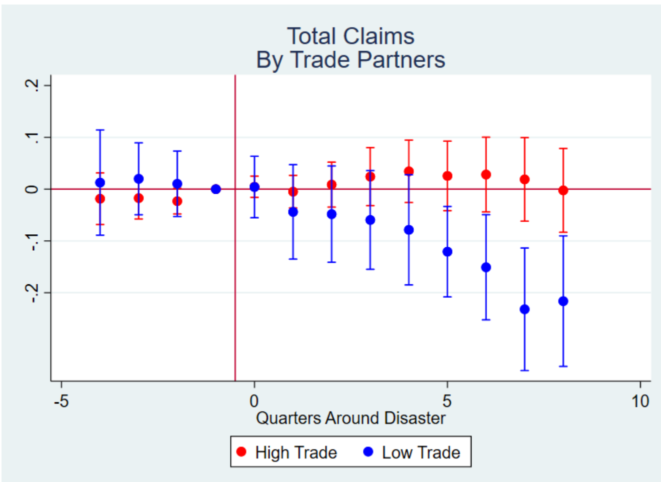
Source: FFIEC 009 Cross Country Exposure Report, EM-DAT, IMF IFS, Thomson Reuters Eikon, OECD, Authors' Analysis. The EM-DAT flat files can be found at www.emdat.be. How the EM-DAT data is used, including any author manipulations of the data, is described in section 2.2.

Figure 5. Dynamic Treatment Effects by Pre-Disaster Trade

These figures present the stacked difference-in-differences bank-level estimates of the dynamic effects of natural disasters one year pre-disaster to two years post-disaster split by banks with an above-median (red) or a below median (blue) share of their parent country's pre-disaster trade the treated country. The red vertical line represents the disaster event quarter, with the coefficient on the quarter before the disaster (not shown) normalized to zero. 95% standard errors are clustered at the country level.



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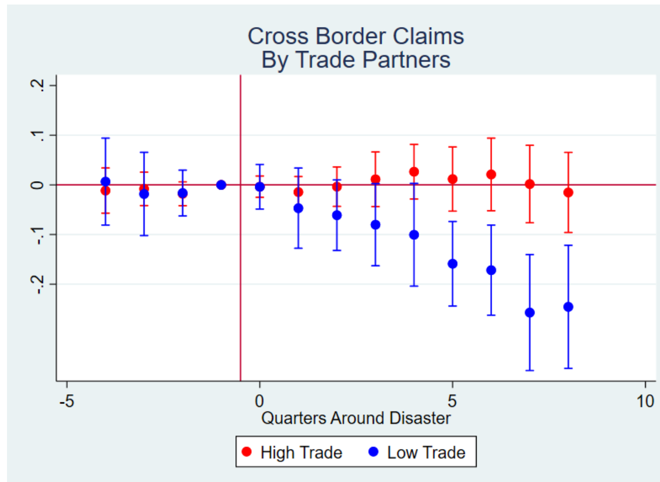

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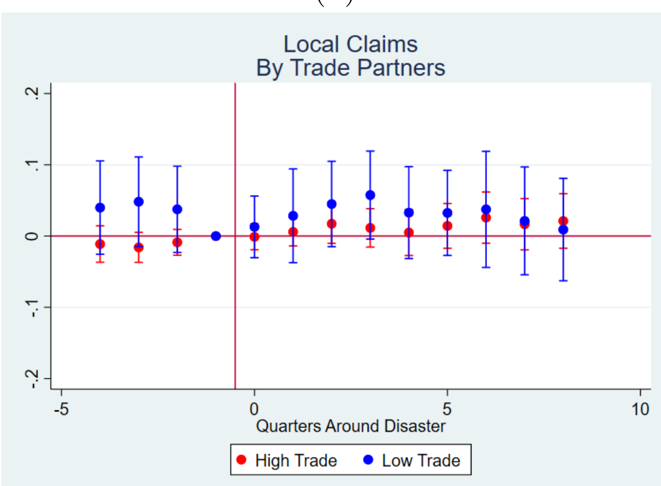

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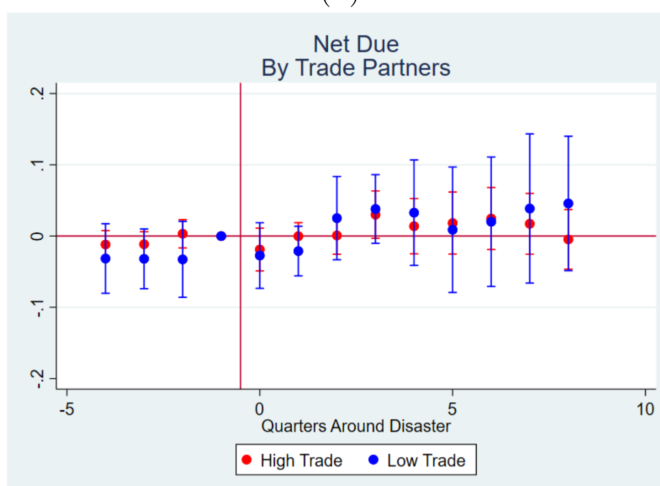

(D)

Source: FFIEC 009 Cross Country Exposure Report, EM-DAT, ITDP-E, IMF IFS, Thomson Reuters Eikon, OECD, Authors' Analysis. The EM-DAT flat files can be found at www.emdat.be. How the EM-DAT data is used, including any author manipulations of the data, is described in section 2.2.

TABLE 2. Bank & Country Summary Statistics: High vs. Low Trade Countries

This table displays summary statistics for variables of interest aggregated at the bank and country level for country offices in countries for which the United States has high and low trade shares. Statistics are displayed for quarters at the beginning and end of the sample, as well as for the entire sample.

		Bank				Country			
		High		Low		High		Low	
		Mean	Median	Mean	Median	Mean	Median	Mean	Median
Number of Offices	1985Q1	4	3	5	2	4	4	7	6
	2019Q1	9	7	5	1	9	9	8	7
	Sample	5	3	4	1	6	6	8	7
Average Local Claims	1985Q1	12.85	0	1.77	0	17.19	1.15	5.68	3.5
	2019Q1	123.59	0	9.2	0	174.77	31.87	38.61	19.38
	Sample	78.95	0	14.21	0	126.78	19.31	47.68	16.35
Average Total Claims	1985Q1	43.51	10.38	17.69	8	53.82	38.36	27.18	18.33
	2019Q1	407.43	17.82	71.66	12.12	553.73	353.76	161.42	66.36
	Sample	251.26	22.77	40.65	6.4	347.12	172.32	99.50	43.76
Average Cross Border Claims	1985Q1	30.65	10.38	15.92	8	36.63	24.50	21.49	12.63
	2019Q1	283.83	17.82	62.45	11.5	378.96	158.46	122.8	28.44
	Sample	172.30	19.45	26.44	5.60	220.34	91.19	51.82	20.02
Average Net Due	1985Q1	4.63	0	0.17	0	5.11	0.16	-1.36	0
	2019Q1	84.98	0	-9.17	0	130.41	6.64	-3.70	2.13
	Sample	19.20	0	-8.08	0	27.70	1.74	-19.04	-0.01

Source: FFIEC 009 Cross Country Exposure Report, ITDP-E, IMF IFS, Thomson Reuters Eikon, OECD, Authors' Analysis.

Table 3. Bank & Country Summary Statistics: High vs. Low Investment Countries

This table displays summary statistics for variables of interest aggregated at the bank and country level for country offices in countries for which banks have high investment share. Statistics are displayed for quarters at the beginning and end of the sample, as well as for the entire sample.

		Bank				Country			
		High		Low		High		Low	
		Mean	Median	Mean	Median	Mean	Median	Mean	Median
Number of Offices	1985Q1	4	3	7	5	6	5	6	6
	2019Q1	7	5	6	2	8	9	6	7
	Sample	5	3	5	3	7	7	8	8
Average Local Claims	1985Q1	16.54	0	0.49	0	34.73	5.65	3.31	0.57
	2019Q1	141.831	0	4.99	0	301.85	14.4	19.98	0.72
	Sample	107.19	0	3.1	0	240.7	43.35	12.79	0.86
Average Total Claims	1985Q1	65.36	19.87	5.14	2	107.69	83.22	12.43	9.68
	2019Q1	497.93	43	19.9	1.45	954.68	746.15	55.64	32.25
	Sample	341.04	47.66	12.88	2.16	589.29	395.45	30.44	17.23
Average Cross Border Claims	1985Q1	48.81	19.87	4.64	2	72.95	65.07	9.12	8.63
	2019Q1	356.10	42.50	14.90	1.45	652.82	413.26	35.65	19.61
	Sample	233.84	39.69	9.77	2.08	348.59	203.05	17.65	10.45
Average Net Due	1985Q1	6.29	0	-0.17	0	9.51	0.65	-1.39	0
	2019Q1	87.69	0	2.63	0	117.99	0.11	4.44	0.11
	Sample	25	0	-0.68	0	29.26	1.25	-5.71	0

Source: FFIEC 009 Cross Country Exposure Report, EM-DAT, ITDP-E, IMF IFS, Thomson Reuters Eikon, OECD, Authors' Analysis. The EM-DAT flat files can be found at www.emdat.be. How the EM-DAT data is used, including any author manipulations of the data, is described in section 2.2.

Table 4. Country Level Treatment Effect

This table shows the stacked difference-in-differences country-level disaster treatment effect estimates. All bank-level claims, liabilities, and net due variables are aggregated to the country level. The $\text{post}_{t^*\to t^*+4}$ variable is an indicator equal to 1 for the first four quarters after the natural disaster occurs, and $\text{post}_{t^*+4\to t^*+8}$ is equal to 1 during the second year after the natural disaster. Treat is an indicator equal to 1 for the country that experienced the natural disaster and 0 otherwise. Each column displays the results for a different dependent variable (Total Claims, Cross-Border Claims, Local Claims, and Net Due). All specifications include disaster-by-country and disaster-year-quarter fixed effects. Standard errors are clustered at the country level and reported below each regression estimate.

	(1)	(2)	(3)	(4)
VARIABLES	Total Claims	Cross-Border Claims	Local Claims	Net Due
$\text{post}_{t^*\to t^*+4}\times$ treat	0.000198	-0.0160	0.0146	0.0371
	(0.0428)	(0.0372)	(0.0179)	(0.0378)
$\text{post}_{t^*+4\to t^*+8}\times$ treat	-0.0404	-0.0878**	0.0448	0.0243
	(0.0609)	(0.0428)	(0.0407)	(0.115)
Disaster-Country FE	Yes	Yes	Yes	Yes
Disaster-Year-quarter FE	Yes	Yes	Yes	Yes
Observations	30,017	30,017	30,017	30,017
R-squared	0.735	0.760	0.836	0.858

*** p<0.01, ** p<0.05, * p<0.1

Source: FFIEC 009 Cross Country Exposure Report, EM-DAT, IMF IFS, Thomson Reuters Eikon, OECD, Authors' Analysis. The EM-DAT flat files can be found at www.emdat.be. How the EM-DAT data is used, including any author manipulations of the data, is described in section 2.2.

Table 5. Treatment Effects by High Versus Low GDP Countries

This table shows the stacked difference-in-differences country-level disaster treatment effect estimates split by countries with above median (panel a) and below median (panel b) GDP. All bank-level claims, liabilities, and net due variables are aggregated to the country level. The $\text{post}_{t^*\to t^*+4}$ variable is an indicator equal to 1 for the first four quarters after the natural disaster occurs, and $\text{post}_{t^*+4\to t^*+8}$ is equal to 1 during the second year after the natural disaster. Treat is an indicator equal to 1 for the country that experienced the natural disaster and 0 otherwise. Each column shows the results for a different dependent variable (Total Claims, Cross-Border Claims, Local Claims, and Net Due). All specifications include disaster-by-country and disaster-year-quarter fixed effects. Standard errors are clustered at the country level and reported below each regression estimate.

Panel A:

VARIABLES	(1) Total Claims	(2) Cross-Border Claims	(3) Local Claims	(4) Net Due
$\text{post}_{t^*\to t^*+4}\times$treat	-0.00146	-0.0199	0.0184	0.0559*
	(0.0408)	(0.0353)	(0.0230)	(0.0310)
$\text{post}_{t^*+4\to t^*+8}\times$treat	-0.00665	-0.0573	0.0497	0.142*
	(0.0762)	(0.0533)	(0.0491)	(0.0837)
Country FE	Yes	Yes	Yes	Yes
Disaster-Year-quarter FE	Yes	Yes	Yes	Yes
Observations	20,228	20,228	20,228	20,228
R-squared	0.695	0.744	0.834	0.878

*** p<0.01, ** p<0.05, * p<0.1

Panel B:

VARIABLES	(1) Total Claims	(2) Cross-Border Claims	(3) Local Claims	(4) Net Due
$\text{post}_{t^*\to t^*+4}\times$treat	-0.0301	-0.0409	0.0108	-0.0567
	(0.120)	(0.108)	(0.0315)	(0.0530)
$\text{post}_{t^*+4\to t^*+8}\times$treat	-0.137	-0.163**	0.0255	-0.287
	(0.0899)	(0.0671)	(0.0703)	(0.284)
Disaster-Country FE	Yes	Yes	Yes	Yes
Disaster-Year-quarter FE	Yes	Yes	Yes	Yes
Observations	8,593	8,593	8,593	8,593
R-squared	0.739	0.751	0.793	0.694

*** p<0.01, ** p<0.05, * p<0.1

Source: FFIEC 009 Cross Country Exposure Report, EM-DAT, IMF IFS, Thomson Reuters Eikon, OECD, Authors' Analysis. The EM-DAT flat files can be found at www.emdat.be. How the EM-DAT data is used, including any author manipulations of the data, is described in section 2.2.

Table 6. Bank-Level Treatment Effect Heterogeneity by Pre-Disaster Investment

This table shows the stacked difference-in-differences disaster treatment effect estimates with heterogeneity by pre-disaster investment shares. The "Low Investment" indicator equals 1 for a bank-country pair around a given disaster if the bank had a below-median share of its foreign claims in the country. The $\text{post}_{t^* \to t^*+4}$ variable is an indicator equal to 1 for the first four quarters after the natural disaster occurs, and $\text{post}_{t^*+4 \to t^*+8}$ is equal to 1 during the second year after the natural disaster. Treat is an indicator equal to 1 for the country that experienced the natural disaster and 0 otherwise. Panel (A) has disaster-bank-country and disaster-quarter FE, while panel B replaces the disaster-quarter time FEs with bank-quarter and country-quarter FEs. Each column shows the results for a different dependent variable (Total Claims, Cross-Border Claims, Local Claims, and Net Due). Standard errors are clustered at the country level and reported underneath the coefficient estimates.

Panel A:

VARIABLES	(1) Total Claims	(2) Cross-Border Claims	(3) Local Claims	(4) Net Due
$\text{post}_{t^* \to t^*+4}$×treat×Low Investment	-0.146***	-0.128***	-0.0265	-0.0293
	(0.0373)	(0.0322)	(0.0197)	(0.0191)
$\text{post}_{t^*+4 \to t^*+8}$×treat×Low Investment	-0.181***	-0.174***	-0.0309	-0.0504
	(0.0644)	(0.0529)	(0.0398)	(0.0347)
Disaster-Bank-Country FE	Y	Y	Y	Y
Disaster-Year-Quarter FE	Y	Y	Y	Y
Bank-Year-Quarter FE	N	N	N	N
Country-Year-Quarter FE	N	N	N	N
Observations	400,972	400,972	400,972	400,972
R-squared	0.913	0.861	0.938	0.800

*** p<0.01, ** p<0.05, * p<0.1

Panel B:

VARIABLES	(1) Total Claims	(2) Cross-Border Claims	(3) Local Claims	(4) Net Due
$\text{post}_{t^* \to t^*+4}$×treat×Low Investment	-0.163***	-0.136***	-0.0572***	-0.0621**
	(0.0424)	(0.0391)	(0.0211)	(0.0277)
$\text{post}_{t^*+4 \to t^*+8}$×treat×Low Investment	-0.162**	-0.157**	-0.0310	-0.0970*
	(0.0704)	(0.0632)	(0.0412)	(0.0517)
Disaster-Bank-Country FE	Y	Y	Y	Y
Disaster-Year-Quarter FE	N	N	N	N
Bank-Year-Quarter FE	Y	Y	Y	Y
Country-Year-Quarter FE	Y	Y	Y	Y
Observations	390,130	390,130	390,130	390,130
R-squared	0.933	0.893	0.953	0.826

*** p<0.01, ** p<0.05, * p<0.1

Source: FFIEC 009 Cross Country Exposure Report, EM-DAT, IMF IFS, Thomson Reuters Eikon, OECD, Authors' Analysis. The EM-DAT flat files can be found at www.emdat.be. How the EM-DAT data is used, including any author manipulations of the data, is described in section 2.2.

Table 7. Bank-Level Treatment Effect Heterogeneity by Pre-Disaster Trade

This table shows the stacked difference-in-differences disaster treatment effect estimates with heterogeneity by pre-disaster investment shares. The "Low Trade" indicator equals 1 for a bank-country pair around a given disaster if the bank's parent country had a below-median share of its trade with the country. The $\text{post}_{t^*\to t^*+4}$ variable is an indicator equal to 1 for the first four quarters after the natural disaster occurs, and $\text{post}_{t^*+4\to t^*+8}$ is equal to 1 during the second year after the natural disaster. Treat is an indicator equal to 1 for the country that experienced the natural disaster and 0 otherwise. Panel (A) has disaster-bank-country and disaster-quarter FE, while panel B replaces the disaster-quarter time FEs with bank-quarter and country-quarter FEs. Each column shows the results for a different dependent variable (Total Claims, Cross-Border Claims, Local Claims, and Net Due). Standard errors are clustered at the country level and reported underneath the coefficient estimates.

VARIABLES	(1) Total Claims	(2) Cross-Border Claims	(3) Local Claims	(4) Net Due
$\text{post}_{t^*\to t^*+4}\times$treat$\times$Low Trade	-0.0842*	-0.0640	-0.0127	0.0234
	(0.0492)	(0.0517)	(0.0321)	(0.0225)
$\text{post}_{t^*+4\to t^*+8}\times$treat$\times$Low Trade	-0.223***	-0.215***	-0.0348	0.0335
	(0.0667)	(0.0685)	(0.0444)	(0.0451)
Disaster-Bank-Country FE	Y	Y	Y	Y
Disaster-Year-Quarter FE	Y	Y	Y	Y
Bank-Year-Quarter FE	N	N	N	N
Country-Year-Quarter FE	N	N	N	N
Observations	400,972	400,972	400,972	400,972
R-squared	0.913	0.861	0.938	0.800

*** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) Total Claims	(2) Cross-Border Claims	(3) Local Claims	(4) Net Due
$\text{post}_{t^*\to t^*+4}\times$treat$\times$Low Trade	-0.0988*	-0.0631	-0.0176	0.00831
	(0.0543)	(0.0530)	(0.0337)	(0.0279)
$\text{post}_{t^*+4\to t^*+8}\times$treat$\times$Low Trade	-0.191**	-0.183*	-0.0197	0.0384
	(0.0830)	(0.0943)	(0.0408)	(0.0393)
Disaster-Bank-Country FE	Y	Y	Y	Y
Disaster-Year-Quarter FE	N	N	N	N
Bank-Year-Quarter FE	Y	Y	Y	Y
Country-Year-Quarter FE	Y	Y	Y	Y
Observations	390,130	390,130	390,130	390,130
R-squared	0.933	0.893	0.953	0.826

*** p<0.01, ** p<0.05, * p<0.1

Source: FFIEC 009 Cross Country Exposure Report, EM-DAT, ITDP-E, IMF IFS, Thomson Reuters Eikon, OECD, Authors' Analysis. The EM-DAT flat files can be found at www.emdat.be. How the EM-DAT data is used, including any author manipulations of the data, is described in section 2.2.

Appendices

TABLE A1. Treatment Effect on Trade and Investment Separately

This table shows the stacked difference-in-differences disaster treatment effect estimates with heterogeneity by pre-disaster investment shares and trade together. The “Low Trade” indicator equals 1 for a bank-country pair around a given disaster if the bank’s parent country had a below-median share of its trade with the country, and the “Low Investment” if the bank had a below-median share of its foreign claims in the country. The $\text{post}_{t^* \to t^*+4}$ variable is an indicator equal to 1 for the first four quarters after the natural disaster occurs, and $\text{post}_{t^*+4 \to t^*+8}$ is equal to 1 during the second year after the natural disaster. Treat is an indicator equal to 1 for the country that experienced the natural disaster and 0 otherwise. Panel (A) has disaster-bank-country and disaster-quarter FE, while panel B replaces the disaster-quarter time FEs with bank-quarter and country-quarter FEs. Standard errors are clustered at the country level and reported underneath the coefficient estimates.

VARIABLES	(1) Total Claims	(2) Cross-Border Claims	(3) Local Claims	(4) Net Due
$\text{post}_{t^* \to t^*+4}$×treat×Low Trade	-0.0354	-0.0228	-0.00469	0.0334
	(0.0492)	(0.0514)	(0.0334)	(0.0212)
$\text{post}_{t^*+4 \to t^*+8}$×treat×Low Trade	-0.159**	-0.159**	-0.0255	0.0492
	(0.0632)	(0.0662)	(0.0461)	(0.0449)
$\text{post}_{t^* \to t^*+4}$×treat×Low Investment	-0.146***	-0.127***	-0.0248	-0.0355*
	(0.0358)	(0.0303)	(0.0210)	(0.0186)
$\text{post}_{t^*+4 \to t^*+8}$×treat×Low Investment	-0.163***	-0.153***	-0.0232	-0.0570
	(0.0590)	(0.0479)	(0.0410)	(0.0344)
Disaster-Bank-Country FE	Y	Y	Y	Y
Disaster-Year-Quarter FE	Y	Y	Y	Y
Bank-Year-Quarter FE	N	N	N	N
Country-Year-Quarter FE	N	N	N	N
Observations	400,972	400,972	400,972	400,972
R-squared	0.913	0.861	0.938	0.800

*** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) Total Claims	(2) Cross-Border Claims	(3) Local Claims	(4) Net Due
$\text{post}_{t^* \to t^*+4}$×treat×Low Trade	-0.0936*	-0.0605	-0.0207	0.00334
	(0.0549)	(0.0545)	(0.0328)	(0.0285)
$\text{post}_{t^*+4 \to t^*+8}$×treat×Low Trade	-0.170**	-0.170*	-0.0188	0.0324
	(0.0825)	(0.0956)	(0.0389)	(0.0402)
$\text{post}_{t^* \to t^*+4}$×treat×Low Investment	-0.166***	-0.137***	-0.0570***	-0.0620**
	(0.0426)	(0.0393)	(0.0210)	(0.0280)
$\text{post}_{t^*+4 \to t^*+8}$×treat×Low Investment	-0.168**	-0.162**	-0.0304	-0.0958*
	(0.0707)	(0.0634)	(0.0414)	(0.0522)
Disaster-Bank-Country FE	Y	Y	Y	Y
Disaster-Year-Quarter FE	N	N	N	N
Bank-Year-Quarter FE	Y	Y	Y	Y
Country-Year-Quarter FE	Y	Y	Y	Y
Observations	390,130	390,130	390,130	390,130
R-squared	0.933	0.893	0.953	0.826

*** p<0.01, ** p<0.05, * p<0.1

Source: FFIEC 009 Cross Country Exposure Report, EM-DAT, ITDP-E, IMF IFS, Thomson Reuters Eikon, OECD, Authors’ Analysis. The EM-DAT flat files can be found at www.emdat.be. How the EM-DAT data is used, including any author manipulations of the data, is described in section 2.2.

Table A2. Variables Used in Main Tests

Variable	Source	How to Calculate	Interpretation of Variable	Example
Claims (i.e., lending)				
$TCBCClaims$	FFIEC009	2006-Present: fcexc915+fcexc916 +fcexc917+fcexm851+fcexm852 fcexm853 1984-2006: fcex8580	Contains all claims on any resident of a country being held on the balance sheet of an affiliate bank not in that country.	If the country C affiliate of bank A lends to a business in country B, this will increase bank A's cross border claims on country B.
$LocalClaims$	FFIEC009	2006-Present: fcexc918+fcexc919 +fcexc920+fcexm854+fcexm855 fcexm856 1984-2006: fcex8583	Contains all claims on any resident of a country being held on the balance sheet of the local affiliate bank.	If the country B affiliate of bank A lends to a business in country B, this will increase bank A's local claims on country B.
$TotalClaims$	FFIEC009	$TCBCClaims + LocalClaims$	All consolidated claims on a given country	
Liabilities				
$NetDue$	FFIEC009	fcex8595	The total amount a foreign affiliate owes to the rest of the banking org. An increase in $NetDue$ represents a capital injection into the foreign affiliate bank.	If bank A sees a profitable investment opportunity in country B, it will shift funds internally to the country B affiliate, increasing the country B affiliate's $NetDue$ to the rest of the banking org.
Other Variables				
$TRADE$	ITPD-E gravity dataset		Sum of Agricultural and manufacturing imports between affected country and the parent company of the bank two years prior to the natural disaster	
$INVESTMENT$	FFIEC009	$\frac{TotalClaims_{iv^*t^*}}{\sum_{s\in S} TOTALCLAIMS_{ist}}$	The fraction of a bank i's total claims that the affected country (v^*) made up two years prior to the natural disaster.	

Source: FFIEC 009 Cross Country Exposure Report, Author's Analysis.